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Research Article

A Systematic Optimization Design Method for Complex Mechatronic Products Design and Development

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Designing a complex mechatronic product involves multiple design variables, objectives, constraints, and evaluation criteria as well as their nonlinearly coupled relationships. The design space can be very big consisting of many functional design parameters, structural design parameters, and behavioral design (or running performances) parameters. Given a big design space and inexplicit relations among them, how to design a product optimally in an optimization design process is a challenging research problem. In this paper, we propose a systematic optimization design method based on design space reduction and surrogate modelling techniques. This method firstly identifies key design parameters from a very big design space to reduce the design space, secondly uses the identified key design parameters to establish a system surrogate model based on data-driven modelling principles for optimization design, and thirdly utilizes the multiobjective optimization techniques to achieve an optimal design of a product in the reduced design space. This method has been tested with a high-speed train design. With comparison to others, the research results show that this method is practical and useful for optimally designing complex mechatronic products.

1. Introduction

It is very difficult to optimally design a complex mechatronic product for many reasons. First, there are a big number of design parameters, usually greater than 100. Second, there are many key performance indicators as either goals or constraints. Third, these parameters are multiple-disciplines related and their determination needs multidisciplinary collaborative efforts. Furthermore, the coupled relations among these parameters and performance indicators are highly nonlinear and vague. In a word, optimally designing a complex mechatronic product is very challenging in a big design space. Therefore, the optimization efficiency is low and it is difficult to obtain a satisfactory solution. In addition, complex mechatronic products are usually composed of many subsystems having different parameters, and their performances are correlated. It is difficult to have an effective system model to describe the relationships between parameters, subsystem performances, and the whole system performances. Thus, Data-Driven Modelling techniques such as artificial neural networks- (ANNs-) based surrogate modelling provide alternative solutions to this problem.

Designing a complex mechatronic product optimally requires considering numerous design parameters and ways of identifying a set of best design variables and obtaining a best design solution effectively under major constraints such as safety/security and stability. The challenges are threefold: (1) the number of design variables or design space is very big; (2) these design parameters have complex system coupling relationships, and it is difficult to take all design parameters in optimization, needing a design space reduction; and (3) a practical model for predicting the coupled vast system performances involves several subsystem performances. Taking a high-speed train as an example, its dynamics performances are related to high-speed train dynamics, high-speed pantograph-catenary dynamics, high-speed train aerodynamics, and high-speed train-track coupling dynamics. Therefore, even with changes in a small set of design variables in practice, the evaluation of the system performances is not straightforward because of their coupled relationships. If each subsystem is modelled as a component, it can be seen that some variables may affect several subsystem models and others may strongly influence only one subsystem. These design variables are coupled and affect different subsystem models. There is a need to construct an overall design performance evaluation model or a goal function for optimal design because so far there is no one established. The ultimate challenge is to develop a systematic optimization design method to solve the above challenges properly and support optimal design of complex mechatronic products.

This paper presents a systematic optimization design method for designing complex mechatronic products. At the beginning, it uses each subsystem dynamics model to conduct design parameter sensitivity analysis and identify key design parameters for design space reduction. Then, a neural network-based surrogate model is established between the identified key design parameters and key performance indicators to describe the whole system performance. Upon the neural network surrogate model, an optimization design model is developed, and finally, an optimal design computing is realized with an improved optimization algorithm for better quality and efficiency. In the current design practice, designing a typical complex mechatronic product such as a high-speed train is mainly by the trial and error method. It lacks a systematic design optimization method for its design. Therefore, we take the optimal design of a high-speed train as a case study to verify the effectiveness of the proposed method.

The paper is structured as follows. Section 2 reviews related work and Section 3 introduces the proposed systematic optimization design method for developing complex mechatronic products. Section 4 shows the case study results, followed by conclusions in Section 5.

2. Related Work

Multiobjective and multidisciplinary optimization in engineering is closely related to our research problems. Many scholars or engineers have conducted a lot of research on optimization frameworks and algorithms. Fabio et al. [1] proposed the use of design optimization techniques to find the ideal truncated full-scale design considering the dynamic effects. Wei et al. [2] proposed a comprehensive framework including a multiobjective interval optimization model and evidential reasoning approach to solve the unit-sizing problem of small-scale integrated energy systems. Lei et al. [3] built a constrained multiphysics model of a motor wheel for an electric vehicle and then optimized it. Liu et al. [4] established a multihierarchical integrated product design data model supporting the multidisciplinary design optimization (MDO) in the Web environment and a Web services-based framework considering uncertainties was proposed. Zheng and Liao [5] improved particle swarm algorithms, which could be applied to many other parameter identification and optimization problems. Zhang et al. [6] presented a modified multiobjective evolutionary algorithm based on the decomposition approach to solve an optimal power flow problem with multiple and competing objectives. Lee et al. [7] proposed a Web services-based MDO framework that enabled the synthesis of available disciplinary and cross-disciplinary resources for MDO via the Globus Toolkit. Gong et al. [8] demonstrated a design sensitivity analysis (DSA) method. Some scholars also applied multidisciplinary optimization to deal with engineering problems in mechanical systems and multibody systems. Kuzmanovic et al. [9] considered damping optimization in a mechanical system excited by an external force. He and McPhee [10] presented a methodology for the design optimization of multibody systems by using genetic algorithms. Hosder et al. [11] considered surrogate functions as an important tool in multidisciplinary design optimization to deal with noisy functions, high computational cost, and the practical difficulty of integrating legacy disciplinary computer codes.

The above methods usually need to establish a large number of equations and formulas for derivation. Thus, their efficiency is low and the solution is not guaranteed. Some scholars proposed using surrogate models to solve optimization problems. Wang and Shan [12] described the meta-modelling techniques in support of engineering design optimization. Golovidov and Kodiyalam [13] described the ideas and methods of how to use an approximate model to do multidiscipline optimizations. Jiang et al. [14] used a neural network model to realize a multiobjective optimization involving process parameters. Kim et al. [15] combined differential and genetic methods for a suspension system design. Yuan et al. [16] promised a methodology for the optimal design of complex mechatronic systems. James and Azad [17] presented two case studies on the use of agent-based modelling in the design of complex systems. Xu et al. [18] proposed two improved strategies for supporting system design optimization. Adaptive meta-model approaches were also proposed. Yi and Malkawi [19] utilized a neural network model for energy simulation. Cheng and Lee [20] explored an efficient back-propagation neural network-based meta-model for approximating optimal solutions. Cheng and Yang studied the optimal design of suspension system parameters for high-speed trains with Kriging model [21].

However, the optimization design of complex mechatronic products is a systematic problem, which involves parameter identification, design space reduction, and optimization strategies. Some scholars studied some of the related problems. Wang [22] considered optimization strategies including sensitivity analysis, surrogate models, and searing algorithms to enable global engineering optimization. Cai et al. [23] presented a general multiagent control methodology for an energy system optimization in a "plug-and-play" manner. Park et al. [24] described the properties of sensitivity analysis between some of the suspension characteristics of the Korean high-speed train as the design variables and the dynamic performance as the response variables. Li et al. [25] presented a new meta-model-based global optimization method using fuzzy clustering for design space reduction. Forrester and Keane [26] reviewed the work on constructing surrogate models and their use in optimization strategies, while Shyy et al. [27] reviewed the fundamental issues arising in surrogate-based analysis and optimization. Zhang et al. [28] presented a new method to identify the key design variables based on the sensitivity analysis for high-speed train design. Kim et al. [29] used a separate meta-model for each performance indicator, requiring multiple meta-models for a multiple-objective optimization. Ma et al. [30] proposed a global sensitivity analysis method by dividing variables in groups. Queipo et al. [31] applied a robust optimization design method to a real complex nonlinear system design. Coello [32] provided a comprehensive discussion on the fundamental issues arising from the use of surrogate-based analysis and optimization.

