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ORIGINAL ARTICLE

Identification of key design parameters of high-speed train for optimal design

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Abstract As a complex mechatronic system, the running stability, safety, and comfort of high-speed train are affected by many design variables. It is of great difficulty to identify a set of effective design parameters to optimize its running performance. The current simulation systems like the SIMPACK can simulate the running dynamics, but cannot be used effectively for optimal design of the train and rail system because there are too many design variables being supposed to be dealt with. Therefore, there is a need to make a software solution from simulation analysis to optimal design so that the computer-aided design (CAD) and engineering (CAE) can be integrated into an integral design process. This paper presents a new method to identify the key design variables against the running performance indicators based on the sensitivity analysis, which in turn bases itself on simulation-oriented surrogate models. In this way, the optimal design of a high-speed train can be successfully conducted because (1) the surrogate model can reduce the simulation time greatly and (2) the design variable space with the key variables will be reduced significantly. The research shows that this method is of practical significance for speeding up the design of high-speed train or similar complex mechatronic systems.

Keyword High-speed train · Surrogate model · Design variable reduction · Sensitivity analysis · Neural network

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1 Introduction

High-speed railway has been developing rapidly in many countries because it is a fast and safe transportation tool with larger capacity, greater comfort, and less environmental impact and CO_2 emissions. As a complex mechatronic system, a high-speed train is composed of control, mechanical, electrical, and communication systems, and its physical performance is determined by the running dynamics, fatigue strength, acoustic, aerodynamic, and other mechanical, especially the dynamic behaviors. Therefore, the relevant structural and functional requirements for its running stability, safety, and comfort performances have to be met by optimizing a big set of design variables. However, the running performances (indicators) are not only related to structural and functional design parameters but also coupled with dynamic interaction between the high-speed train itself and the rail via the wheel rail contact. This system is always associated with high-order nonlinearity, extremely complicated simulation and calculation, long calculation time, large resource consumption, and many difficulties to find reasonable optimization solution. Therefore, the optimal design of high-speed train involves the integration of a very large number of design variables and comprehensive engineering design simulations such as stability analysis and wheel-rail contact dynamics analysis, which are greatly time-consuming and labor-intensive. Decreasing the complexity of design space is becoming a bigger problem in performance design of high-speed train.

This paper presents a neural network-based surrogate model, "the model of models," to identify key design variables from their sensitivity evaluation so as to greatly reduce the design space, the simulation and calculation difficulties, and significantly shorten the design cycle. This technology means to use a small number of sample data, obtained through simulation computation based on SIMPACK, to build a

Table 1 Physical abstraction of high-speed train model

The physical system description (number of each car)	The simulation system description (number of each car)	Notes
Car body (10)	Car body (1)	The body
Framework (2)	Framework (2)	The body
Axle box (8)	Axle box (8)	The body
Wheel set (4)	Wheel set (4)	The body
Axle box spring of primary system (8)	Three direction force element (No. 05) (8)	Force element
Vertical damping of primary system (8)	Springs in series—damping force element (No. 06) (8)	Force element
Tumbler joint of primary system (8)	Tumbler joint of primary system (No. 05) (8)	Force element
Air spring of secondary system (4)	Three direction force element (No. 05) (4)	Force element
Vertical damping of secondary system (4)	Springs in series—damping force element (No. 06) (4)	Force element
Lateral damping of secondary system (4)	Springs in series—damping force element (No. 06) (4)	Force element
Yaw damper (4)	springs in series—damping force element (No. 06) (4)	Force element
Pull rod spring (2)	Three direction force element (No. 05) (4)	Force element
Lateral backstop (4)	Springs in series—damping force element (No. 06) (4)	Force element
Joint between can box and wheelset (8)	Revolute joint (8)	Joint

relatively simple mathematical approximation model without any reduction of the accuracy. This simple mathematical model can be continuously updated in the optimization iteration process and the accuracy of surrogate model will be improved as well. The method has such advantages as small amount and short period of calculation, which help to significantly improve the efficiency of optimization.

In this paper, the main contributions are as follows.

1. The 29 CHST's input variables and 7 performance indicators as response outputs are determined. The Latin hypercube sampling design is carried out and the corresponding 97+6 sample points are generated with SIMPACK software for surrogate model generation. A

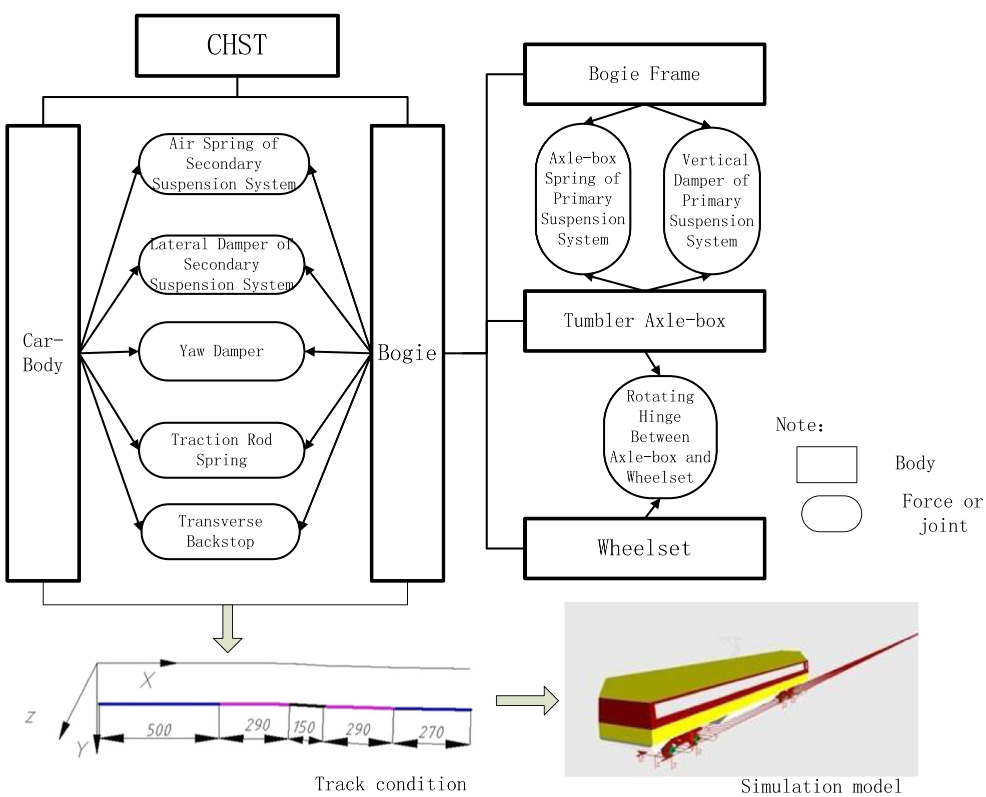

Fig. 1 Track condition and computational simulation model with topological relations of CHST

