

# Model Updating for High Speed Aircraft in Thermal Environment Using Adaptive Weighted-Sum Methods

He Huan<sup>1</sup>, He Cheng<sup>2\*</sup>, Chen Guoping<sup>1</sup>

1. The State Key Lab of Mechanics and Control for Mechanical Structures,

Nanjing University of Aeronautics and Astronautics, Nanjing 210016, P. R. China;

2. Research Institute of Pilotless Aircraft, Nanjing University of Aeronautics and Astronautics,  
Nanjing 210016, P. R. China

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**Abstract:** Model updating for aircraft in a high temperature environment (HTE) is proposed based on the hierarchical method. With this method, the problem can be decomposed into temperature field updating and dynamic structural updating. In order to improve the estimation accuracy, the model updating problem is turned into a multi-objective optimization problem by constructing the objective function which combined with residues of modal frequency and effective modal mass. Then the metamodeling, support vector regression (SVR) is introduced to improve the optimization efficiency, and the solution can be determined by adaptive weighted-sum method (AWS). Finally, the proposed method is tested on a finite element (FE) model of a reentry vehicle model. The results show that the multi-objective model updating method in HTE can identify the input parameters of the temperature field and structure with good accuracy.

**Key words:** hierarchical; high temperature environment (HTE); support vector regression (SVR); multi-objective optimization; model updating

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## 0 Introduction

The United States is developing scramjet engine technology that is expected to be needed by the next generation of high speed air breathing vehicles. NASA, through the X-43A program, is developing hydrogen fueled scramjet engines and has demonstrated Mach number of approximately 7 to 10. The structural integrity of proposed high-speed aircraft can be seriously affected by the extremely high surface temperatures and large temperature gradients throughout the vehicle's structure, which can seriously affect the structure's elastic characteristics. Fortunately, the finite element (FE) method, as a important and practical numerical analysis tool, can be used to simulate dynamic characteristics of structural. Hence, the accuracy of FE model is crucial for

structural dynamic analysis.

On the one hand, the complexity of dynamic analysis in high temperature environment (HTE), caused by the thermal effects, has made it difficult to directly establish an accurate dynamic model; on the other hand, the FE model of a structure is normally constructed on the basis of highly idealized engineering blueprints and designs that may not truly represent all the aspects of an actual structure. As a result, the analytical predictions from a FE model often differ from the results of a real structure. These discrepancies originate from the uncertainties in simplifying assumptions of structural geometry, materials as well as inaccurate boundary conditions. FE model updating is a viable approach to increase the correlation between the dynamic response of a structure and the predictions from a model. This

\* Corresponding author, E-mail address: hechengary@163.com.

method based on residuals between a measurement set and the corresponding model predictions to adjust the uncertain parameters of FE models by optimization approach. Typical experimental data include the modal model (natural frequencies and mode shapes), the frequency response functions and effective modal mass. The choice of objective function, and also the optimization approach, have been the subject of much research and are well covered by the authors' survey paper<sup>[1-2]</sup>.

If the structure of interest is represented by, e. g. a large FE model, the large number of computations involved can rule out many approaches due to the expense of carrying out many runs. In addition, the FE analysis programs at present do not have parameterized modeling function since the parameters need to be updated in the estimation process. To overcome those problem, we have focused on using metamodels (or surrogate models) that can mimic the behavior of the simulation model as closely as possible while being computationally very efficient and convenient to evaluate since the objective function have be parameterized. Amongst existing metamodels, such as the conventional response surface method<sup>[3]</sup>, radial basic function<sup>[4]</sup> neural networks<sup>[5]</sup> and support vector regression (SVR)<sup>[6]</sup>, the latter are found to be excellent predictors of numerical model behaviour with small samples. In recently, many additional applications (largely a consequence of the increased use of computational analyses) have broadened the range of application of SVR in the statistical and engineering literature.