In summary, the surrogate model technology is useful for the optimization of complex electromechanical systems, and it has a successful application in the optimization of some products. There are a body of work on surrogate modelling and multiobjective optimization. However, for optimally designing complex mechatronic products, it still lacks a systematic approach to guide and guarantee the optimization design of such complex systems. Therefore, this paper proposes a systematic optimization method based on integral design space reduction and system surrogate modelling techniques for designing complex mechatronic products optimally.

3. Systematic Optimization Design Method

In order to improve the design efficiency and reduce the difficulty of performance evaluation (simulation) calculation, this paper puts forward a new systematic optimization design method based on the surrogate model and intelligent multiobjective optimization techniques for designing complex mechatronic products. It includes five stages. In Stage 1, according to the topology structure, design parameters, and boundary conditions of a complex system, the design parameters of the complex system are extracted. In Stage 2, the design parameter space is reduced by expert knowledge or by the parameter sensitivity analysis with each subsystem evaluation (simulation) model. In Stage 3, the key design parameters affecting the whole system design objectives (or running performances) are obtained, forming a reduced design space. In Stage 4, a surrogate model describing the relationship between the whole system performances and the key design parameters is established, and then a corresponding optimization model is developed based on the surrogate model. In Stage 5, intelligent optimization algorithms are used for the optimization design of a complex mechatronic product.

The system optimization design flow is shown in Figure 1. It includes (1) specifying design parameters and objectives, (2) conducting design space reduction, (3) setting up a system surrogate model, (4) setting up an optimization model, and (5) conducting optimization computing.

3.1. Specifying Design Parameters and Objectives. Figure 2 shows the optimal design problem space of a complex mechatronic product related to product structure, design parameters, and performance indicators. For a complex mechatronic product, there are many design parameters associated with a number of subsystems. The design parameters are divided into structural design parameters and performance design parameters. The number of parameters usually is very big and the data range is very wide. At the same time, the running performances of the complex mechatronic product are synthesized in different aspects, so there are a lot of performance indicators (or design objectives).

In order to solve the optimization design problem for a complex mechatronic product, it is necessary to define what the design parameters (variables) are and what the objective indicators are. The objectives of the optimization are defined by considering the comprehensive requirements of the performances. Usually setting up a set of the design objectives is very important, while the design goal (comprehensive objective) function is usually formed by summing up all of the weighted objectives. Weights for each individual objective are determined based on their relative importance and previous design knowledge. So the system optimization is transformed into solving the maximum or minimum value of the comprehensive objective function.

3.2. Design Space Reduction. Within a huge design space, there are many parameters and the coupled relationships between these design parameters and objectives are very complex and usually nonlinear. If m is used to represent the number of design parameters and n for objectives, the design space is a $m \times n$ multidimensional problem. Because the design space is large and high dimensional, it is necessary but difficult to identify the key design variables in the optimal design.

To solve this problem, a method for design space reduction is proposed with two rounds. In round 1, important parameters are chosen by experts with related domain knowledge. In round 2, the important parameters will be used to establish surrogate models against each performance indicator, and then sensitivity analysis is conducted based on the established surrogate models. Finally, according to the sensitivity analysis results, the key design parameters are determined based on a predefined sensitivity threshold. The specific process is shown in Figure 3 and the details can be found in [28].

3.3. Setting Up a System Surrogate Model. For a complex mechatronic product, usually, there is no practical model for describing whole system performances, and instead, there are several subsystem performance (simulation) models within multidisciplinary fields. The whole system performances are nonlinearly coupled with the subsystem performances. Thus, the direct use of subsystem performance simulation models in the optimal design process is difficult because it requires a coupled system simulation method with spatiotemporal synchronization process control over subsystem simulation computing [33]. One big problem with this kind of coupled system simulation is being time consuming and requiring huge computing resources. Especially for the whole system optimal design, this requires persistently iterative simulation and optimization. The cost of computing becomes much higher. For this reason, a whole system surrogate model is proposed as a very good alternative model, to reduce the difficulty of optimization and improve the efficiency of optimization.

The surrogate model is a mathematical model for fitting discrete data using an approximation approach, which can

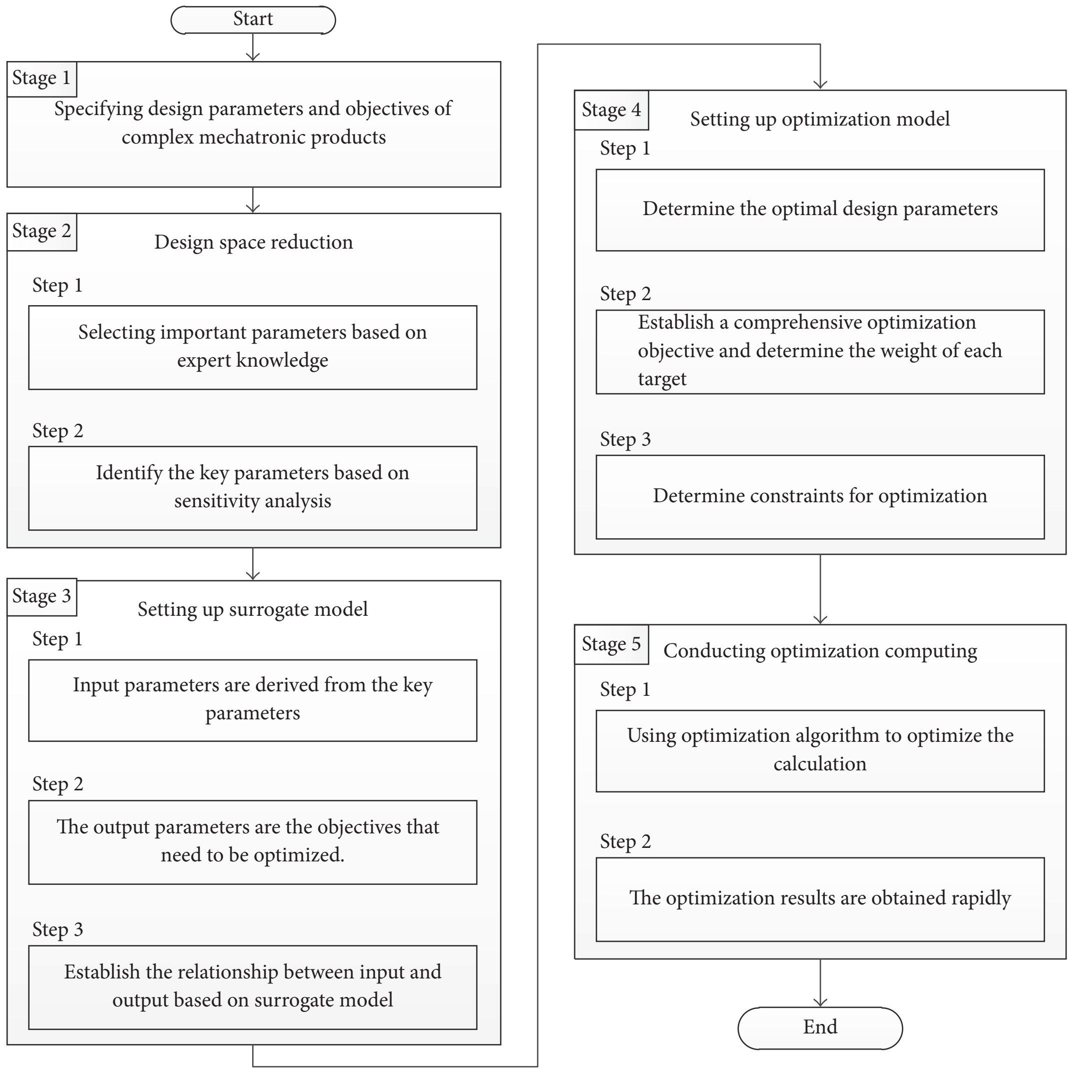

Figure 1: Optimization design flow.

