

Structural Design Examples Using Metamodel-Based Approximation Model

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Abstract - Weight reduction for automobile component, railroad vehicles, aircraft and etc. has been sought to achieve fuel efficiency and energy conservation. There are two approaches in reducing their weights. One is by using material lighter than steel, and the other is by redesigning their structures. In this study, we introduce examples of structural design using metamodel-based approximation model for weight reduction. And a kriging interpolation method is introduced as metamodel-based approximation model.

Key-Words: - Kriging, Metamodel, Shape optimization, Structural optimization, Control arm, Automotive door

1 Introduction

Recently methods of structural design are developing and applied for a lightweight nature of an automobile, railroad vehicle and aircraft because of demands for development of eco-friendly machinery. Particularly a method of structural optimization is included in many commercial softwares and frequently adopted. Because a structural design optimization include a number of degrees of freedom in finite element analysis, it is important to reduce computation time. And a structural design of vehicle components include shape design optimization which require to set up shape variables.

A method of structural design optimization in 1980~1990 solved any problem after that is approximated to first-order function made by optimization algorithm. Another process to solve problem was to use a response surface model of the problem. And optimum value of RSM is solved by optimization algorithm. Approximate methods are suitable to problems of structural analysis requiring much computation time, difficult computational sensitivity problems and problems having noise. In 2000, approximate methods including neural network, radial basis method, kriging and etc. [3-4] using metamodel were adopted in structural design. Kriging has been utilized at ANSYS Workbench in commercial software. In this study, we review examples of structural design optimization using method of metamodel based on kriging.

Because kriging's characteristic has interpolation, kriging method is suitable to highly nonlinear problems than popular method of RSM. And kriging

enable to set up constraints as maximum stress or maximum deformation. Thus kriging could provide advantages of simplifying optimization problems. In case of the shape design optimization, classical method in existing commercial software[1, 2] could have a difficulty preventing mesh distortions during optimization process. To overcome these difficulties, the optimization scheme using metamodel is utilized for shape design optimization. However, in this case, it is not only difficult to define the number of sample points to build metamodel, but also the method require new sample points to assess model. In this study, we review examples based on kriging metamodel including structural design of an automotive door made by TWB(tailor welded blank) [5], structural design of automotive control arm [6], optimization of a driver-side airbag [7] and a robust design [8].

2 Kriging Interpolation Method

In this study, we analyze examples with kriging interpolation method of the building method of metamodel. Kriging is a method of interpolation named after a South African mining engineer D. G. Krige, who developed the technique while trying to increase accuracy in predicting ore reserves. Hereafter, DACE model in Sacks [3] has been applied widely to structural design after 1990. In the DACE model [3-4], the global approximation model is represented as

$$y(\mathbf{x}) = g(\mathbf{x}) + z(\mathbf{x}) \quad (1)$$

where \mathbf{x} is the design variable vector, $g(\mathbf{x})$ is a known function of \mathbf{x} , and $z(\mathbf{x})$ is the realization of a stochastic process with mean zero, variance σ^2 , and non-zero covariance. When $g(\mathbf{x})$ is treated as the constant β , Eq. (1) is rewritten as

$$y(\mathbf{x}) = \beta + z(\mathbf{x}) \quad (2)$$

Let $\hat{y}(\mathbf{x})$ be an approximation model. When the mean squared error between $y(\mathbf{x})$ and $\hat{y}(\mathbf{x})$ is minimized, $\hat{y}(\mathbf{x})$ becomes

$$\hat{y}(\mathbf{x}) = \hat{\beta} + \mathbf{r}^T(\mathbf{x})\mathbf{R}^{-1}(\mathbf{y} - \hat{\beta}\mathbf{q}) \quad (3)$$

where $\hat{\beta}$ is the estimated value of β , \mathbf{R}^{-1} is the inverse of correlation matrix \mathbf{R} , \mathbf{r} is the correlation vector, \mathbf{y} is the observed data with n_s sample data and \mathbf{q} is the vector with n_s components of ones.

The correlation matrix is defined as

$$R(\mathbf{x}^j, \mathbf{x}^k) = \text{Exp}\left[-\sum_{i=1}^n \theta_i |x_i^j - x_i^k|^2\right] \quad (4)$$

$(j=1, \dots, n_s, k=1, \dots, n_s)$

$$\mathbf{r}(\mathbf{x}) = [R(\mathbf{x}, \mathbf{x}^{(1)}), R(\mathbf{x}, \mathbf{x}^{(2)}), \dots, R(\mathbf{x}, \mathbf{x}^{(n_s)})]^T \quad (5)$$

where θ_i is the i -th correlation parameter corresponding to i -th design variable.