Structural model parameter estimation problems based on measured modal data (e. g. Ref. [5—7]) are often formulated as weighted least-squares problems in which modal metrics, measuring the residuals between measured and model predicted modal properties, are build up into a single weighted modal residuals metric formed as a weighted average of the individual modal metrics using weighting factors. Standard optimization techniques are then used to find the optimal values of the structural parameters that

minimize the single weighted residuals metric representing an overall measure of fit between measured and model predicted modal properties. Due to model error and measurement noise, the results of the optimization are affected by the values assumed for the weighting factors. The choice of the weighting factors depends on the model adequacy and the uncertainty in the available measured data, which are not known a priori. Different values of the weights result in different optimal models and consequently different predictions from the optimal models.

In this work, the structural model updating in HTE using multi-objective optimization method is proposed. As one of metamodels, support vector regression (SVR), will be introduced to improve the efficiency of estimation, and adaptive weighted-sum method (AWS), as a multi-objective optimization method, is employed to update the structural parameters in HTE.

## 1 Hierarchical Methodology in Model Updating of High-Temperature System

### 1.1 Model updating of temperature field

It is well know the mechanical and thermal aspects are coupled and inseparable: high surface temperatures and large temperature gradients will affect the modal characteristics of the structure. Similarly, the temperature distribution of a structure can also vary with its deformation, but this change are so slightly that Nowinski<sup>[8]</sup> suggested discounting the coupling in practice and separately evaluating the temperature and deformation fields in this order. Cheng et al. have proposed an model updating method in HTE based on hierarchical ideology. With this method, the temperature field updating of a structure is taken as the first stage, and the temperature distribution achieved from the former is imposed on the structure as a thermal load to complete the model updating in HTE. The thermo-physical properties are the important factors that affect temperature distribution of structure. In the case of thermal loads are

determined, the model updating problem of temperature distribution model can be translated into the estimation of thermo-physical parameters problem.

Inverse parameter estimation methods are based on the minimization of an objective function containing both estimated and measured temperatures. Ordinary least squares estimator is by far the most frequently used method for the estimation of thermo-physical parameters as no prior knowledge is needed, therefore, the optimization problems can be formalized as follows

$$\begin{cases} \min \sum_{h=1}^n |T_h^a(\boldsymbol{\chi}) - T_h^e(\boldsymbol{\chi})| \\ \text{s. t. } \boldsymbol{\chi}^L \leq \boldsymbol{\chi} \leq \boldsymbol{\chi}^U \end{cases} \quad (1)$$

where  $\boldsymbol{\chi} = \{\chi_1, \chi_2, \dots, \chi_{N_\chi}\}$  is the thermo-physical parameter vector,  $T_h^e$  the temperature from the  $h$ th sensor, and  $T_h^a$  the calculated temperature from the mathematical model governing the heat transfer phenomena with respect to the estimated parameter vector, which is the general function of the temperature. “L” and “U” represent the upper and lower bounds of parameter coefficient vector, respectively.

## 1.2 Model updating of dynamic structure in HTE

As discussed before, the dynamic responses in HTE, which can be expressed as<sup>[9]</sup>

$$J = J(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma}) \quad (2)$$

where  $\hat{\boldsymbol{\chi}}$  is the thermophysical parameters vector after updating, and  $\boldsymbol{\theta}, \boldsymbol{\gamma}$  are the temperature-dependent parameters and temperature-independent parameters of the dynamic model, respectively.

For model updating techniques, either identified modal parameters such as eigenvalues and eigenvectors or measured frequency response functions (FRFs) are widely used as reference data<sup>[10-11]</sup>. In recent years, some new dynamic parameters have also been used in the model updating. Aerospace engineers make wide use of the effective modal mass concept in structural spacecraft design<sup>[12]</sup>. The effective modal mass, as is known, represents the participation of an elastic mode to the reaction at the junction and therefore the knowledge of such a parameter is useful for

the analysis of the dynamic behaviour of satellites and aerospace substructures coupled with the launcher. Therefore, the effective modal mass, as a complement could provide more information for model updating to reduce the ill-posed problem which caused by the errors arise from uncertainties.

