Applied Acoustics 116 (2017) 139–151

Contents lists available at ScienceDirect

Applied Acoustics

journal homepage: www.elsevier.com/locate/apacoust

Structural-borne acoustics analysis and multi-objective optimization by using panel acoustic participation and response surface methodology

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ARTICLE INFO

Article history:
Received 29 July 2016
Accepted 12 September 2016

Keywords:
Panel acoustic participation
Design of experiment
Response surface methodology
Structural-borne acoustics
Multi-objective optimization

ABSTRACT

This paper is aimed to investigate the structural-borne acoustics analysis and multi-objective optimization of an enclosed box structure by using the panel acoustic participation (PAP) and response surface methodology (RSM). The acoustic frequency response function is applied to achieve the critical frequency of interest under each excitation. The PAP analysis is then carried out at all critical frequencies and the remarkable acoustic panels are identified. The correlation coefficient matrix method is proposed for reselecting and grouping the positions of acoustic panels identified to paste damping layer to control noise. With the help of faced central composite design, an efficient set of sample points are generated and then the second-order polynomial functions of sound pressure response at each critical frequency are computed and verified by the adjusted coefficient of multiple determination. The functional relationships between sound pressure responses and the thicknesses of damping layers are investigated, and multi-objective optimization of the thicknesses of damping layers is developed. The results indicate that, by using the PAP and RSM, the structural-borne acoustics at critical frequencies are calculated conveniently and controlled effectively. The optimization process of the explicit optimization model proposed in this paper is simple and the computational time is saved.

1. Introduction

There are numerous engineering applications of shell structures. The body of vehicle, aircraft and submarine are some examples for which evaluation of a structure-borne acoustics in an enclosed cavity is very important. In general, these thin-walled structures are vulnerable to vibrate and radiate noise into the passenger compartment when they are excited by dynamic force, especially when the exciting frequency is close to the natural frequencies of shell structures or the air cavity. Thus, it is an important and meaningful task for engineers to control and optimize the sound radiation of shell structures to design quiet products.

Structure-borne noise [1], which is a typical coupled vibro-acoustic problem, is characterized by the sound pressure radiation from the vibrating panel structures into an enclosed cavity. The underlying physics governing of this dynamic behavior can be represented by the acoustic frequency response function [2]. In analyzing the acoustic frequency response functions for structure-borne acoustic which is a low frequency noise problem [3], the applications of finite element models to both the body structure and cavity acoustics [4–7], and mixed finite-boundary element theory where the cavity acoustics is represented as a boundary element model [8–10] are often employed. Damping material is widely used to control vibration and noise of the thin-walled structures, and the literatures on this aspect are surprisingly voluminous. We have compiled a selective to provide background information and useful cross-references on the subject. Refs. [11,12] reduced the sound power or noise radiation from the shell structures by redistribution the unconstrained damping layers. Literatures [13,14] analyzed the response of a sandwich viscoelastic structures under dynamic loads to describe the behavior of different types of surface damping treatments. Using the panel acoustic participation (PAP) method, literatures [15,16] identified the main acoustic panels and the damping layer was pasted here to refine the interior sound field of the cavity. In order to control the noise and vibration effectively, some optimization algorithms in conjunction with finite element method have been developed for layer damping treatment, such as optimal position or shape of the constrained-layer damping for vibration suppression by using the energy approach [17–19], modified gradient method

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http://dx.doi.org/10.1016/j.apacoust.2016.09.013

[20], layer-wise theory [14] or topology optimization [21]. The finite element method or boundary element method have been applied to compute the vibro-acoustic problem successfully, which is a highly nonlinear process, while the optimization algorithm for reducing the structural acoustics is complex and time consuming, especially for a large complex structure.

However, the response surface methodology (RSM) can be employed to compute and optimize the vibro-acoustic problem effectively, if the mathematical formulations of RS model close to the physics (being modeled) significantly. The article by Box and Hunter [22] provided an outline of the basic principles of RSM, i.e. fitting a response surface function (RS function) related the inputs and outputs using a small number of data sets which are chosen in the design space rigorously. Due to these superiorities, the RSM has been applied to optimize the vibration or acoustic problem. Ganguli [23] decoupled the analysis problem and presented an improved design to reduce vibratory loads at the rotor hub. In order to reduce the sound radiation, the RSM is utilized to analysis the effect of design parameters on the sound radiation from the damping structure [24,25]. Maarten et al. [26]developed a hybrid-global optimization and interval arithmetic-procedure for interval and fuzzy envelope frequency response functions calculation. Shokuhfar et al. [27]optimized the volume fraction, the orientation and the through thickness location of the shape memory alloy wires to minimize the maximum transverse deflection of the hybrid composite plate. Park [28] conducted multi-objective optimization of the tooth surface in helical gear for low gear noise. Although the RSM has been successfully applied to reduce or optimize the sound radiation of shell structures (e.g. Refs. [24,25]), the literatures about the positions where the damping layers pasted are significant to reduce the sound radiation and how to effectively control the sound pressure in cavity, which is excited by many dynamic forces, are handful. For example, the papers [15,16] identified the main acoustic panels from many thin-walled structures to paste the damping layer, while the structure is excited by single dynamic load and the RSM is not used to optimize damping layer thicknesses.