The likelihood function, L is defined as

$$L(\mathbf{y}, \theta, \beta, \sigma^2) = \frac{(2\pi\sigma^2)^{-n_s/2}}{\sqrt{|\mathbf{R}|}} \cdot \text{Exp}\left[-\frac{(\mathbf{y} - \beta\mathbf{q})^T \mathbf{R}^{-1}(\mathbf{y} - \beta\mathbf{q})}{2\sigma^2}\right] \quad (6)$$

By differentiating log-likelihood function defined from Eq.(6) with β and σ , respectively, and letting them be equal to 0, the maximum likelihood estimators of β and σ^2 are determined as

$$\hat{\beta} = (\mathbf{q}^T \mathbf{R}^{-1} \mathbf{q})^{-1} \mathbf{q}^T \mathbf{R}^{-1} \mathbf{y} \quad (7)$$

$$\hat{\sigma}^2 = \frac{(\mathbf{y} - \hat{\beta}\mathbf{q})^T \mathbf{R}^{-1}(\mathbf{y} - \hat{\beta}\mathbf{q})}{n_s} \quad (8)$$

The unknown correlation parameters of $\theta_1, \theta_2, \dots, \theta_n$ are calculated from the formulation as follows

$$\text{maximize } -\frac{[n_s \ln(\hat{\sigma}^2) + \ln|\mathbf{R}|]}{2}, \quad (9)$$

where $\theta_i (i=1,2,\dots,n) > 0$.

Computation time is excessive for solving Eq.(9) in problems with many sample point using a global optimization algorithm. Thus reliable optimum parameter θ can be obtained by using gradient-based algorithm and changing a few initial values. To assess the approximate model, the error in surrogate model can be measured by

$$RMSE = \sqrt{\frac{1}{n_t} \sum_{i=1}^{n_t} (y_i - \hat{y}_i)^2} \quad (10)$$

$$MAXERR = \text{MAX}[|y_i - \hat{y}_i|, i = 1, 2, \dots, n_t], \quad (11)$$

$$\text{Ave. \% error} = \frac{1}{n_t} \sum_{i=1}^{n_t} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \times 100 \quad (12)$$

$$CV = \sqrt{\frac{1}{n_s} \sum_{i=1}^{n_s} (f_i - \hat{f}_i)^2} \quad (13)$$

where n_t is the number of sample points for validation.

3 Structural Design Examples

3.1 Design of an automotive door

TWB(Tailor-welded blank) is a manufacturing technology that cuts two or more flat blank, welds them, and then forms them, rather than forming a single steel panel. Materials for TWB are high-strength steel, aluminium alloy 5000 and 6000 series, etc. The parting lines in TWB technology are linear, and the door is composed of three parts, therefore allowing each part to take a different thickness. Thus it could be applied by method of optimization based on metamodel. The optimization formulation for TWB design of an inner panel can be defined as

$$\begin{aligned}
 & \text{Minimize } Weight(t_1, t_2, t_3, t_4, t_5, l_1, l_2) \\
 & \text{Subject to } \delta_i - \delta_{i0} \leq 0 \quad (i=1, 2, 3, 4) \\
 & \quad \omega_0 - \omega_1 \leq 0 \\
 & \quad -2t_4 + t_1 \leq 0 \\
 & \quad 0.6\text{mm} \leq t_i \quad (i=1, \dots, 5) \leq 1.5\text{mm} \\
 & \quad -25.0\text{mm} \leq l_i \quad (i=1, 2) \leq 25.0\text{mm}
 \end{aligned} \tag{14}$$

where design values t_1, t_2, t_3, t_4 and t_5 are thickness of each part. l_1 and l_2 are shape design variable defining lengthwise position of the parting line. δ_i ($i=1, \dots, 4$) is displacement of the force direction resulting from the loading condition and δ_{i0} is its allowable value. ω_1 is first natural frequency and ω_0 is its allowable value. These are a problem of discrete and continuous design.

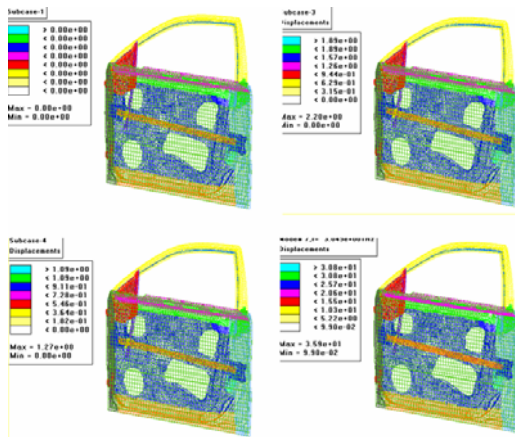


Fig.1 Stiffness analysis of a door assembly

Optimum values are [1.30, 0.90, 1.00, 0.65, 0.70, -25.00, -16.68]mm. The weight decreased by around 1kg [5].