The model updating problem has recently been formulated in a multi-objective context<sup>[13]</sup> that allows the simultaneous minimization of the multimodal indicators, which include eigenvalues, eigenvectors and effective modal mass, etc. Then, the problem of model updating for identifying the model parameter values that given the best fit in all groups of modal properties can be formulated as a multi-objective optimization problem. In this work, the multi-objective model updating method based on residuals of modal frequency ( $\omega$ ) and effective modal mass ( $M$ ) are introduced, the multi-objective optimization problem can be written as

$$\begin{cases} \text{Min. } J_1 = \sum_{i=1}^{N_\omega} \left| \frac{\omega_i^a(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma}) - \omega_i^e(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma})}{\omega_i^e(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma})} \right| \\ \text{Min. } J_2 = \sum_{i=1}^{N_M} |M_i^a(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma}) - M_i^e(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma})| \\ \text{s. t. } \boldsymbol{\theta}^L \leq \boldsymbol{\theta} \leq \boldsymbol{\theta}^U \end{cases} \quad (3)$$

where  $\boldsymbol{\theta} = \{\theta_1, \theta_2, \dots, \theta_{N_\theta}\}$  is the parameter vector. The most popular way of solving the multi-objective optimization problem is to reduce it to a scalar problem of the form

$$J(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma}, \lambda_1, \lambda_2) = \lambda_1 J_1(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma}) + \lambda_2 J_2(\boldsymbol{\theta}(\hat{\boldsymbol{\chi}}), \boldsymbol{\gamma}) \quad (4)$$

where  $J$  is an aggregated, weighted sum of the individual objectives, the relative importance of the residual in different modal parameters are reflected in the choice of the weights  $\lambda_i$ . Typically, weights are chosen such that  $\sum_i \lambda_i = 1$  and  $\lambda_i \geq 0$  leading to a convex combination of objectives.

Although the weighted-sum approach is simple to understand and easy to implement, the traditional weighted-sum approach has two main drawbacks which are hard to avoid<sup>[14]</sup>: First, an even distribution of the weights among objective

functions does not always result in an even distribution of solutions on the Pareto front; Second, the weighted-sum approach cannot find solutions on non-convex parts of the Pareto front, although such non-dominated solutions (Pareto optimal solutions) do often exist. For that reasons, Kim<sup>[14]</sup> propose a new adaptive method, based on the weighted-sum approach, for multi-objective optimization—adaptive weighted-sum method (AWS). In this approach, the weights are not predetermined, but they evolve according to the nature of the Pareto front of the problem. The AWS algorithm produces an even spread of points along the Pareto front, even for problems for which the relative scaling of the objectives are vastly different. Firstly, the uniform step size of the weighting factor  $\Delta\lambda$  is determined. By using a large step size of the weighting factor,  $\Delta\lambda$ , a coarse representation of the solution is generated and regions where more refinement is needed are identified. The specific regions are then designated as a feasible region for sub-optimization by imposing inequality constraints in the objective space. In this region, the typical weighted-sum multi-objective optimization is performed. The algorithm will terminate when all the regions of the Pareto front reach a pre-specified resolution. More details about the AWS method in terms of advantages and drawbacks can be found in Ref. [14].

## 2 Overview of Support Vector Regression

SVR-based FE model updating is an approach to achieve the global approximations of the structural response feature objectives and constraints based on functional evaluations at various points in the design space. Let  $(x_1, y_1), \dots, (x_p, y_p)$ , where  $x_i \in \mathbf{R}^n$  and  $y_i \in \mathbf{R}^n$  are the training data points available to build a regression model. The SVR algorithm applies a transformation function  $\Phi$  to the original data points from the initial input space ( $\mathbf{R}^n$ ) to a generally higher dimensional feature space ( $F$ ). In this new space,

a linear model  $f$  is constructed, which represents a non-linear model in the original space

$$\Phi: \mathbf{R}^n \rightarrow F, \mathbf{w} \in F$$

$$f(x) = \langle \mathbf{w}, \Phi(x) \rangle \Phi(x) + b \quad (5)$$

When the identity function is used, i. e.  $\Phi(x) \rightarrow x$ , no transformation is carried out, and linear SVR models are obtained.