determine key parameters and their value ranges with less training samples and advanced trial design methods. [27, 32] Back-propagation neural network (BPN) is one of these effective surrogate models, and its structure is shown in Figure 4.

The design performances of a complex product are considered at the same time with different performance indexes. When performing an optimal design, it is necessary to meet all these indexes at the same time and thus synthesize these indexes into a comprehensive goal function. Lastly, a multiobjective optimization model can be established based on the surrogate model.

Another aspect is to establish a radial basis function network for the parameters. The establishment of the back-propagation neural network (BPN) parameters includes the accuracy of the model and diffusion factor. The mean square error of the same model can also affect the adjustment of the BPN surrogate model.

For having a surrogate model with high accuracy, RRMSE (Relative Root Mean Square Error) error criterion is used in training. RRMSE of the model is defined as follows:

$$\text{RRMSE} = \sqrt{\frac{\sum_{k=1}^{m}\left(y\left(x^k\right) - \hat{y}\left(x^k\right)\right)^2}{\sum_{k=1}^{m}\left(y\left(x^k\right) - \overline{y}\left(x^k\right)\right)^2}}. \tag{1}$$

Among them, $y(x^k)$ is the actual values with response to the test points x^k; $\hat{y}(x^k)$ is the actual values, with response to the test points x^k; m is the number of the test points; x^k represents test samples set. $\overline{y}(x^k)$ refers to the mean value of the actual responses.

3.4. Setting Up the Optimization Model. The optimization model can be described with the surrogate model as follows:

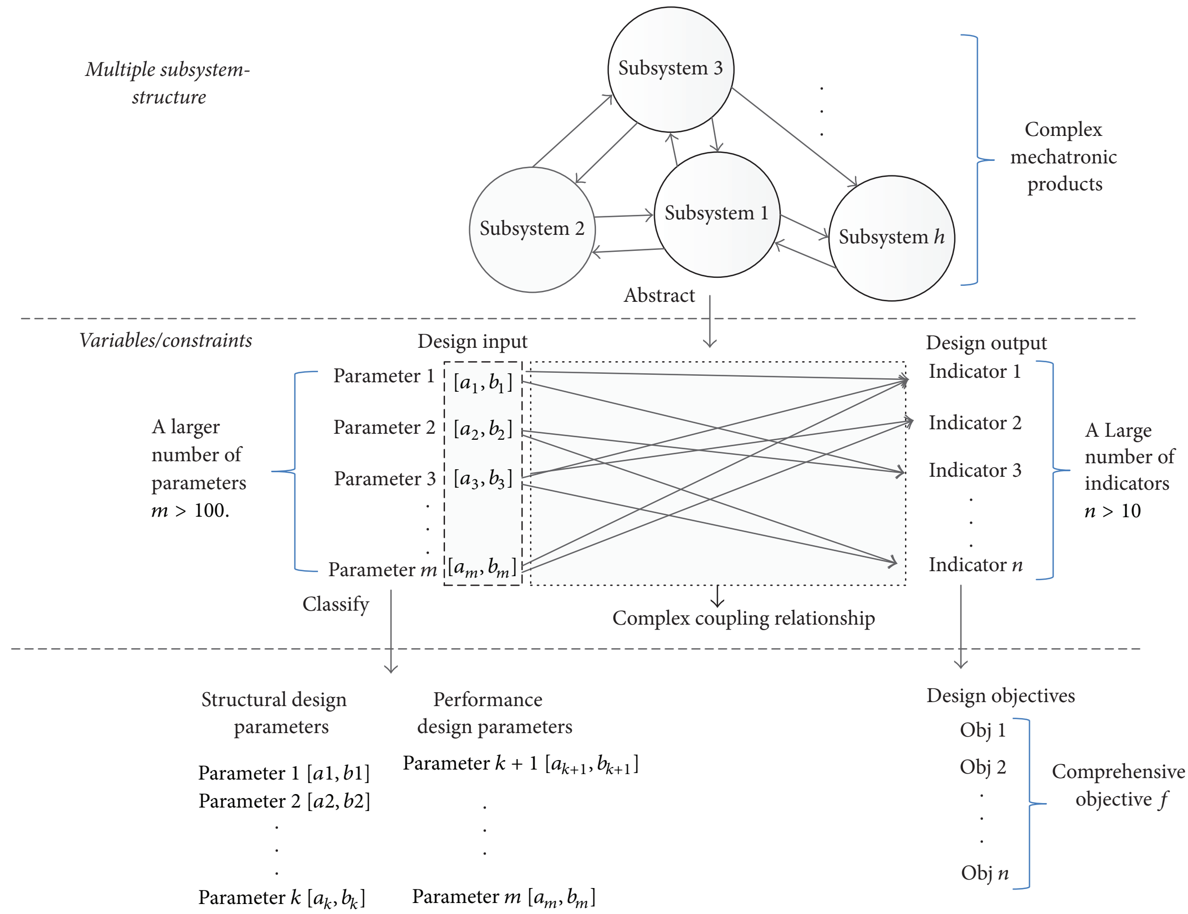

Figure 2: Optimal design problem space of a complex mechatronic product.

(1) Design variables (key design parameters): $x_1, x_2, x_3, \ldots, x_m$

(2) Optimization goal function with subperformance functions (indicators): $f_1, f_2, f_3, \ldots, f_n$

When constructing the optimization goal function F, we need to obtain the best overall performance indicator with a set of design parameters within their constraints. In the optimal design, the target is to obtain the minimum of F. The F can be represented in (2) with subfunctions. For some subfunctions such as $f_{m+1}, \ldots, f_{n-1}, f_n$, they are transformed into the minimum value of F with their reciprocal substitutions because they are expected to achieve the biggest values in real term

$$\begin{aligned} F &= \alpha_1 f_1 + \alpha_2 f_2 + \cdots + \alpha_m f_m + \alpha_{m+1} \frac{1}{f_{m+1}} + \cdots \\ &\quad + \alpha_{n-1} \frac{1}{f_{n-1}} + \alpha_n \frac{1}{f_n} = \sum_{i=1}^{m} \alpha_i f_i + \sum_{j=m+1}^{n} \alpha_j f_j^{-1}, \end{aligned} \tag{2}$$

where $f_1, f_2, \ldots, f_m, f_{m+1}, \ldots, f_n$ represent objective 1, objective 2, ..., objective m, objective $m+1$, and objective n, and $\alpha_1, \alpha_1, \ldots, \alpha_n$ are the corresponding weight coefficients. The multiobjective optimization is to find the minimum F solution. Thus, the goal is to obtain

$$\min \quad (F) = \min \left(\sum_{i=1}^{m} \alpha_i f_i + \sum_{j=m+1}^{n} \alpha_j f_j^{-1} \right). \tag{3}$$

3.5. Conducting Optimization Computing. The optimization of complex mechatronic products is a very complex problem, involving many parameters, indicators, and boundary conditions. Meanwhile, it also requires considering the efficiency and accuracy of optimization. Intelligent optimization algorithm is a good method for speeding up the optimization. Intelligent optimization algorithms include genetic algorithm, differential evolution algorithm, and particle swarm algorithm. Cai and Aref [34] developed a genetic algorithm-(GA-) based optimization procedure. Zheng and Liao [5] realized parameter identification of nonlinear dynamic systems using an improved particle swarm optimization. Qin et al. [35] utilized the differential evolution algorithm (DE) for global numerical optimization.