Table 2 Design variables

Variable	Meaning	Unit	Basic value range	Belong to
x1	Distance between bogie centers	mm	17,000–18,000	Body
x2	Train body quality	Kg	28,000–40,000	Body
x3	Moment of inertia -X	Kg m^2	70,000–120,000	Body
x4	Moment of inertia -Y	Kg m^2	1,200,000–1,700,000	Body
x5	Moment of inertia -Z	Kg m^2	1,100,000–1,500,000	Body
x6	The height from the rail surface to the center of gravity	mm	1,400–1,600	Body
x7	Fixed wheel base	mm	2,400–2,600	Framework
x8	The architecture quality	Kg	2,100–3,100	Framework
x9	Scroll wheel diameter (nominal diameter)	mm	790–860	Wheel set
x10	Wheel back distance	mm	1,351–1,355	Wheel set
x11	Wheel set quality	Kg	1,800–2,200	Wheel set
x12	Moment of inertia -X	Kg m^2	500–750	Wheel set
x13	Moment of inertia -Y	Kg m^2	65–100	Wheel set
x14	Moment of inertia -Z	Kg m^2	500–800	Wheel set
x15	Longitudinal stiffness of the round spring (per box)	KN/m	800–1,150	Primary suspension system
x16	Lateral stiffness of the round spring (per box)	KN/m	800–1,200	Primary suspension system
x17	Vertical stiffness of the round spring (per box)	KN/m	1,000–1,500	Primary suspension system
x18	Vertical damping (per box)	kN s/m	10–30	Primary suspension system
x19	Vertical damping joint stiffness (per box)	MN/m	3–6	Primary suspension system
x20	Longitudinal stiffness of axle box tumbler joint (per box)	MN/m	5–10	Primary suspension system
x21	Lateral stiffness of axle box tumbler joint (per box)	MN/m	4–10	Primary suspension system
x22	Air spring lateral span	mm	2,400–2,500	Secondary suspension system
x23	Yaw damper lateral span	mm	2,400–2,800	Secondary suspension system
x24	Air spring longitudinal stiffness (per spring)	KN/m	100–200	Secondary suspension system
x25	Air spring lateral stiffness (per spring)	KN/m	100–200	Secondary suspension system
x26	Air spring vertical stiffness (per spring)	KN/m	120–300	Secondary suspension system
x27	Vertical damper	KN s/m	20–60	Secondary suspension system
x28	Lateral damper	KN s/m	30–50	Secondary suspension system
x29	Yaw damper joint stiffness (per joint)	MN/m	5–13	Secondary suspension system

neural network surrogate model is established for the replacement of the original complex simulation models such as SIMPACK to reduce the computing time and cost. The accuracy of the model is satisfactorily verified with evaluations.

2. Sensitivity analysis is conducted based on the surrogate model. Then, a set of the key parameters for CHST has been identified. Thus, the design space is greatly decreased.
3. This new design and optimization strategy has been evaluated initially and it is suitable for other complicated systems.

2 Related works

The surrogate model is also named as meta-model, which is frequently used by many scholars to solve some engineering

Table 3 Dynamics indexes

No.	1	2	3	4	5	6	7
Indexes	Lateral stability	Vertical stability	Derailment coefficient	The ratio of wheel load reduction	Lateral wheelset force	Overturning coefficient	Critical speed
Unit					KN		Km/h

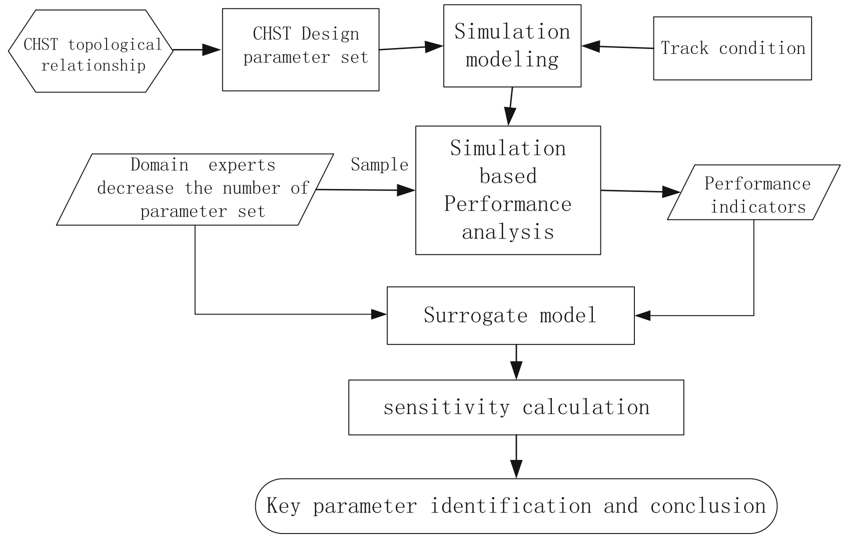

Fig. 2 Design flow

problems and has achieved significant effects. Wang [1], Forrester [2], Simpson [3], and other scholars summarized surrogate model technology and its application in engineering field, many examples among which are related to aerospace applications. Golovidov and Hosder etc. [4, 5] established a response surface model for optimization design of high-speed passenger aircraft flight, and obtained the good result; Unal et al. [6] solved layout optimization problems of a spacecraft by using the response surface surrogate model; Knill et al. [7, 8] predicted the aircraft Euler solution of supersonic drag with the response surface model. Yan [9] predicted and improved combustion rate of natural gas/diesel dual fuel engine. Yi and Malkawi [10] utilized computational fluid dynamics with neural network model to predict site-specific wind parameters for energy simulation. Jiang et al. [11] effectively optimized high-pressure die-casting process parameters by artificial neural network. Yao et al. [12, 13] have done a lot of similar researches. Gorissen [14] had a detailed study of the computer-aided modeling technology-surrogate model in his doctoral dissertation, developed ToolBox SUMO which could be used in MATLAB [15], and provided the development tools for the engineering application technology.

In surrogate model-based researches, the sampling strategy is of great importance, which focuses on how to design the required number of sample points of surrogate model and the multidimensional distribution of these data. Experimental design methods are commonly used, such as orthogonal experimental design [16] and Latin hypercube experimental design [17]. Lee put forward the theory of maximum entropy to select sample points, and applied boundary constraint surrogate model to the reliability optimization [18]. A sequence of exploring experimental design method was put forward by Lin [19] to produce new sample points. Jin et al. used simulated annealing method to generate optimal samples quickly [20]. Surrogate model design space exploration technologies can help engineers not only to determine whether targets or constraints can be ignored, combined, or corrected, but also to reduce the design variables and their value range, and these