The goal when using the  $\epsilon$ -insensitive loss function is to find a function  $f$  that fits given training data with a deviation less or equal to  $\epsilon$ , and at the same time is as flat as possible in order to reduce model complexity. Slack variables  $\xi_i, \xi_i^*$  are introduced to allow error levels greater than  $\epsilon$ , leading to the following optimization problem

$$\begin{cases} \min_{\mathbf{w}, b} & \frac{1}{2} \|\mathbf{w}\|^2 + C \cdot \sum_{i=1}^p (\xi_i + \xi_i^*) \\ \text{s. t.} & y_i - \langle \mathbf{w}, \Phi(x_i) \rangle - b \leq \epsilon - \xi_i \quad i=1, \dots, p \\ & \langle \mathbf{w}, \Phi(x_i) \rangle + b - y_i \leq \epsilon - \xi_i^* \quad i=1, \dots, p \\ & \xi_i, \xi_i^* \geq 0 \end{cases} \quad (6)$$

where  $\|\mathbf{w}\|^2$ , the structure risk, is used to represent the complexity of the surrogate model.  $\sum_{i=1}^l (\xi_i + \xi_i^*)$  is the empirical risk, used to represent the error of surrogate model. The penalty coefficient  $c$  is used to balance the structure risk and empirical risk. A Lagrange function is constructed. Once applying saddle point conditions to solve the problem stated in Eq. (3), the following formulation is obtained.

$$\begin{cases} \max_{\alpha, \alpha_i^*} & -\frac{1}{2} \sum_{i,j=1}^p (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) \cdot \\ & \langle \Phi(x_i), \Phi(x_j) \rangle + \sum_{i=1}^p (\alpha_i - \alpha_i^*) y_i - \\ & \epsilon \sum_{i=1}^p (\alpha_i + \alpha_i^*) \\ \text{s. t.} & \sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0, 0 \leq \alpha_i, \alpha_i^* \leq C, \\ & i = 1, 2, \dots, p \end{cases} \quad (7)$$

This is the quadratic optimization problem which has to be solved to obtain the solution of the SVR model. This solution will be function of the dual variables  $\alpha_i$  and  $\alpha_i^*$ . Using saddle point conditions it can be shown that Eq. (8) holds<sup>[15]</sup>. Replacing this expression in Eq. (1), the final

solution of the SVR algorithm is obtained.

$$f(x) = \sum_{i=1}^p (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \quad (8)$$

where the expression  $K(x_i, x_j)$  is known as the kernel function, which is equal to  $\langle \Phi(x_i), \Phi(x_j) \rangle$  [16]. Some of the most commonly used Kernel Function include

(1) Polynomial:  $k(x, x_i) = ((x, x_i) + c)^p$ ,

$p \in \mathbf{R}, c \geq 0$ ;

(2) Gaussian:  $k(x, x_i) = \exp[-|x - x_i|^2 / \sigma^2]$ ; (9)

(3) Exponential:  $k(x, x_i) = \exp(-a |x - x_i|)$ ,  $a > 0$ ;

The penalty coefficient  $c$  can be determined by cross validation method.

### 3 Numerical Examples and Discussion

The FE model of reentry vehicle structure in an HTE will be used as an example to check the feasibility of the multi-objective identification method for structural model updating methodology proposed in this paper, as shown in Fig. 1. A simplified system of the reentry vehicle and its internal structure, by assuming that the aircraft is in the sub orbital flight and will be subjected to extremely high surface temperatures and large temperature gradients. The model comprises two parts; the surface of reentry vehicle is made by ceramic matrix composites (C-SiC) and internal structure made of oxide dispersion strengthened super alloys (PM1000), both of them are exist in inside and outside of the structure in order to withstand the high temperatures generated by aerodynamic heating, interlayer with reinforcing ribs connected. The ambient temperature is  $20^\circ\text{C}$ , and we ignore the influence of installation location of bolts at the specimen on the temperature distribution.