Each algorithm has its own characteristics. DE (differential evolution) is a parallel optimization algorithm evolved from GA (genetic algorithm), and it has excellent characteristics for global optimization. We select DE in our application

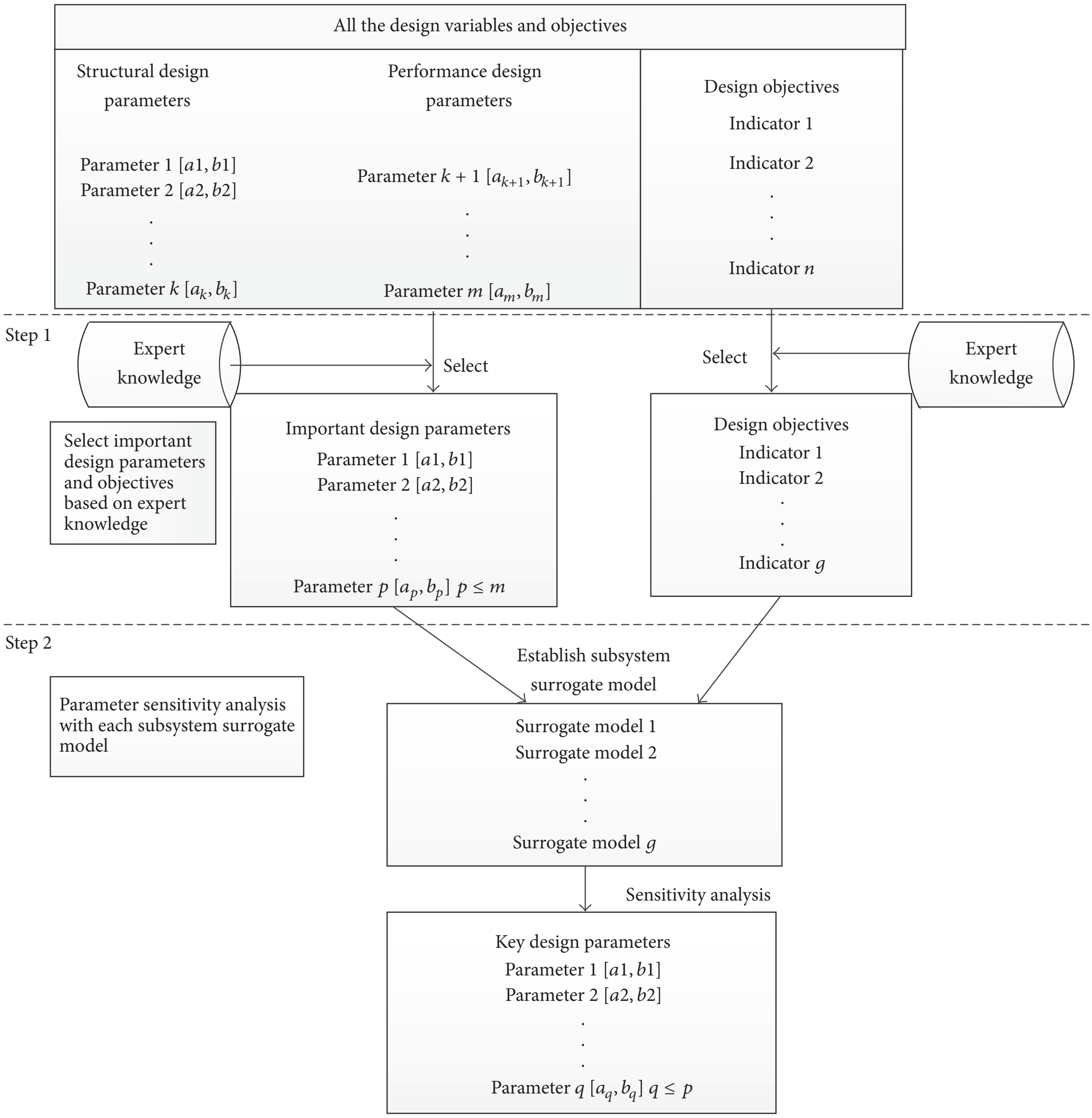

FIGURE 3: The flow of design space reduction.

because DE reportedly has a more effective evolutionary strategy [35] to generate new individuals, which makes it an efficient and powerful population–based stochastic search technique for solving optimization problems over continuous space and the implementation of DE is relatively easy.

The novelty of this systematic optimization design method has twofold. Firstly, it can effectively couple design space reduction and the system surrogate modelling techniques into the system optimization modelling. In the existing literatures, these two techniques are discussed separately; thus, when applying the surrogate modelling technique to develop a surrogate model for describing complex system relationships, there is a general difficulty in determining what parameters in both inputs and outputs should be chosen to establish an effective surrogate model for use in the optimization. Secondly, it demonstrates that the identified key variables from the space reduction are well qualified as the input variables for establishing the corresponding system surrogate model and the optimization model, thus, providing a general form of the system optimization modelling and solving techniques for complex mechatronic product optimal design.

4. Case Study

Here, we demonstrate the proposed optimal design method with a high-speed train design. We validate the system optimization from the following three aspects. The first is to

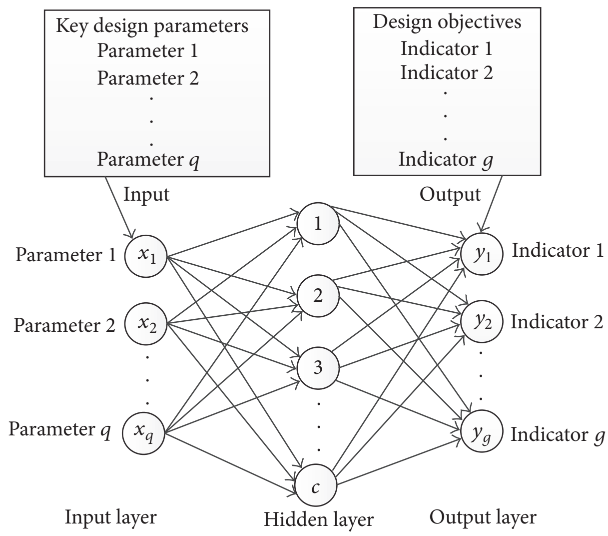

FIGURE 4: The framework of the BPN.