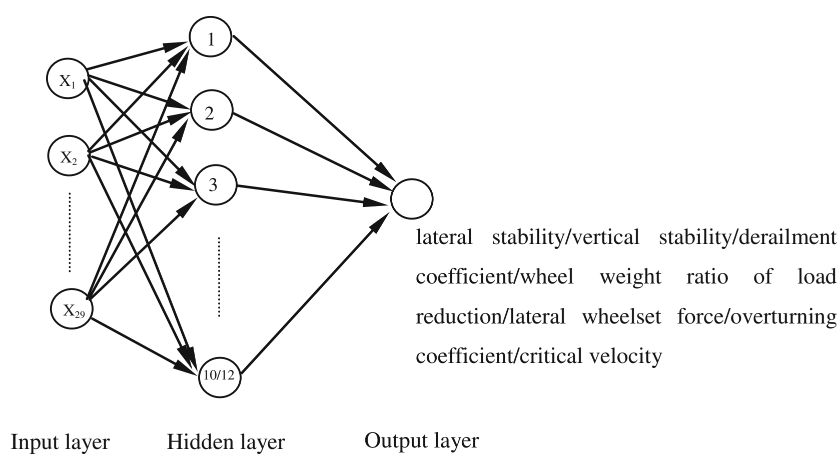

Fig. 3 The structure of neural network

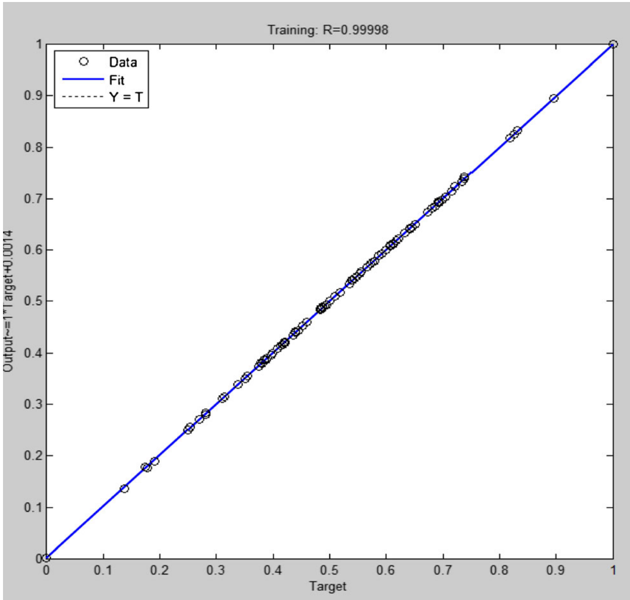

Fig. 4 Correlation coefficient of lateral stability r_1

technologies need less training samples to build accurate surrogate model. Latin hypercube experimental design is widely applied to uncertainty analysis and computer simulation experiment design. Latin hypercube sampling (LHS) [21] is a statistical method to generate samples of plausible collections of parameter values from a multidimensional distribution. The technique was first described by McKay in 1979 [22] and then was further elaborated by Iman et al. [23] in 1981. Detailed computer codes and manuals were later published [24]. There are a lot of relevant review articles, such as [25] and [26].

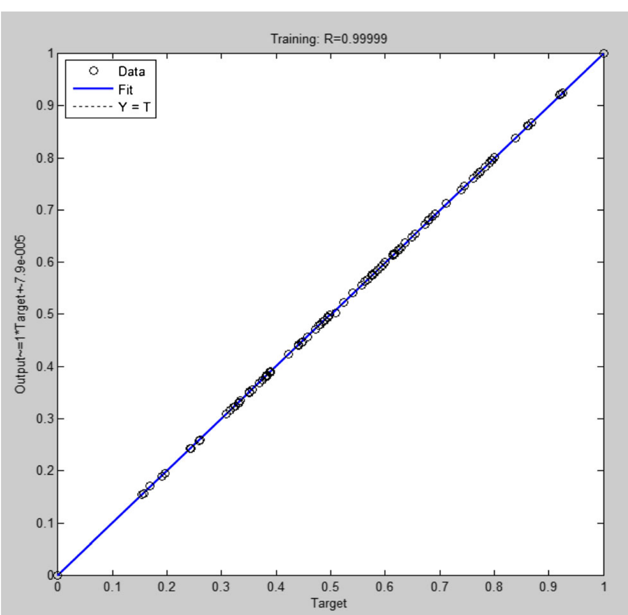

Fig. 5 Correlation coefficient of vertical stability r_2

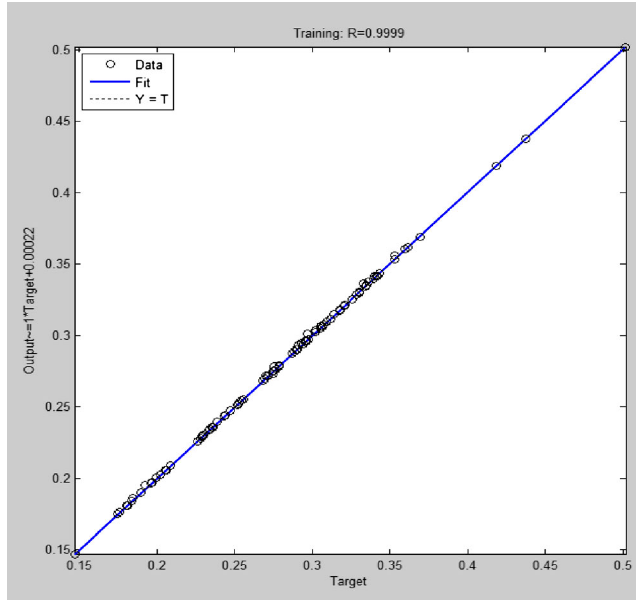

Fig. 6 Correlation coefficient of derailment coefficient r_3

Surrogate model itself is a key factor to be considered in this kind of research. Response surface method, Kriging method, radial basis function, and neural network method are frequently-used surrogate models. Neural network method has the characteristics of simple and mapping ability. As long as the neural network structure is set, the training process will be done automatically by the network. This model can approximate arbitrary function theoretically. Any continuous function can be made by a three-layer forward artificial neural network, and input can be either a discrete function or a continuous variable. However, there are defects such as “over