3.2 Design of a control arm

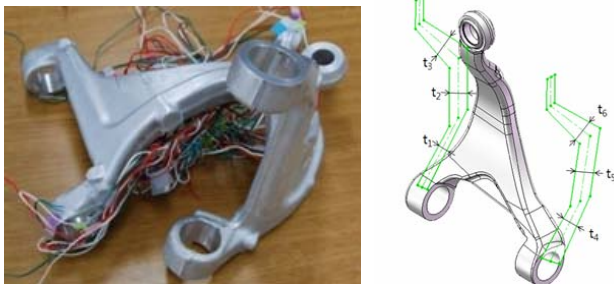


Fig.2 Control arm

The structural design of a control arm in Fig.2 is included in the category of shape optimization. A classical structural optimization method [1, 2] has difficulties in defining complex shape design variables and preventing mesh distortions during the optimization process. To overcome these difficulties, this study performs the shape optimization using metamodels. The structural optimization of the upper control arm can be formulated as

$$\begin{aligned}
 & \text{Minimize } weight(\mathbf{t}) \\
 & \text{subject to } \sigma_{max} \leq \sigma_a \\
 & \quad t_L \leq \mathbf{t} \leq t_U
 \end{aligned} \tag{15}$$

σ_{max} is replaced with kriging metamodel. And then the optimum value is obtained easily by using the metamodel. Optimum values are [8.79, 15.83, 17.25, 15.85, 14.26, 17.35] mm [6].

3.3 Design of an airbag

An approximate optimization is utilized by RSM in existing airbag design. However, Kriging interpolation method is better than RSM in highly nonlinear problem of occupant behavior. In the airbag design, to minimize the probability of combined injury, the optimization formulation can be defined as follows:

$$\text{Minimize } P_{com}(x_1, x_2, x_3, x_4, x_5) \tag{16}$$

where x_1, x_2, x_3, x_4, x_5 is design variable for airbag. The optimization process is performed with Kriging approximation model of P_{com} . in Eq.(16) [7].

3.4 Robust design

In Robust design, the robustness can be measured by the mean and variance of f . The formulation for a robust design is defined to minimizing multi-object function as

$$\text{Minimize } [(\mu_f - m_f)^2, \sigma_f^2] \tag{17}$$

where μ_f is mean of f , m_f is target value of f , σ_f^2 is variance of f . To calculate μ_f and σ_f^2 in Eq. (17), first or second-order approximation could be substituted for μ_f and σ_f^2 . One's response function f is approximated to kriging metamodel, we easily obtain mean and variance of f [8].

4 Conclusion

A response function or response defined in discrete design, shape optimization and robust design problems is replaced with kriging approximation model. The surrogate model efficiently suggests solutions.

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References:

- [1] MSC.Software Corporation, *MSC.NASRAN 2004 Design Sensitivity and Optimization User's Guide*, 2004
- [2] VR & D., *GENESIS Ver.6.0 Users Manual*, 2000.
- [3] Sacks, J., Welch, W.J., Mitchell, T.J. and Wynn, H.P. Design and Analysis of Computer Experiments, *Statistical Science*, Vol.4, No.4, 1989, pp 409-435.
- [4] Fang, K.-T. Li, R. and Sudjianto, A., *Design and Modeling for Computer Experiments.*, Chapman & Hall/CRC, London
- [5] Lee, K.H. and Kang, D.H., Structural Optimization of an Automotive Door Using the Kriging Interpolation Method, *Journal of Automobile Engineering*, Vol. 221, No. 12, 2007, pp. 1525 - 1534.
- [6] Song, B.C., Park, Y.C., Kang, S.W., Lee, K.H., Structural Optimization of an Upper control Arm, considering the Strength, *Journal of Automobile Engineering*, Vol. 223, No. 6, 2009, pp. 727 - 735.
- [7] Lee, K.H., Optimization of a Driver-Side Airbag Using Kriging Based Approximation Model, *Journal of Mechanical Science and Technology*, Vol. 19, No. 1, 2005, pp. 116-126.
- [8] Lee, K.H., Kang, D.H., A Robust Optimization Using the Statistics Based on Kriging Metamodel, *Journal of Mechanical Science and Technology*, Vol. 20, No. 8, 2006, pp. 1169-1182.