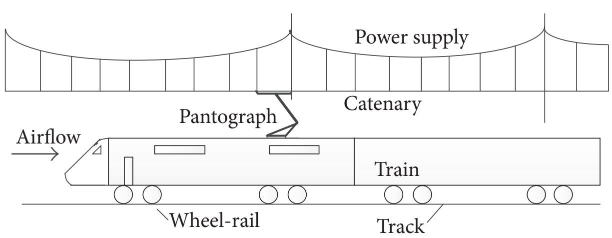

FIGURE 5: High-speed train and its running environment.

approve that the proposed systematic method is necessary and solution-guaranteed by the comparison of a direct surrogate model without design space reduction and the one with this operation. The second is to compare the convergence speed and accuracy of the surrogate model under different design parameters. This indicates that, without a design space reduction operation, the resultant surrogate model will perform quite differently. The last is to prove the effectiveness of the system method in terms of its efficiency and accuracy. We overall demonstrate the usefulness of the method by comparing three different tests.

4.1. Specifying Design Parameters and Objectives of High-Speed Train. High-speed train is a typical complex mechatronic product. As a means of rapid transportation, it has been widely appreciated and vigorously developed. However, design and development of a high-speed train need to evaluate its dynamics behaviors and performances under various running environments to meet its safety and running performance requirements. It has several subsystems (shown in Figure 5), and its total number of design parameters are very big (more than 100), involving parameters related to structure design, mechanical design, bogie design, dynamics performance design, and so on.

Therefore, here, we only take dynamics performance-related design as an example because it is the top level of design for high-speed trains. The running performances of a high-speed train include 7 performance indicators as our design objectives; the number of initial design parameters possibly affecting the performance indicators is more than 100 (shown in Table 1). In addition, some performance indicators might be affected and coupled with other indicators. For instance, its safety indicator is mainly influenced and affected by coupled system dynamics among the train, the track, the catenary, and the airflow. The 7 performance indicators are lateral stability f_1, vertical stability f_2, derailment coefficient f_3, the ratio of wheel load reduction f_4, lateral wheelset force f_5, overturning coefficient f_6, and critical speed f_7.

Due to the complexity of mechatronic products, the optimal design of a mechatronic product is a very complex problem. Some papers suggest that the surrogate modelling technique can be applied to this problem [12–15]. When focusing on high-speed train, we choose the typical neural network surrogate model based on design space reduction and intelligent optimization algorithm to optimize its design.

The number of initial design parameters of high-speed train is more than 100. The relationship between design parameters is very complicated and highly nonlinearly coupled in the wheel/rail contact model. The construction of a surrogate model of a complex electromechanical product requires big enough samples to train the model. Therefore, in order to get enough good samples, a Railway System Dynamics simulation Package SIMPACK Rail is utilized to generate a set of corresponding data between a set of inputs of design variables and a set of performance indicators. When we prepare the design variable values for simulation, there is a difficulty in knowing the right value range of each design parameter. Thus, we use experts' guessed values as our references.

Figure 6 illustrates a high-speed train topological structure and its dynamics model. The software Package SIMPACK Rail is an "add-on" module for use with SIMPACK to simulate rail system dynamics (http://www.simpack.com/uploads/media/datasheet_wheel-rail.pdf). In the SIMPACK software, the design parameters are the inputs to the system and then SIMPACK uses embedded wheel/rail contact model to calculate and output performance indicators such as Ride Comfort indicator and Derail coefficient. It is worth noting that using such system dynamics analysis software is quite time consuming, but it is still doable and cheaper comparing with real tests; thus, we use SIMPACK Rail to generate our sampling data.

Next, we take a unified approach to determine the range of each parameter. Based on the initial range value of the parameter, the upper and lower 10% are used as the initial range value of each parameter. We use this range to carry out the experimental design to get hundreds of test data sets. We use the experimental data as input and use the SIMPACK software to simulate performances of each sample design. Due to the mismatch of parameters, only 58 sets of 100 can produce simulation results. For the remaining 42 sets, we cannot get simulation results; thus, as a result, there are no enough samples to train the surrogate model with only 58% of the calculation results.

Table 1: The all design parameters of high-speed train.

Parameter	Name	Unit
Parameter 1	Nominal wheel radius	mm
Parameter 2	Distance between backs of wheel flanges	mm
Parameter 3	Wheelset roll moment of inertia	Kg·m^2
Parameter 4	Wheelset yaw moment of inertia	Kg·m^2
Parameter 5	Longitudinal stiffness of primary suspension per axle side	KN/m
Parameter 6	Vertical damping of primary suspension per axle side	KN·s/m
Parameter 7	Longitudinal stiffness of axle box tumbler joint per axle side	MN/m
Parameter 8	Yaw damper lateral span	mm
Parameter 9	Lateral stiffness of secondary suspension per bogie side	KN/m
Parameter 10	Vertical stiffness of secondary suspension per bogie side	KN/m
Parameter 11	Secondary vertical damper	KN·s/m
Parameter 12	Secondary lateral damper	KN·s/m
Parameter 13	Wheelset mass	Kg
Parameter 14	Lateral stiffness of axle box tumbler joint per axle side	MN/m
Parameter 15	Longitudinal stiffness of secondary suspension per bogie side	KN/m
Parameter 16	Longitudinal stiffness of Yaw damper joint per bogie side	MN/m
Parameter 17	Carbody roll moment of inertia	Kg·m^2
Parameter 18	Lateral distance between the secondary suspension of the two sides of the bogie	mm
Parameter 19	Carbody mass	Kg
Parameter 20	Lateral stiffness of primary suspension per axle side	KN/m
Parameter 21	Longitudinal distance between bogie centers	mm
Parameter 18	Carbody yaw moment of inertia	Kg·m^2
Parameter 19	Vertical distance from the rail surface to the center of gravity	mm
Parameter 20	Wheelbase	mm
Parameter 21	Vertical stiffness of primary suspension per axle side	KN/m
Parameter 22	Carbody pitch moment of inertia	Kg·m^2
Parameter 23	Framework mass	Kg
Parameter 24	Wheelset pitch moment of inertia	Kg·m^2
Parameter 25	Vertical damping joint stiffness per axle side	MN/m
Parameter 26	Nominal wheel radius	mm
Parameter 27	Distance between backs of wheel flanges	mm
Parameter 28	Wheelset roll moment of inertia	Kg·m^2
Parameter 29	Air spring vertical stiffness (per spring)	KN/m
⋮	⋮	⋮
Parameter 100	Lateral damper joint stiffness of secondary suspension per bogie side	MN/m
Parameter 101	Lateral stop clearance of secondary suspension	mm
Parameter 102	Vertical damping transverse span of secondary suspension	mm
Parameter 103	Yaw damper lateral span	mm
Parameter 104	Traction drawbar mass	Kg
Parameter 105	Swing stiffness of traction joint of secondary suspension	Nm/rad

Therefore, it is not feasible to use the full parameters in the original design space to establish a surrogate model. In order to solve this problem, we need a system method to have a guaranteed solution. Thus, in this paper we propose a method with design space reduction as a key step.

4.2. Design Space Reduction. The proposed design space reduction method has two rounds. In round 1, important parameters are selected by experts with related domain knowledge. In round 2, the important parameters will be used to establish surrogate models against each performance

Table 2: The design parameters sorted as the importance.