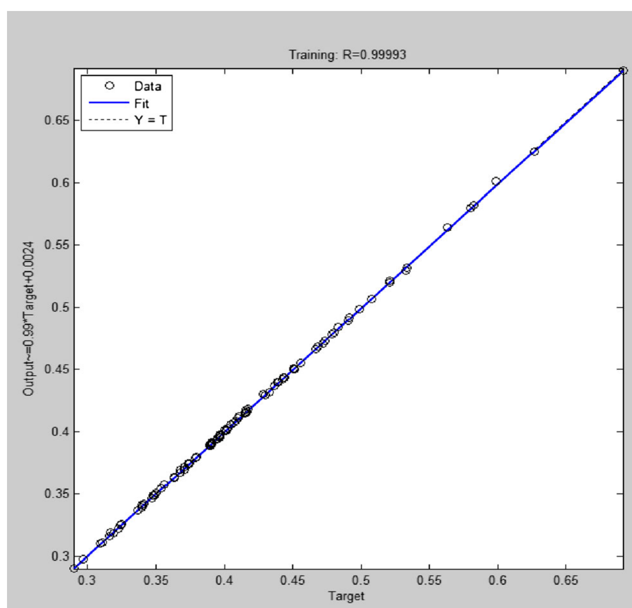

Fig. 7 Correlation coefficient of ratio of wheel load reduction $r4$

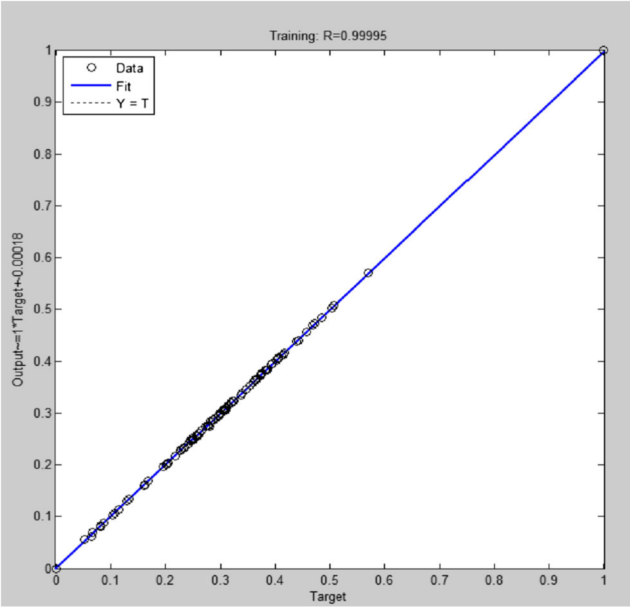

Fig. 8 Correlation coefficient of lateral wheelset force r_5

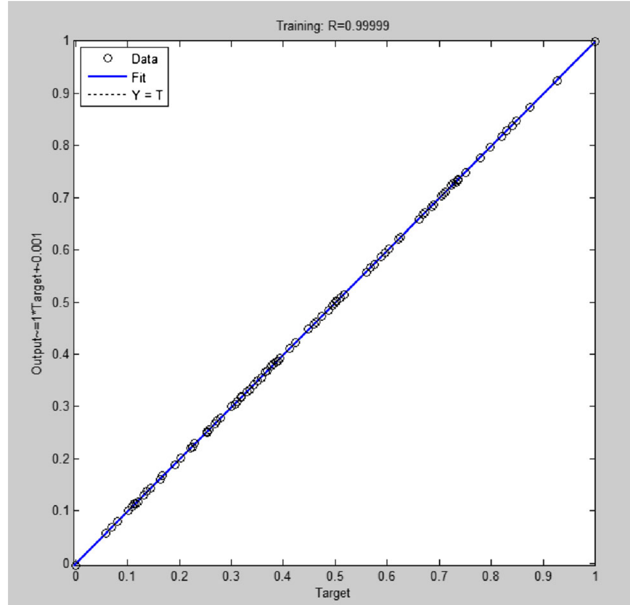

Fig. 10 Correlation coefficient of critical velocity r_7

learning" and "black box" for the neural network mode. Artificial neural networks (ANN) are widely applied in the global approximate model. Most applications of feedback neural network are related to back-propagation neural network (BPN), which is the most mature and widely used neural network technology. By combining the differential method and genetic method, Kim et al. [27] optimized and validated the BNP structure, and used it in CAE design optimization of suspension with an optical flying head. Lee et al. [28] explored the development of the efficient back-propagation neural network (BPN)-based meta-model that ensured the constraint feasibility of approximate optimal solution. Due to the fact that a "black box" effect of a neural network model could not explain the process to make the decision, many commercial companies are originally doubtful about this method. Through the experiment in [29], a method was provided to find the relationship between the input and output and to make sensitivity analysis possible.

A lot of hybrid innovative or novel approaches, such as Cuckoo search, differential evolution algorithm, colony algorithm, particle swarm optimization algorithm, Taguchi's

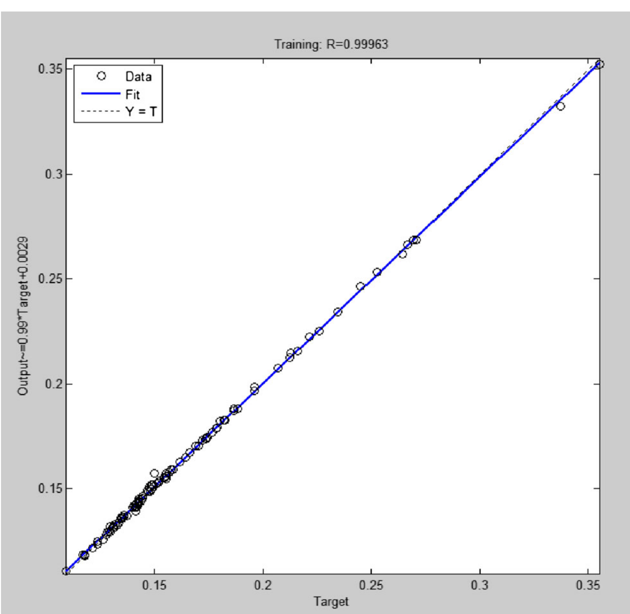

Fig. 9 Correlation coefficient of overturning coefficient r_6

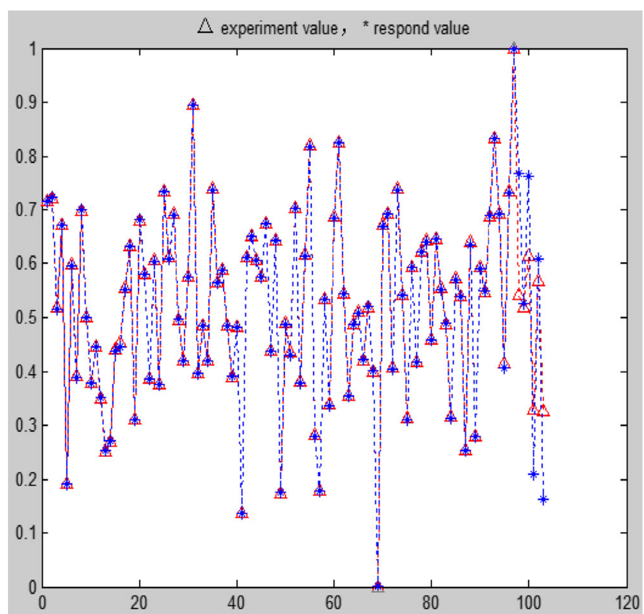

Fig. 11 Numerical comparison of lateral stability

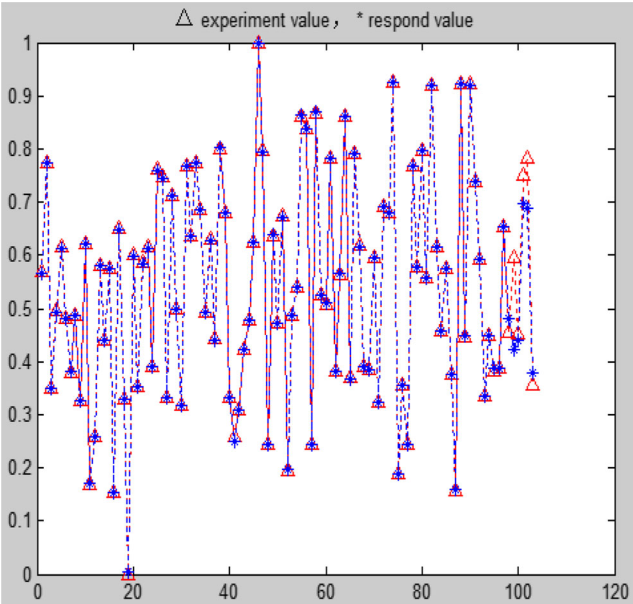

Fig. 12 Numberial comparison of vertical stability

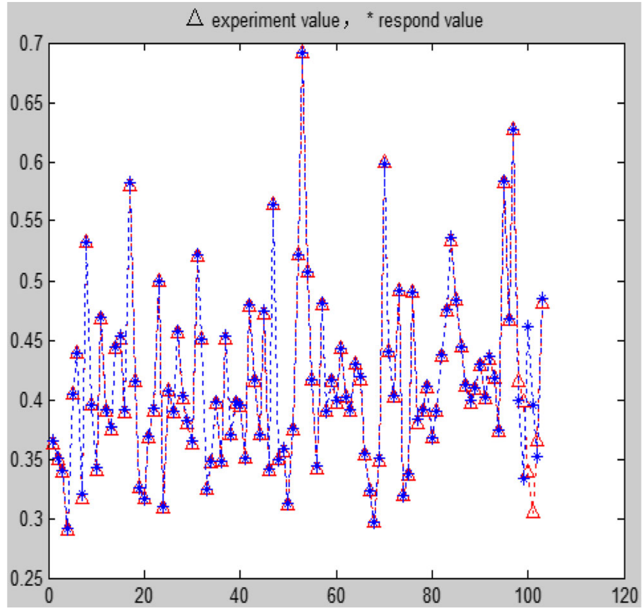

Fig. 14 Numberial comparison of the rate of wheel load reduction

method, and immune algorithm, have been developed and applied in the structural optimal design of vehicle components [40–47] for better performance and lower computational cost. However, the application of surrogate model in high-speed train is very limited. Based on Kriging model, Ding [30] solved bogie fatigue structure optimization. Cheng studied the robust design of suspension system parameters for high-speed trains with Kriging model [31]. Kim used a surrogate model of high-speed train of South Korea (KHST) to study the optimization design and sensitivity analysis [32, 33], respectively. These seem very similar to the method proposed in this paper, but there are some obvious difference in model, design strategy, variable selection, boundary conditions, and design objectives. Sensitivity analysis is very useful for complex engineering design [34–39]. This paper takes into consideration not only the suspension systems but also the body, framework, and wheelset to build model, which makes the original variable set much bigger. Besides the derailment coefficient, stability, the ratio of wheel load reduction, and ride comfort, overturning coefficient and critical velocity are also selected to be taken as safety indexes. Thus, the sensitivity between variables and response performance indexes of

