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Use of support vector regression in structural optimization: Application to vehicle crashworthiness design

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Abstract

Metamodel is widely used to deal with analysis and optimization of complex system. Structural optimization related to crashworthiness is of particular importance to automotive industry nowadays, which involves highly nonlinear characteristics with material and structural parameters. This paper presents two industrial cases using support vector regression (SVR) for vehicle crashworthiness design. The first application aims to improve roof crush resistance force, and the other is lightweight design of vehicle front end structure subject to frontal crash, where SVR is utilized to construct crashworthiness responses. The use of multiple instances of SVR with different kernel types and hyper-parameters simultaneously and select the best accurate one for subsequent optimization is proposed. The case studies present the successful use of SVR for structural crashworthiness design. It is also demonstrated that SVR is a promising alternative for approximating highly nonlinear crash problems, showing a successfully alternative for metamodel-based design optimization in practice.

Keywords: Support vector regression; Metamodel; Crashworthiness; Vehicle lightweight design; Structural optimization

1. Introduction

For dealing with analysis and optimization of computationally expensive simulation-based models in engineering design practice, there is a growing interest in using metamodel (also called surrogate model or approximation model) to fit the nonlinear relationship between the input variables and output response from the results of limited sparse design points. Although various approximation techniques like polynomial response surface (PRS), radial basis neural network (RBNN), and kriging (KRG) are available for engineering design in aerospace [5,3], automotive industry [10,4] and other disciplinary [8], support vector regression (SVR) gradually shows powerful alternative in engineering application [2,11]. Nowadays, structural design optimization related to crashworthiness is of particular importance to automotive industry, which often involves highly nonlinear computational analysis and optimization with high dimensional variables. In practice, optimization through finite element (FE) crash simulations and

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trial-and-error approach directly is prohibitively inappropriate due to massive computational cost. As a consequence, metamodel-based design optimization (MBDO) is extensively used to achieve the global optimum efficiency [17]. Also with the help of metamodel, it is convenient to perform global sensitivity analysis and reliability analysis, etc.

SVR is a particular implementation of support vector machines (SVM), which is a method from statistical learning disciplinary [14]. The main idea of SVM is to map a nonlinear problem in an input space to a linear problem in a higher-dimensional feature space, a reproducing kernel Hilbert space. Prediction accuracy or generalization performance of SVR depends on a good setting of kernel function, kernel parameters, regularization parameters C and insensitivity ε [1,16]. Practitioners have dealt with the issue of model selection for engineering optimization to avoid the risk of misleading the optimum [7]. Although practical recommendation on hyper-parameters (C and ε) has been proposed in [1], suggestion is available for Gaussian radial basis function (GRBF) kernel. Besides, previous researches on generalization performance of SVR for engineering optimization focused on GRBF kernel mostly and other kernel functions are not taken into consideration generally [2].

In the present study, the industrial applications of using SVR on vehicle crashworthiness design are presented. The first case is crashworthiness design of vehicle upper body structures to resist roof crush, and the second one is lightweight design of vehicle front end structures under frontal crash. The paper is organized as follows. In Section 2, an overview of the three existing metamodeling techniques is given and a brief review of SVR is presented in Section 3. The general parameters for SVR are setup in Section 4. Section 5 introduces two engineering optimization case studies related to vehicle crashworthiness design, followed by conclusive remarks in Section 6.

2. Existing metamodeling techniques

This section briefly presents an overview of the three metamodeling techniques against which SVR is compared, including polynomial response surface, radial basis neural network and kriging. These techniques were chosen based on their widespread use in supporting engineering design and optimization.

2.1. Polynomial response surface

Polynomial response surface (PRS) fits the functions by using the least squares method on a series of points in the design variable space. The most commonly used PRS model is the second-order model in the form of a second-degree algebraic polynomial functions as

$$f_{pred}(x) = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{i=1}^{k} b_{ij} x_i x_j \tag{1}$$

where k is the number of design variables, and b_0, b_i, b_{ii}, b_{ij} are the unknown coefficients to be determined by the least squares technique.

2.2. Radial basis neural network

Radial basis neural network (RBNN) is an artificial neural network which uses radial basis function as transfer functions. RBNN consist of two layers: a hidden radial basis layer and an output linear layer. The output of the network is thus

$$f_{pred}(x) = \sum_{i=1}^{N} a_i d(\mathbf{x}, \mathbf{c}_i) \tag{2}$$

where N is the number of neuron in the hidden layer, $\mathbf{c}_i$ is the center vector for neuron i, and a_i are the weights of the linear output neuron. The norm is typically taken to be the Euclidean distance and the basis function is taken to be the following

$$d(\mathbf{x}, \mathbf{c}_i) = exp\left(-\frac{||\mathbf{x} - \mathbf{c}_i||^2}{\sigma}\right) \tag{3}$$