It is possible to imagine many different parameterizations for updating the FE of the reentry vehicle structure. In this paper, the heat transfer derivative of cone and pyramidal structure,  $\chi_1$  and  $\chi_2$ , are chosen as the updating parameters, which

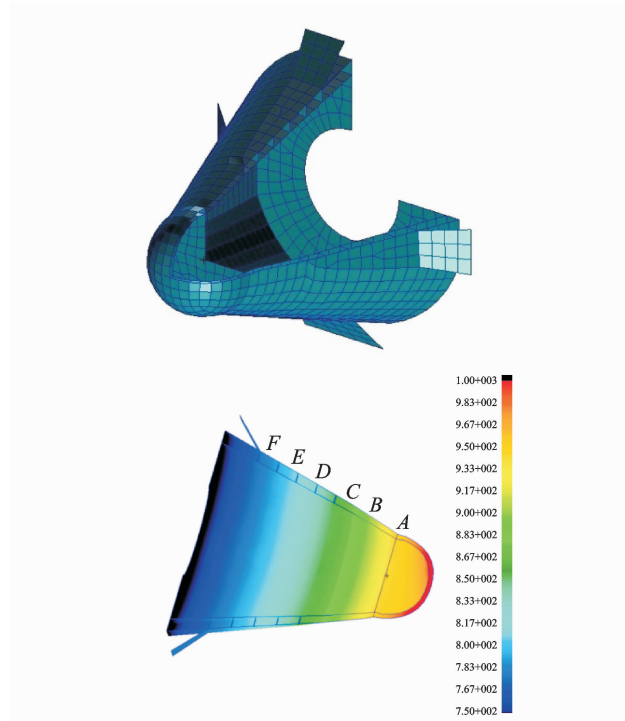


Fig. 1 Temperature distribution of reentry vehicle and its cutaway view of FE model

have significantly effects on temperature distribution of the reentry vehicle by using sensitivity analysis. Similarly, the elastic modulus of cone  $E_1$  and thickness of pyramidal structure  $t_2$  are chosen as updating parameters for structural dynamic model updating. Then, we will employ the SVR-GS to update the FE model of thermal transfer and dynamic structures, respectively, based on hierarchical method in HTE proposed by Ref. [9] once they are confirmed to be updating parameters.

**Table 1** Initial design space of thermal parameters modify

Bound	$\chi_1 / (\text{W} \cdot \text{mm}^{-1})$	$\chi_2 / (\text{W} \cdot \text{mm}^{-1})$
Upper bounds	0.25	0.14
Lower bounds	0.35	0.26

Table 1 shows the initial design space of thermal parameters by trying. The normalization process is described as transition from the original interval  $[x_{1i}, x_{2i}]$  of the design variables  $x_i$  to the new interval  $[-1, 1]$  of the design variables  $y_i$ , where  $i = 1, 2, \dots, k$  for convenience. Assume that the target values of required thermal correction parameters are  $\alpha_1 = 0.3 \text{ W/mm}$  and  $\alpha_2 = 0.2 \text{ W/}$

mm, which are used to calculate temperature distribution as the real value. Pick up 16 sample points randomly using the Latin hypercube design in the initial design space of thermal parameters, and calculate the temperature value as the theoretical value. Approximately substitute the SVR-GS surrogate models for the relation between objective function and design variables. The temperature residual model is shown in Fig. 2 in the form of SVR-GS. Then we get the optimal solution by the genetic algorithm owing to their excellent performance in the global optimization problem. The updated thermal parameter values are shown in Table 2.

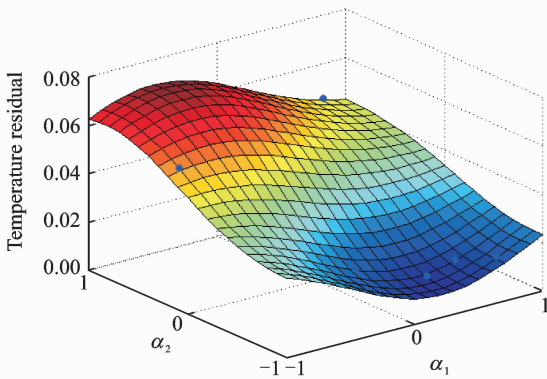


Fig. 2 SVM-GS surrogate model

Table 2 Modified thermal parameter values

Method	$\alpha_1 / (\text{W} \cdot \text{mm}^{-1})$	$\alpha_2 / (\text{W} \cdot \text{mm}^{-1})$
SVM-GS	0.306 8	0.209 0
SVM-ZS	0.303 5	0.212 4