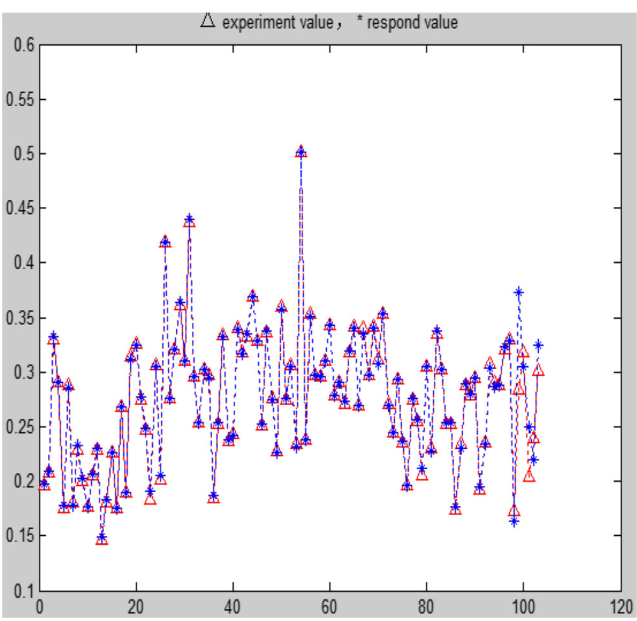

Fig. 13 Numberial comparison of derailment coefficient

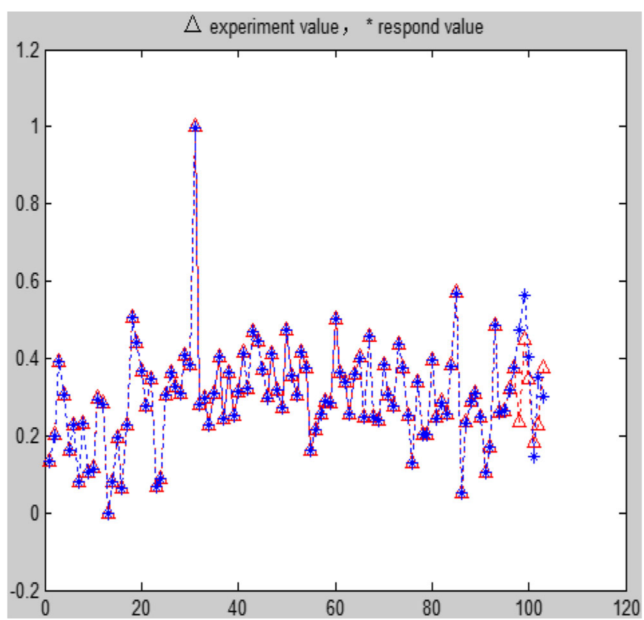

Fig. 15 Numberial comparison of lateral wheelset force

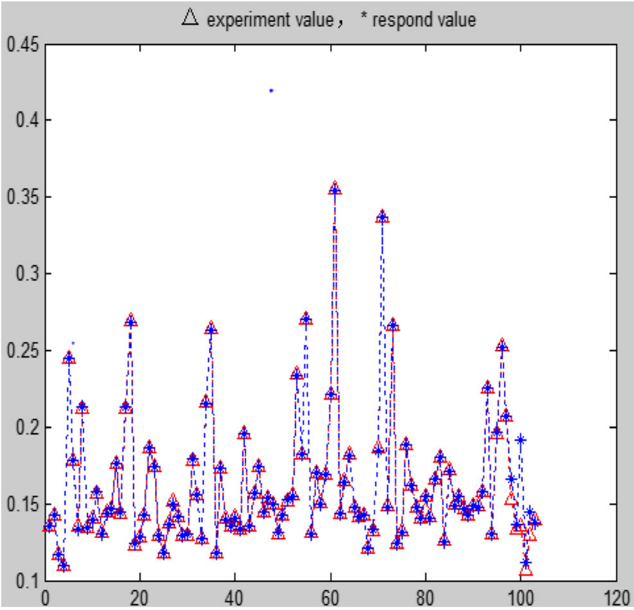

Fig. 16 Numberial comparison of overturning coefficient

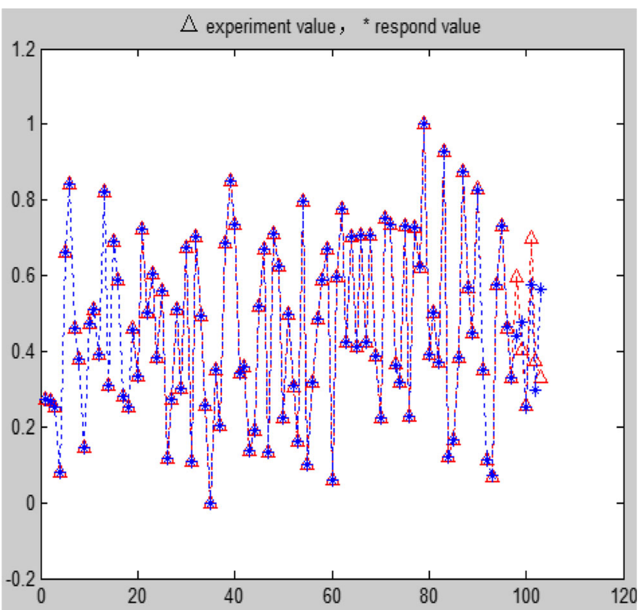

Fig. 17 Numberial comparison of critical velocity

high-speed train should be discussed and built first, and then the key parameters can be identified and evaluated for the later optimization design.

Chinese high-speed train (CHST) are developing fast, and its running speed can exceed 350 km/h. Therefore, it is very necessary to find some ways to guide the optimal selection of design parameters. This paper aims to decrease design complexity and is trying to find out the key performance design parameters and finally to improve the design performance, to reduce the design iterations, and to save design cost.

3 Design space descriptions

For some type of CHST, the dynamic analysis model is mainly composed of car body, bogie (frame, axle, and wheel), and force elements of the primary suspension system and the second suspension system. Physical demonstration of the dynamic simulation model is shown below (Table 1).

From Table 1, the characteristics of the design space can be found as follows:

1. The whole vehicle system is described as a rigid yet flexible multibody system, of which the body, frame, and wheel can be considered flexible to increase the accuracy of calculation. Thus, the freedom and the calculation complexity are greatly increased.
2. Part of the structure is considered as a nonlinear model, such as the air spring, rubber mats, and so on. Therefore, the computational complexity of the system is increased.
3. The inherent wheel-rail system is much more complicated and accurate at a higher speed, which can be calculated by finite element method. The difficulty of the system calculation is increased.
4. The track contains a vibration system with complex degree of freedom, which also increases the difficulty for calculation.

Table 4 Sensitivity values on lateral stability

x1	x2	x3	x4	x5	x6	x7	x8
0.553068	−0.18516	−0.09401	0.212025	−0.57596	0.093828	0.347285	0.160732
x9	x10	x11	x12	x13	x14	x15	x16
−0.081	−0.56868	−0.29709	−0.07118	0.418756	0.190382	0.575498	−0.1654
x17	x18	x19	x20	x21	x22	x23	x24
0.202027	−0.39208	0.043349	−0.0476	0.23383	−0.37717	0.260376	0.045056
x25	x26	x27	x28	x29			
0.955629	0.213424	−0.17297	0.651861	0.144135			

Table 5 Sensitivity values on vertical stability

x1	x2	x3	x4	x5	x6	x7	x8
−0.11026	−0.26768	0.165961	0.079206	−0.11236	−0.25663	−0.41095	−0.23455
x9	x10	x11	x12	x13	x14	x15	x16
0.086186	0.081418	0.172164	0.271894	0.138432	−0.1703	−0.37253	−0.13008
x17	x18	x19	x20	x21	x22	x23	x24
0.377495	−0.00369	0.02351	0.079619	−0.05032	−0.00316	0.068953	−0.39967
x25	x26	x27	x28	x29			
−0.39939	0.360948	1.021231	0.125493	−0.39795			

From the above analysis, we can see even without considering the influence of air dynamics, the dynamic system of high-speed train is so complex and the optimization of performance parameters is of great difficulty. Therefore, it is very meaningful and useful to study the feasibility of a surrogate model-based design method in order to figure out the sensitivity relationship between the vehicle performance parameters and dynamic responses in a multidimensional space to establish a global optimization model, and to find the solution to parameter optimization and improvement for the CHST design.