Parameter	Name	Unit	Section
x_1	Nominal wheel radius	mm	395–430
x_2	Distance between backs of wheel flanges	mm	1,351–1,355
x_3	Wheelset roll moment of inertia	Kg·m^2	500–750
x_4	Wheelset yaw moment of inertia	Kg·m^2	500–800
x_5	Longitudinal stiffness of primary suspension per axle side	KN/m	800–1,150
x_6	Vertical damping of primary suspension per axle side	KN·s/m	10–30
x_7	Longitudinal stiffness of axle box tumbler joint per axle side	MN/m	5–10
x_8	Yaw damper lateral span	mm	2,400–2,800
x_9	Lateral stiffness of secondary suspension per bogie side	KN/m	100–200
x_{10}	Vertical stiffness of secondary suspension per bogie side	KN/m	120–300
x_{11}	Secondary vertical damper	KN·s/m	20–60
x_{12}	Secondary lateral damper	KN·s/m	30–50
x_{13}	Wheelset mass	Kg	1,800–2,200
x_{14}	Lateral stiffness of axle box tumbler joint per axle side	MN/m	4–10
x_{15}	Longitudinal stiffness of secondary suspension per bogie side	KN/m	100–200
x_{16}	Longitudinal stiffness of Yaw damper joint per bogie side	MN/m	5–13
x_{17}	Carbody roll moment of inertia	Kg·m^2	70,000–120,000
x_{18}	Lateral distance between the secondary suspension of the two sides of the bogie	mm	2,400–2,500
x_{19}	Carbody mass	Kg	28,000–40,000
x_{20}	Lateral stiffness of primary suspension per axle side	KN/m	800–1,200
x_{21}	Longitudinal distance between bogie centers	mm	17,000–18,000
x_{22}	Carbody yaw moment of inertia	Kg·m^2	1,100,000–1,500,000
x_{23}	Vertical distance from the rail surface to the center of gravity	mm	1,400–1,600
x_{24}	Wheelbase	mm	2,400–2,600
x_{25}	Vertical stiffness of primary suspension per axle side	KN/m	1,000–1,500
x_{26}	Carbody pitch moment of inertia	Kg·m^2	1,200,000–1,700,000
x_{27}	Framework mass	Kg	2,100–3,100
x_{28}	Wheelset pitch moment of inertia	Kg·m^2	65–100
x_{29}	Vertical damping joint stiffness per axle side	MN/m	3–6

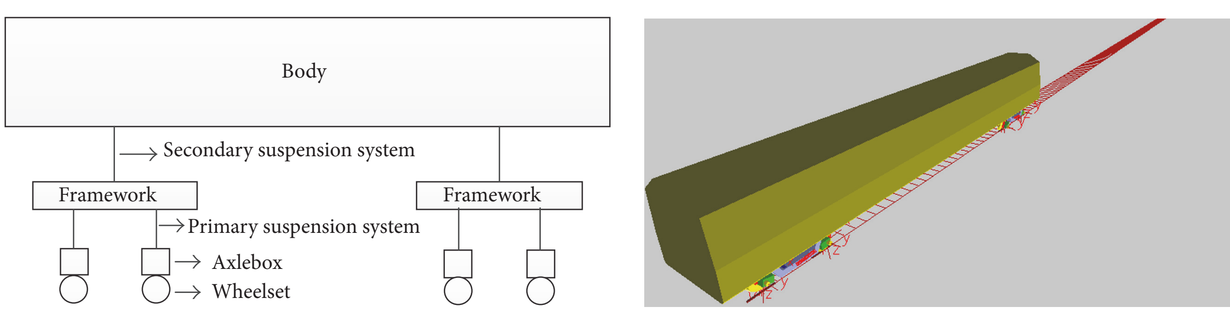

Figure 6: Topological structure and dynamics model in SIMPACK software of high-speed train.

indicator, and then sensitivity analysis is conducted based on established surrogate models.

The details of the design space reduction technique have been reported in [28] with some domain expert involvement. As a result, in round 1 reduction, the 29 important design parameters (shown in Table 2) are selected by experts from more than 100 parameters and in round 2 reduction, the 16 key design variables are finally identified from the sensitivity analysis based on individual performance indicator models [28]. According to the sensitivity analysis, the parameters are sorted according to their importance (shown in Table 2).

4.3. Setting Up the System Surrogate Model. Based on the results obtained from the design space reduction, the system

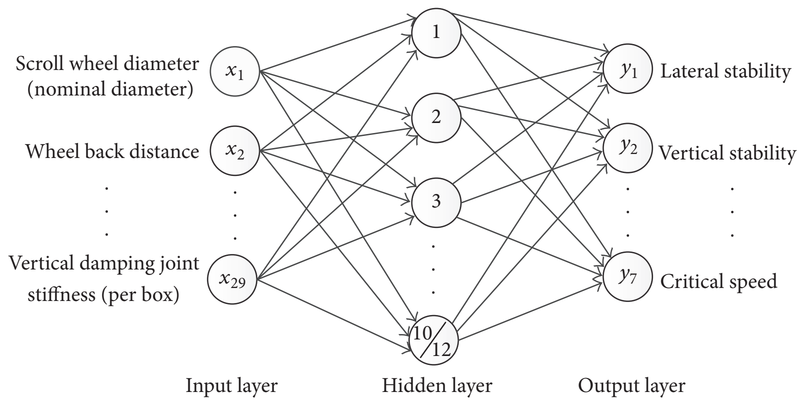

FIGURE 7: The surrogate model structure of high-speed train based on different parameter groups.

TABLE 3: Six surrogate models.

	BPN1	BPN2	BPN3	BPN4	BPN5	BPN6
Data set	U	V	W	X	Y	Z
The number of parameters	12	16	18	20	25	29
The number of iterations	68	93	126	195	256	291

surrogate model with the 16 key design parameters and performance indicators was established. In order to prove the system approach and justify the reason for choosing the 16 key design parameters in the system surrogate model (named as BPN2), we construct other 5 surrogate models for comparison. The result comparisons with the 6 surrogate models are detailed in the next section.

We use the same structure (see Figure 7) to construct the 6 surrogate models, namely, BPN1, BPN2, BPN3, BPN4, BPN5, and BPN6, with the numbers of design parameters: 12, 16, 18, 20, 25, and 29, respectively. When a parameter in Table 2 is not chosen as a design variable, its value is fixed to the middle of its range values. In this way, the sampling design of a design available is based on Latin hypercube sample design method and the sample data are produced with SIMPACK software. The details associated with the six surrogate models BPN1 to BPN6 are shown in Table 3.

Figure 7 shows the structure of the neural network surrogate model. For example, when n equals 29, the 29 design variables are in the surrogate model. The 29 variables first generate 100 samples, and then these samples are inputted into SIMPACK simulation software to generate the corresponding performance indicator values. Because these parameters range differently, all parameters in the input layer and the output layer are then normalized for training a model with 95 samples and testing the model with the other 5 samples in its establishment process. In this way, we establish the six surrogate models.

The convergence rates of these surrogate models are shown in Figure 8. The numbers of iterations for each model are shown in Table 3 (last row). It is clear that the number of iterations increases as the sampling parameter increases. The maximum number of times is 5 times more than the minimum number. Therefore, the more the sampling parameters are, the slower the convergence of the model is, and the more resources and time it takes.