Table 3 shows the temperature deviations before and after modification for  $A, B, C, D, E, F$  (Fig. 1) six points. We found that the largest temperature deviation based on the SVM-GS model is no more than 0.909 9%, which indicates

that the temperature distribution of vehicle calculated by the updated parameters agrees well with the true temperature distribution. Then, the process of structural dynamics model updating is conducted based on the updated steady-state temperature distribution. The 16 sample points are selected randomly by the Latin hypercube design in the initial design space of each thermal parameter, and the first fourth-order natural frequency is calculated as the theoretical value. Assume that  $E_1 = 90 \text{ GPa}$  and  $t_2 = 3 \text{ mm}$  are the error resource of structural dynamics parameters needed to be updated, and calculating the first fourth-order natural frequency of vehicle in HTE as experimental values based on the true values. The residuals of the theoretical value and the experimental value of each order natural frequency and effective modal mass are built by Eq. (3), respectively. Similarly, the SVM-GS predictor of objective function in Eq. (3) could be established to estimate the elastic modulus ( $E_1$ ) and thickness ( $t_2$ ). The identified Pareto curve is composed of 15 Pareto optimal solutions and shown in Fig. 3 by using the AWS described above.

Tables 3—4 present the updated parameters and the errors of reentry vehicle dynamic characteristic using AWS. It is observed that the maximum error of updated parameters is no more than 2.727%, and the maximum error of updated frequency is no more than 2.9%. There are slight differences between the parameters of the updated model and the test ones, which indicates that the model updating method proposed in this paper is available for practical applications.

Table 3 Comparison of test frequencies with updated temperature

Measuring point	Real/ $^{\circ}\text{C}$	Initial/ $^{\circ}\text{C}$	Initial error/%	Updated by SVM-GS/ $^{\circ}\text{C}$	Error of		Error of updated by SVM-ZS/%
					updated by SVM-ZS/%	Updated by SVM-ZS/ $^{\circ}\text{C}$	
A	794.520 7	707.427 0	10.961 8	792.049 4	0.311 1	791.777 9	0.345 2
B	812.786 6	726.883 9	10.568 9	809.294 5	0.489 8	808.910 8	0.476 8
C	843.256 1	759.402 3	9.944 0	838.099 8	0.611 5	837.526 5	0.679 5
D	874.698 1	793.241 4	9.312 6	868.038 5	0.761 4	867.262 9	0.850 0
E	899.443 5	828.783 3	7.856 0	907.703 0	0.909 9	898.450 2	0.110 4
F	959.182 4	884.612 4	7.774 3	951.455 0	0.805 6	950.508 7	0.904 3

**Table 4** Initial design space of dynamic structural updating parameters

Bound	$E_1/\text{GPa}$	$t_2/\text{mm}$
Upper bounds	80	2.5
Lower bounds	100	3.5

**Table 5** Comparison between updated parameters and real parameters

No.	$E_1/\text{GPa}$	Error/%	$t_2/\text{mm}$	Error/%
1	89.539	-0.512	3.081 8	2.727
2	89.572	-0.476	3.072 9	2.430
3	89.603	-0.441	3.064 3	2.143
4	89.630	-0.411	3.056 1	1.870
5	89.653	-0.386	3.048 1	1.603
6	89.670	-0.367	3.040 3	1.343
7	89.682	-0.353	3.032 7	1.090
8	89.686	-0.349	3.025 4	0.847
9	89.720	-0.311	3.018 4	0.613
10	89.755	-0.272	3.011 4	0.380
11	89.812	-0.209	3.004 6	0.153
12	89.897	-0.114	2.997 7	-0.077
13	89.958	-0.047	2.991 0	-0.300
14	90.101	0.112	2.984 1	-0.530
15	90.219	0.243	2.977 2	-0.760