4 Design methodologies

4.1 Design modeling

Based on the physical model of a high-speed train, a simulation model is built with SIMPACK V8.904 software. The running speed is set at 300 km/h for simulation. The rail line is set to consist of a 500-m long straight line segment, a 290-m long easement curve, and a 150-m long circular curve with an orbit high line of 102.6 mm. Activation condition is the actual test track spectrum. Tread shape is LAM. The track condition and computational simulation model with the topological relations of CHST is shown in Fig. 1.

4.2 Design strategy and process

To reduce the design space and complexity of optimization, first, some field experts are invited to have a focus group study to identify an initial set of important variables needed to be taken into account. All members have their expert knowledge and experience in high-speed railway design. As a result, 29 design variables (Table 2) are found from a wide range of variables based on some type of CHST. They influence greatly on the performance indicators such as safety, stability, comfort, and so on (Table 3). The relationship between the 29 design parameters (Table 2) and 7 performance indicators (Table 3) are then modeled with neural network-based surrogate models, and finally from the surrogate models, sensitivities of the 29 design variables on each performance indicator are analyzed, which are synthesized for the key design parameters identification, design space reduction, and improvement of design performance.

Because of the complexity and time cost of simulation analysis model for each performance indicator, there is a need for establishing a surrogate model (such as neural network-based) with a small amount of simulation sample points in order to conduct sensitivity analyses between each design variable and a performance indicator. With the established surrogate model, the sensitivity analysis can be conducted to identify the key design parameters which are most sensitive to

Table 6 Sensitivity values on derailment coefficient

x1	x2	x3	x4	x5	x6	x7	x8
−0.28851	0.118128	−0.40208	−0.28359	−0.1391	−0.37688	−0.28342	−0.28004
x9	x10	x11	x12	x13	x14	x15	x16
0.133628	−0.16204	0.270299	0.00514	0.056794	−0.444214	−0.05221	0.160779
x17	x18	x19	x20	x21	x22	x23	x24
0.110178	−0.01557	−0.04688	−0.25194	−0.3524	−0.29869	0.471582	0.242644
x25	x26	x27	x28	x29			
0.093611	−0.70535	0.152008	0.135359	0.008344			

Table 7 Sensitivity values on the rate of wheel load reduction

x1	x2	x3	x4	x5	x6	x7	x8
−0.5628	−0.52574	0.409342	−0.22393	0.338866	0.141708	0.231543	−0.37955
x9	x10	x11	x12	x13	x14	x15	x16
0.177526	0.310217	0.836211	0.398576	0.122738	0.841346	−0.85626	0.562881
x17	x18	x19	x20	x21	x22	x23	x24
0.182546	−0.71756	0.117753	0.11272	0.257886	−0.11586	−0.39315	0.644711
x25	x26	x27	x28	x29			
−0.13578	−0.48712	0.293608	−0.01054	−0.52786			

the performance. As a result, some less sensitive parameters can be taken out of the design iterations afterward. Thus, the design space will be reduced. This design strategy can be shown in Fig. 2.

The initial set of design parameters for China high-speed train (CHST) design is derived from the train topological relationship analysis, and then these parameters are used to establish simulation models in connection with track condition. In order to perform simulation studies, domain experts provide advice on the range of each parameter and which parameter should be active and then the corresponding performance indicators from the simulation studies are obtained. The mapping between the parameters and the performance indicators are finally used to establish a surrogate model for conducting the sensitivity analysis and identifying a set of key parameters.

4.3 Surrogate model

4.3.1 Simulation calculation sample design of CHST vehicle dynamics based on Latin hypercube function

In order to construct a neural network-based surrogate model, a set of input data and the corresponding output data are needed to train and evaluate the neural network. Therefore, the simulation calculation sampling design is conducted based on the initially selected 29 design parameters and 7 performance indicators. The sampling design is based on Latin hypercube sample design method and the sample data are produced with SIMPACK software. The process is as follows:

1. Take the initial 29 design variables as input in an initial design space and take the preidentified performance indicators as evaluation outputs.
2. A basic value range of each design parameter is suggested by the experts in the group study. Use Latin hypercube sample design method to normalize the 29*100 parameters. Then the range of value is evenly put into 100 divisions. From the 100 divisions, 3 divisions are removed because they give worse performance responses. As a result, there are 29 variables in total and each has 97 divisions. In this way, the initial value ranges are refined and corrected.
3. After using Latin hypercube sample design method to normalize the final 29*97 parameters, each parameter is divided into 6 levels in the normalized space (i.e., normalized with 97 divisions and clustered into 6 levels). The verification sampling space is 29*6 and generated with the MATLAB standard Latin hypercube sampling function.
4. With SIMPACK software, conduct 97 plus 6 (in total 103) simulation analyses with the sampling parameters as

Table 8 Sensitivity values on lateral wheelset force

x1	x2	x3	x4	x5	x6	x7	x8
−1.5747	−1.94638	0.024928	−1.31955	0.961355	0.470232	−1.26579	0.239503
x9	x10	x11	x12	x13	x14	x15	x16
0.069955	0.271103	−0.61365	1.296224	−0.10191	−0.03598	−0.18304	−0.60379
x17	x18	x19	x20	x21	x22	x23	x24
−0.29683	−1.40372	0.521793	−2.29671	−0.84849	−2.10043	−0.92088	−0.32664
x25	x26	x27	x28	x29			
2.998878	0.603372	0.193924	−1.05531	−1.30514			

Table 9 Sensitivity values on overturning coefficient

x1	x2	x3	x4	x5	x6	x7	x8
0.58394	−0.85565	0.580239	−0.72968	−0.20726	0.409222	0.24316	0.484439
x9	x10	x11	x12	x13	x14	x15	x16
−0.24057	0.052536	0.373142	1.567612	0.13685	0.420285	0.12467	−0.46934
x17	x18	x19	x20	x21	x22	x23	x24
0.006769	0.095373	0.15215	0.990946	0.537664	−0.86491	−1.02585	0.068676
x25	x26	x27	x28	x29			
0.022446	−0.16306	−0.9974	1.25568	0.245026			

inputs and generate the corresponding outputs of key performance indicators for establishing the surrogate model.

4.3.2 Build a high-speed train neural network surrogate model

In this study, a neural network model consists of an input layer, a hidden layer, and an output layer (shown on Fig. 3). The number of neurons in the input layer and the output layer are, respectively, set according to the number of design variables and the performance responses (indicators). The inputs and outputs for 97 simulations are used to train the BP neural network by regression algorithm. In total, there are seven neural network models being established to study the sensitivities of design parameters against each key performance indicators (indexes), namely the lateral stability, vertical stability, derailment coefficient, the ratio of wheel load reduction, lateral wheelset force, overturning coefficient, and critical velocity, all of which are related to the stability, comfort, and safety of this type train.

4.4 Verification and evaluation

In the 97+6 group data built by Latin hypercube function, the 97 groups are used to establish BP neural network surrogate models, and the 6 groups are used to verify the correctness of the models.