4.4. Setting Up the Optimization Model. Design variables are corresponding to the 6 BPN models, and they are a subset of $\{x_1, x_2, x_3, \ldots, x_{29}\}$ for each model (shown in Table 2), where $0 \le x_j \le 1$, $j = 1, 2, \ldots, 29$. According to the design requirements of the high-speed train, the main design objectives are the 7 performance indicators: $f_1, f_2, \ldots, f_7$.

According to the design requirements and specifications of high-speed train in China, the range of the 7 indexes can be obtained. In this way, we regard the performance requirements as the boundary conditions of the optimization design. Constraints are

$$\begin{aligned}
&0 < f_1 < 2.5,\\
&0 < f_2 < 2.5,\\
&0 < f_3 < 0.8,\\
&0 < f_4 < 0.8,\\
&f_5 > 0,\\
&0 < f_6 < 0.8,\\
&f_7 > 0;
\end{aligned} \tag{4}$$

with these boundary conditions for f_1 to f_6, the smaller the better regarding the performance of high-speed train. However, to critical speed f_7, the higher the better regarding performance of high-speed train. With the reciprocal of f_7 into the optimization function, we get the goal function.

The function is

$$\begin{aligned}
\min \quad (F) &= \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3 + \alpha_4 f_4 + \alpha_5 f_5 + \alpha_6 f_6 \\
&\quad + \alpha_7 \frac{1}{f_7},
\end{aligned} \tag{5}$$

where α is the weight coefficient. For high-speed trains, we think the 7 indicators are of the same importance. In

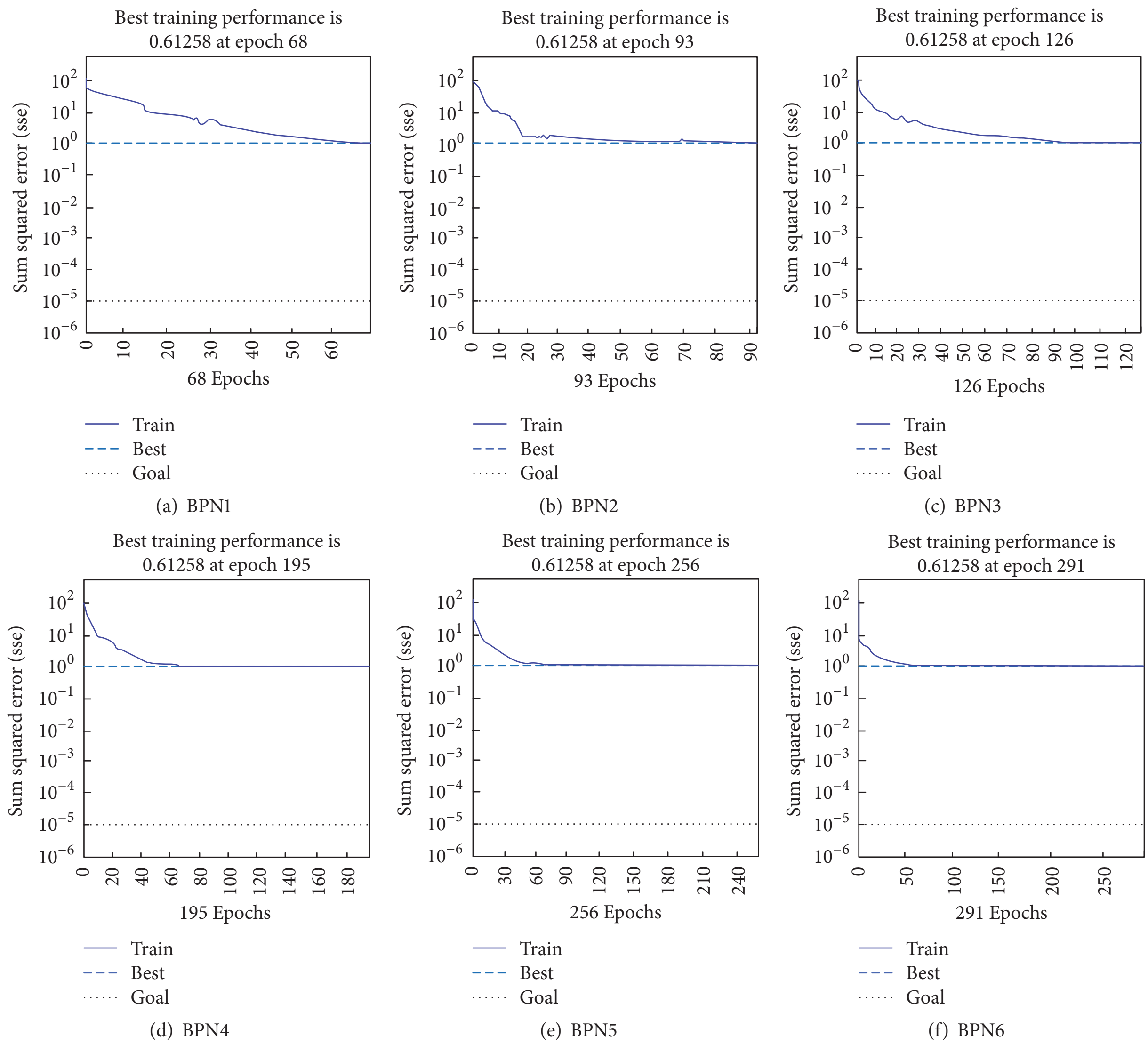

Figure 8: The convergence rate of BPN surrogate models.

practice, because the different units of the variables need to be normalized into dimensionless variables, the weight coefficient can be set to a specific value:

$$\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 = \alpha_7 = \frac{1}{7}. \qquad (6)$$

The optimization function is simplified as

$$\min \quad (F) = f_1 + f_2 + f_3 + f_4 + f_5 + f_6 + \frac{1}{f_7}. \qquad (7)$$

4.5. Conducting Optimization Computing of High-Speed Train. In order to compare the optimization results, we use each of the 6 surrogate models as an optimization analyzer to get the corresponding results between the input variables and 7 key indicator outcomes; in this way, we establish 6 optimization models corresponding to the BPN1, BPN2, BPN3, BPN4, BPN5, and BPN6 surrogate models. We use the same optimization algorithm (differential evolution algorithm) to solve the 6-optimization models. The optimization algorithm is implemented within MATLAB.

The optimization times for each case are shown in Figure 9. For example, it takes 2.2 minutes to obtain the optimization result from BPN1 with 12 variable parameters. Figure 9 shows that the optimization time with BPN6 is 14 times of that with BPN1 and 10 times of that with BPN2. Therefore, the number of design variables involved in optimization affects the optimization time greatly and it is necessary to identify a suitable number of parameters in optimization with acceptable quality of the results.

The optimization results are shown in Table 4 with varied performance parameters in the goal function. From Table 4, it can be seen that the optimization method is with good accuracy and effectiveness. In comparison with the initial performance parameters, the corresponding optimization results with the performance improvement percentages are shown in Table 5.

Table 4: Comparison table of optimization results.

	Lateral stability	Vertical stability	Derailment coefficient ∗ 10	The ratio of wheel load reduction ∗ 10	Lateral wheelset force/10 (KN)	Overturning coefficient ∗ 10	Critical speed/200 (km/h)
Initial performances	2.3804	2.0245	1.497	1.978	1.2232	1.98	2.98
BPN1	2.2162	2.0235	1.568	2.104	1.12513	2.054	3.03
BPN2	2.1935	2.0021	1.272	1.828	1.02541	1.939	3.43
BPN3	2.1925	2.001	1.253	1.82	1.02465	1.915	3.40
BPN4	2.192	2.0003	1.248	1.806	1.01683	1.867	3.44
BPN5	2.178	1.9986	1.232	1.79	1.01485	1.819	3.35
BPN6	2.1715	1.9927	1.211	1.781	1.01312	1.804	3.39

Table 5: The table of performance improvement percentage (%).