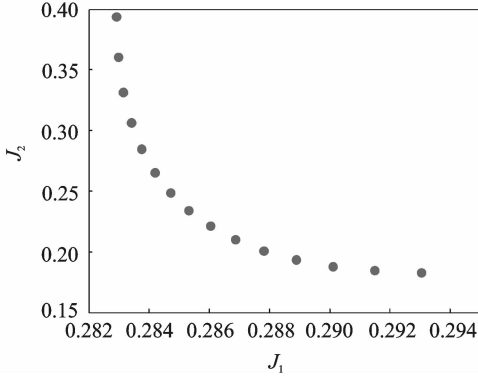


Fig. 3 Pareto frontier calculated by AWS

**Table 6** Comparison between updated results and experiment values of Pareto frontier

Pareto front	Error of frequency/%				Error of effective modal mass /%			
	1	2	3	4	1	2	3	4
1	1.453 2	1.802 4	1.937 6	2.014 3	0.987 6	1.121 3	1.243 7	1.435 2
2	1.521 4	1.923 5	1.987 5	2.153 7	0.953 4	1.098 6	1.210 7	1.410 2
3	1.634 7	2.012 4	2.168 4	2.241 5	0.901 4	1.068 7	1.184 7	1.384 3
4	1.710 4	2.104 3	2.219 6	2.331 4	0.873 7	1.021 7	1.159 4	1.357 4
5	1.784 3	2.175 1	2.278 1	2.397 4	0.853 4	0.984 3	1.124 6	1.321 8
6	1.832 4	2.234 2	2.348 9	2.431 7	0.827 9	0.953 4	1.098 9	1.304 1
7	1.895 3	2.294 6	2.387 9	2.497 3	0.801 7	0.934 7	1.067 4	1.274 6
8	1.934 8	2.354 7	2.454 8	2.534 7	0.753 9	0.901 6	1.024 7	1.243 8
9	2.014 2	2.418 6	2.510 4	2.575 1	0.731 8	0.871 7	1.005 4	1.210 9
10	2.143 1	2.506 8	2.592 5	2.624 7	0.705 6	0.857 9	0.975 4	1.187 6
11	2.210 4	2.604 2	2.610 7	2.678 4	0.679 4	0.824 6	0.946 3	1.156 4
12	2.298 7	2.653 1	2.696 7	2.713 8	0.653 7	0.798 9	0.910 7	1.124 8
13	2.321 4	2.706 7	2.740 5	2.754 8	0.627 3	0.772 1	0.881 3	1.097 3
14	2.457 6	2.754 3	2.796 4	2.847 3	0.593 8	0.751 7	0.852 9	1.065 7
15	2.501 2	2.834 7	2.831 4	2.901 2	0.577 3	0.735 3	0.822 7	1.003 5

### 4 Conclusions

An inverse approach for solving the model updating in HTE is presented. The following conclusions can be drawn:

- (1) By employing the hierarchical method, we decompose the problem into temperature field updating and dynamic structural updating. To improve the efficiency and robustness of estima-

tion, the proposed method is constructed from SVR and AWS by turning the estimation of physical properties into a multi-objective optimization problem, with an approach of constructing the objective function, which combines the residues of modal frequency and effective modal mass. The method is verified by an FE model of the re-entry vehicle with respect to the effect of temperature change.

- (2) The developed method based on multi-

objective optimization can improve the stability which influenced by the error of SVR.

(3) The estimation algorithm is proposed based on the thermal analysis module of MSC. Nastran code thus can be applied to estimate the physical properties of complex structures for model updating.

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Dr. **He Huan** is an associate professor in Nanjing University of Aeronautics and Astronautics (NUAA). He received his first degree and Ph. D. degree in NUAA. His research interests focus on computational structural dynamics.

Dr. **He Cheng** is a research assistant in NUAA. He received his Ph. D. degree in NUAA. His research interests focus on computational structural dynamics, emission and recovery for UAV.

Dr. **Chen Guoping** is a professor and doctoral supervisor in NUAA. He received his Ph. D. degree from NUAA. His research interests focus on structural dynamics.