The validation formula is as follows (X_1 is simulation values, and X_2 is model values):

$$\text{Absolute error } E = |X_1 - X_2| \tag{1}$$

$$\text{The relative error } \Delta\varepsilon = E/X_1 \tag{2}$$

For the lateral stability, the number of hidden layer neurons in the corresponding model is set at 12 after continuous debugging, and then a BP neural network with the 29-12-1 neuron structure is established. The corresponding BP neural networks with the 29-10-1 neuron structure are built by continuous debugging for other indicators, namely the vertical stability, derailment coefficient, the ratio of wheel load reduction, lateral wheelset force, overturning coefficient, and critical velocity. The correlation coefficients $r1$, $r2$… $r7$, gained from the training, are close to 1, as shown from Figs. 4, 5, 6, 7, 8, 9 to 10. The comparison between the performance values obtained by the surrogate models and experimental values by SIMPACK simulation experiments are shown from Figs. 11, 12, 13, 14, 15, 16 to 17.

The error values of the 97 groups between experimental values and response values of the surrogate model are relatively small, e.g., the maximum relative error of lateral stability is 0.18%. The maximum relative errors are, respectively, 0.22, 1.50, 0.30, 0.11, 4.72, and 0.32 % for vertical stability,

Table 10 Sensitivity values on critical velocity

x1	x2	x3	x4	x5	x6	x7	x8
−0.17982	0.142401	−0.14187	−0.05709	0.331733	−0.26248	−0.18909	−0.33921
x9	x10	x11	x12	x13	x14	x15	x16
0.669435	−0.82283	−0.20049	−0.06745	0.047772	−0.05848	−0.21411	0.139287
x17	x18	x19	x20	x21	x22	x23	x24
−0.00868	0.209083	0.084324	0.83001	−0.65628	0.269717	0.103244	0.224015
x25	x26	x27	x28	x29			
0.359262	−0.33035	0.221772	−0.38468	0.601366			

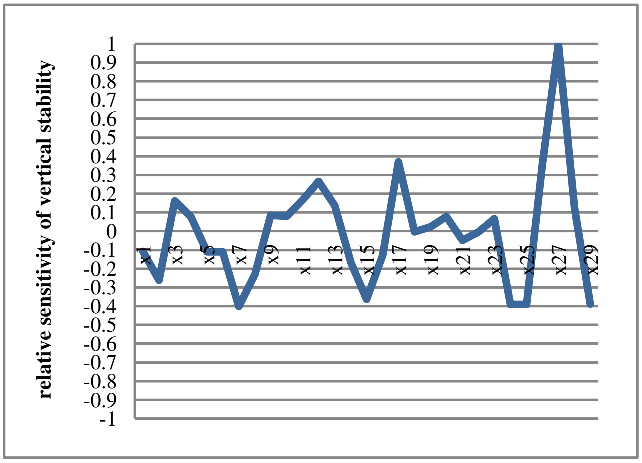

Fig. 18 Relative sensitivity on vertical stability

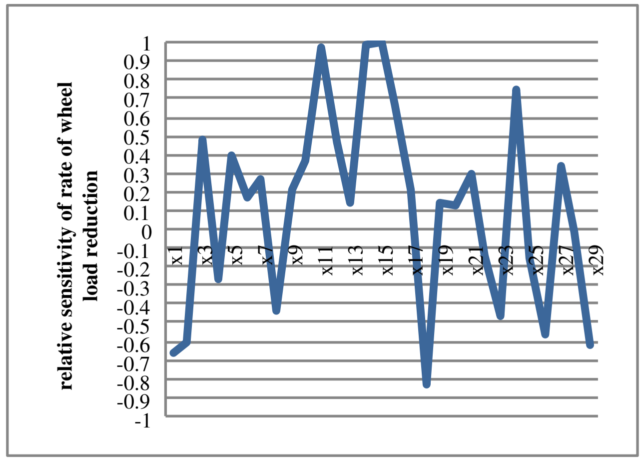

Fig. 20 Relative sensitivity on derailment coefficient

derailment coefficient, the rate of wheel load reduction, lateral wheelset force, overturning coefficient, and the critical velocity.

The six group experimental values from SIMPACK, which are not a part of the training data, are compared with the response values directly from each surrogate model. The maximum relative errors are, respectively, 6.09, 5.88, 7.88, 8.56, 9.38, 9.61, and 4.27 % for the lateral stability, vertical stability, derailment coefficient, the rate of wheel load reduction, lateral wheelset force, overturning coefficient, and the critical speed. The errors of seven surrogate models are less than10 %, and all of average relative errors are no more than 6 %. Therefore, the precision of the models is good enough for identifying sensitivities.

5 Sensitivity analysis

According to the [33], the sensitivity calculation formula is

$$S_{\mathrm{ik}} = \frac{x_i}{o_k}\sum_{j=1}^{n} w_{ij}w_{jk} \tag{3}$$

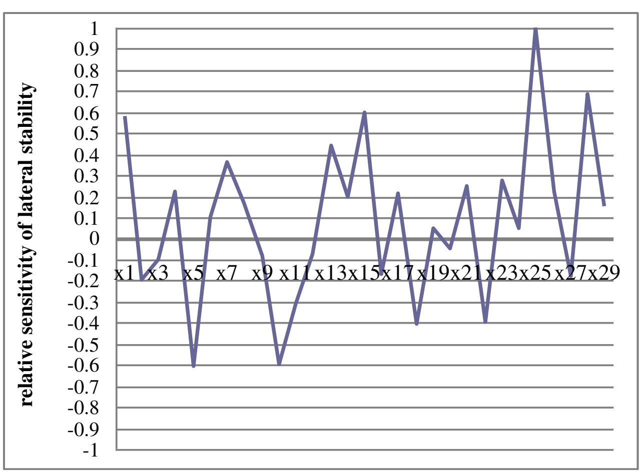

Fig. 19 Relative sensitivity on lateral stability

S_{ik} is the input variable x_i's ($1 \le i \le 29$) sensitivity on the output neuron (response indicator) O_k ($1 \le k \le 7$), w_{ij} ($1 \le j \le n$, in which n is number of hidden layer neurons) is the weighting matrix from input layer neurons to hidden layer neurons, and w_{jk} is the weighting matrix from neurons in hidden layer to output layer neuron. The bigger $|S_{ik}|$ is, the stronger the correlation is. If $|S_{ik}|$ <0, it is a negative correlation.

Take the weighting matrixes of the BP neural network into the formula 4, then 29 input variable's sensitivity values are received to the 7 performance outputs, respectively (shown as Tables 4, 5, 6, 7, 8, 9, and 10).