	Lateral stability	Vertical stability	Derailment coefficient	The ratio of wheel load reduction	Lateral wheel force	Overturning coefficient	Critical speed
BPN1	6.90%	0.05%	−4.74%	−6.37%	8.02%	−3.74%	1.68%
BPN2	7.85%	1.11%	15.03%	7.58%	16.17%	2.07%	15.22%
BPN3	7.89%	1.11%	16.30%	7.58%	16.23%	3.28%	14.28%
BPN4	7.91%	1.19%	16.63%	8.70%	16.87%	5.70%	15.69%
BPN5	8.50%	1.28%	17.70%	9.50%	16.87%	8.13%	12.62%
BPN6	8.78%	1.36%	19.11%	9.96%	17.17%	8.89%	14.30%

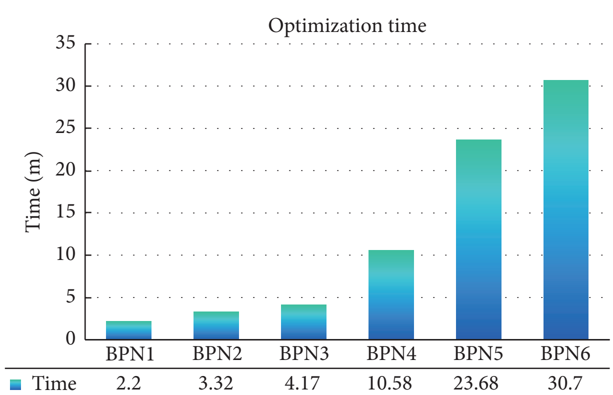

Figure 9: The time histogram required for obtaining optimal results based on six surrogate models.

In order to show the optimization results more intuitively, the optimized performance results in Table 4 are shown in Figure 10, while the performance improvement percentages in Table 5 are illustrated in Figure 11.

Figures 9, 10, and 11 together lead to three new understandings of the big system optimization. First, when the number of design variables is inadequate comparing to the number of the key variables, the optimization results are quite poor. Therefore, we need to avoid this kind of case. Second, when the number of the design variables is bigger than that of key variables, the optimization results are better. Third, when the number of the design variables is much bigger than the number of key variables, the optimization result is just slightly better but the optimization times are far worse. For example, the results from BPN5 with 25 variables are not significantly improved when comparing with BPN2, but the computing time and resources are greatly increased.

In summary, using just the key variables can give a system surrogate model with a better balance between the quality of optimization results and computational costs. This is a balanced system solution. In our case study, the surrogate model BPN 2 with 16 key variables is identified as the system surrogate model and supports the system optimization very well with a good balance between the optimization quality and time. It can be concluded that the system optimization method based on the system surrogate model with only key design parameters is more effective in terms of optimization accuracy and computational cost. The importance of the design space reduction and the effectiveness of the system optimization method for complex mechatronic products are proved.

5. Conclusion

Due to the complexity of complicated mechatronic products, the multiplicity of parameters, and the intricate relationship between design parameters and performance indicators, the optimal design of such a product is very sophisticated with hard problems. Therefore, it is almost impossible to ensure that all parameters are optimal. Because of the complex relationship among subsystems, the whole system simulation model is difficult to build, and the coupled simulation time is too long and the cost is huge, it is necessary to provide a data-driven modelling and optimization design method for complex mechatronic product design from a systemic perspective to balance the system executing time and effectiveness.

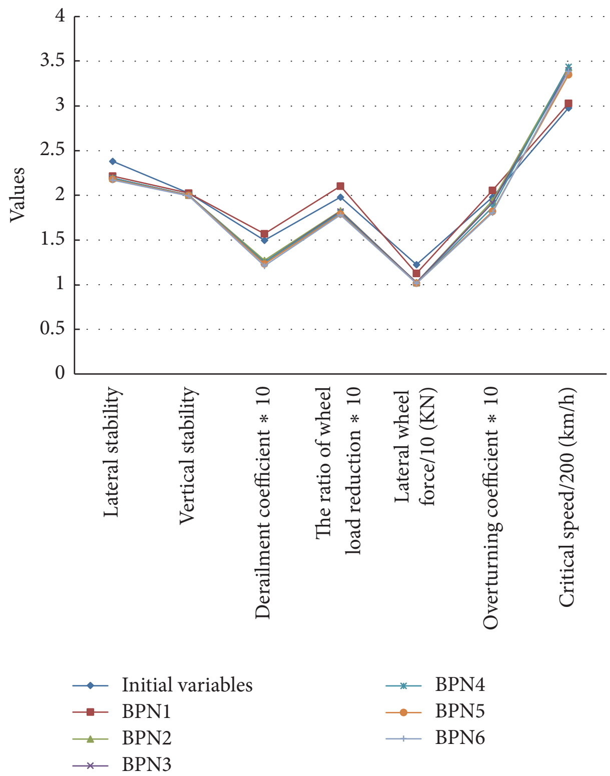

Figure 10: Comparison chart of optimization results.

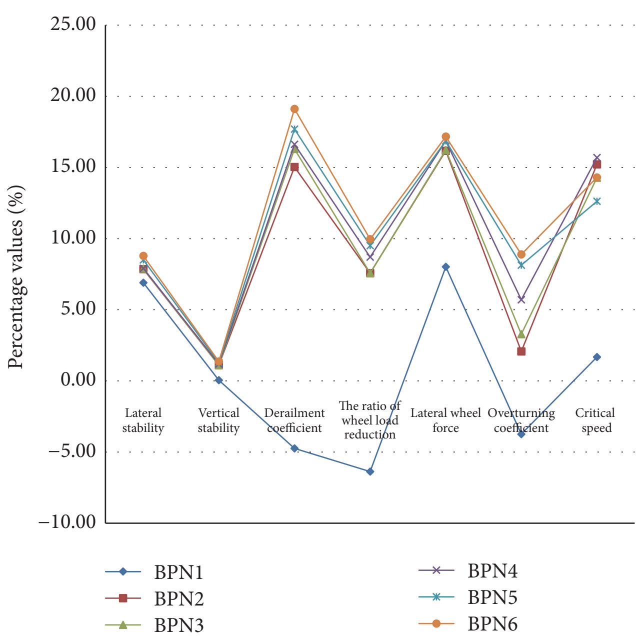

Figure 11: The chart of performance improvement percentage.

This paper has proposed a systematic design optimization method for complex mechatronic products from the identification of initial design parameters and objectives, to design space reduction for key variable identification, setting up a system surrogate model with just the key variables, establishing a system optimization model, and optimization computing.

The implementation of this method has been demonstrated through a case study of China high-speed train design with 6 different surrogate models. From the comparison study, it can be seen that the appropriate design space reducing is very important, which leads to not only the identification of key variables but also the establishment of the system surrogate and optimization models. The system optimization method based on the system surrogate model established with just key design parameters is more effective in terms of optimization accuracy and computational cost. The ability to produce a better design solution with the proposed method has been validated and demonstrated.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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