6 Key parameter identification

From the formula 4 (below), the relative sensitivity S'_{ik} can be calculated from Tables 4, 5, 6, 7, 8, 9, and 10.

$$S'_{ik} = S_{ik}/S_{ik\max} \tag{4}$$

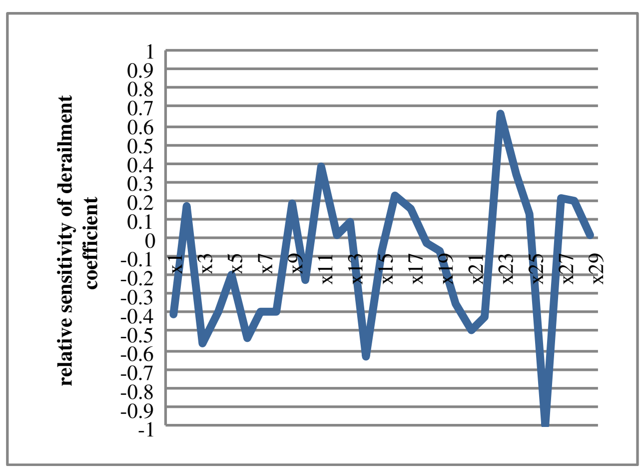

Fig. 21 Relative sensitivity on the rate of wheel load reduction

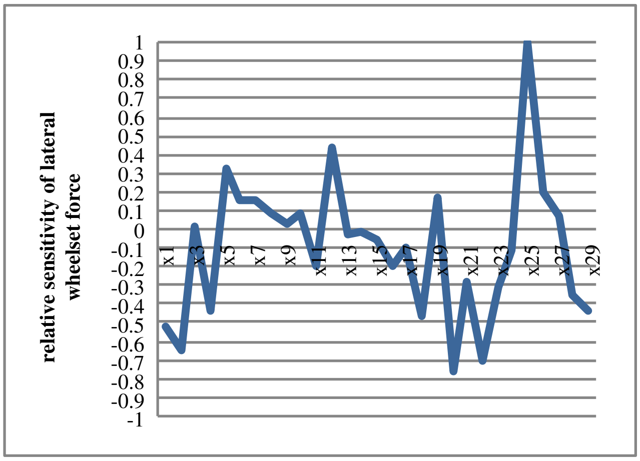

Fig. 22 Relative sensitivity on lateral wheelset force

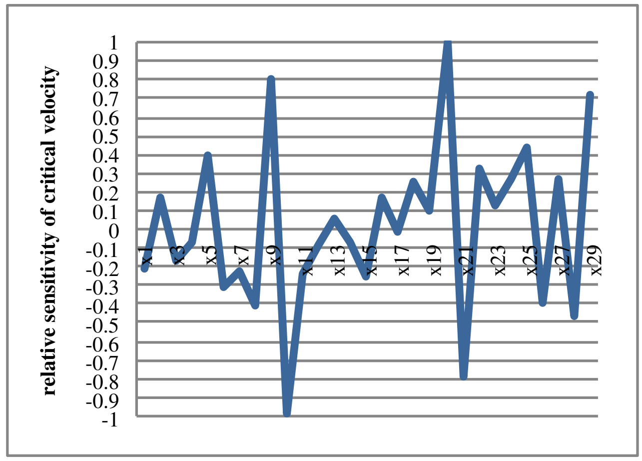

Fig. 24 Relative sensitivity of critical velocity

$S_{ik\max}$ is the biggest sensitivity value in the corresponding table. According to the calculated values, relative sensitivity line chart of 29 input variables on the 7 performance indicators are obtained separately. Figures 18, 19, 20, 21, 22, 23, and 24 show relative sensitivities in terms of lateral stability, vertical stability, derailment coefficient, the rate of wheel load reduction, lateral wheelset force, overturning coefficient, and critical velocity.

With the experience, we set up the key parameter selection criteria as follows: variables with the top five absolute values of relative sensitivity and greater than 65 %, then the table of key effective parameters for each performance is as below (arranged in the correlation order). Only one parameter is suitable under this condition for the vertical stability, so another design parameter is added for more coordination.

The data from the table are analyzed, and the key parameters for the overall design are identified in order to help the further design.

1. The key parameters for the overall design are X9, X10, X11, X12, X14, X15, X18, X20, X21, X24, X25, X26, X27, X28, and X29, which correspond to Scroll wheel diameter, the wheel back distance, wheelset quality, moment of inertia –X, moment of inertia –Z, longitudinal stiffness of the round spring, vertical damping, longitudinal stiffness of axle box tumbler joint, lateral stiffness of axle box tumbler joint of primary suspension, air spring longitudinal stiffness, air spring lateral stiffness, air spring vertical stiffness, vertical damper, lateral damper, and yaw damper joint stiffness of secondary suspension system, respectively. The number of key design variables is reduced from 29 to 15, which greatly reduces the design space.
2. X9, X10, and X11 are structural design parameters, while the others are performance design parameters. This shows that both the input parameters and the structural design parameters have influence on comfort, stability, and safety of the train. But the effect of performance parameters on the high-speed train is much stronger. This is recognized and accepted by mostly relevant field experts. Besides, in this recommendation table, without the structure factor being considered, the key parameters of lateral stability, vertical stability, and critical velocity almost are the same as the analysis in [39]. Therefore, the results are reliable.

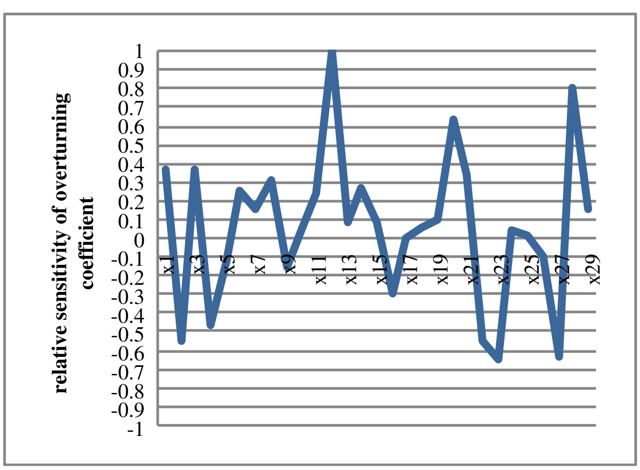

Fig. 23 Relative sensitivity on overturning coefficient

Table 11 Key effective parameters

Key parameters Performance indexes	1	2	3	4	5
Lateral stability	X25	X28			
Vertical stability	X27	X18			
Derailment coefficient	X26	X23			
The rate of wheel load reduction	X15	X14	X11	X18	X24
Lateral wheelset force	X25	X20			
Overturning coefficient	X12	X28			
Critical velocity	X20	X10	X9	X21	X29

3. According to Table 11, the key parameters are figured out according to the correspondent response indicators. The design can be adjusted reasonably based on the sensitivity in order to achieve the optimal effect. For example, the weight value should be increased according to the big sensitivity value for the design optimization, i.e., the greater sensitivity is, the greater the weight value will be. At the same time, X18, X20, X25, and X28, corresponding to vertical damping, longitudinal stiffness of axle box tumbler joint of primary suspension system, air spring lateral stiffness, and lateral damper of secondary suspension system, have great influence on more than one response indicator. So, the optimization design should be adjusted with much greater weight values.

7 Conclusion

During the design of a high-speed train or a similar complex mechatronic system, the practical test/running data cannot be reached. Therefore, simulation experiments are widely used to verify the feasibility of a design at the conceptual design stage. However, building up various complex simulation models and running them require a large amount of calculation, time, and cost. Thus, if all design variables are considered in all design iterations, the optimal design process will be extremely slow. There is a need to identify a set of key design variables based on their sensitivity analysis to participate in the optimal design process to reduce time and complexity.

This paper demonstrates the feasibility to simplify complex simulation models by using neural network-based surrogate models and the possibility to find out the key design variables from the surrogate models based on sensitivity analysis. Consequently, a set of key design variables can be identified and the design parameters space will be reduced. These identified key design variables can be used effectively in an optimal design process at the conceptual design stage with less time and higher efficiency. The surrogate models are useful and effective to replace many cross-domain simulation models, which can speed up the design process with many design iterations. The proposed design method of using surrogate models generated from multiple-domain simulation models and the key design variables identified from sensitivity analysis based on the surrogate models is applicable to many similar design applications and scenarios.

During the model building process, experience is still needed in such aspects as the number of level set, the number of hidden layer neurons and evaluation standard, etc. Meanwhile, the neural network itself is “over-learnt,” so the accuracy of the surrogate model needs to be improved. In the further study, different agent model should be used to make a comparison and test the results or to feedback the analysis by further optimization computation. In this way, the accuracy will be continuously increased.

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