To practical engineering structures, such as the body of vehicle which is consisted of numerous thin-walled structures and excited by many dynamic forces, the noise control for them are complex. To achieve significant noise reduction for these engineering thin-walled structures, three critical technological problems need to be addressed. The first one is the identification of acoustic panels from the numerous thin-walled structures. The second one is confirming the positions of pasting damping layer to control noise effectively at multi-excitations. The third one is that the multi-objective optimization of the thicknesses of damping layers should be efficient and less computational time for the acoustic problem which is a high non-linear processes. The current paper is partly motivated by these investigations and carries out related research. Using the analytical and FE simulation methods, three critical technological problems mentioned above are resolved sequentially. The remainder of this paper is organized as follows. Section 2 formulates the theory method for the problem. Section 3 establishes the simulation model of the coupled vibro-acoustics system. Section 4 develops the second-order RS models for the structure-borne acoustics. Section 5 proposes an explicit multi-objective optimization model to optimize the thicknesses of pasted damping layers. Section 6 gives conclusions.

2. Theory of response surface methodology for structure-borne acoustics

RSM is based on employing the statistical and experimental techniques, when reasonably applied, to deal possibly with more configurations of the input parameters to be tested and explore deeply the domain of the problem's solutions [23]. The RS function is a smooth, explicit and analytic form which is obtained simply by carrying out limited experiments run and regression analysis, and the construction process of RS function is illustrated as follows.

2.1. Construction method of response surface function

Generally, the relationship between system response of interest denoted by y and design factors denoted by vector $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^{\mathrm{T}}$ is

$$y = g(x_1, x_2, \ldots, x_n) + \varepsilon \tag{1}$$

where ε is the random experimental error term and its mean value is zero. With the help of design of experiment, the approximate response function of system can be written as [24,25]

$$y = f(x_1, x_2, \ldots, x_n) + \varepsilon \tag{2}$$

where $f(x_1, x_2, \ldots, x_n)$ is a function of $\boldsymbol{x}$ whose elements consist of powers and cross products of powers of $x_1, x_2, \ldots, x_n$ up to a certain degree. For many practical engineering applications, the order of polynomial of $f(x_1, x_2, \ldots, x_k)$ is not more than three [25,26,28]. In terms of a second-order RS function, the $f(x_1, x_2, \ldots, x_k)$ is expressed as

$$f(\boldsymbol{x}, \boldsymbol{\alpha}) = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_i + \sum_{i=1}^{n} \alpha_{ii} x_i^2 + \sum_{i=1}^{n} \sum_{j<i} \alpha_{ij} x_i x_j \tag{3}$$

To estimate the unknown parameters $\boldsymbol{\alpha} = (\alpha_0, \alpha_1 \ldots, \alpha_n, \alpha_{11} \ldots, \alpha_{nn}, \alpha_{12} \ldots, \alpha_{(n-1)n})$, a series of experiments run are conducted and the corresponding responses y are measured. At the kth experimental run, the design factor $\boldsymbol{x}$ is set to $\boldsymbol{x}^{(k)} = (x_1^{(k)}, x_2^{(k)}, \ldots, x_n^{(k)})$, and $y^{(k)}$ denotes the corresponding response value. From Eqs. (2) and (3) we then have

$$\begin{aligned} y^{(k)} &= f(x_1^{(k)}, x_2^{(k)}, \ldots, x_n^{(k)}) + \varepsilon^{(k)} \\ &= \alpha_0 + \sum_{i=1}^{n} \alpha_i x_i^{(k)} + \sum_{i=1}^{n} \alpha_{ii} \left(x_i^{(k)}\right)^2 + \sum_{i=1}^{n} \sum_{j<i} \alpha_{ij} x_i^{(k)} x_j^{(k)} + \varepsilon^{(k)} \end{aligned} \tag{4}$$

Eq. (4) can be rewritten in a matrix form as

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\alpha} + \boldsymbol{\varepsilon} \tag{5}$$

$$\boldsymbol{X} = \begin{bmatrix} 1 & x_1^{(1)} & \cdots & x_n^{(1)} & \left(x_1^{(1)}\right)^2 & \cdots & \left(x_n^{(1)}\right)^2 & x_1^{(1)} & x_2^{(1)} & \cdots & x_{n-1}^{(1)} & x_n^{(1)} \\ \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & & \vdots & \\ 1 & x_1^{(k)} & \cdots & x_n^{(k)} & \left(x_1^{(k)}\right)^2 & \cdots & \left(x_n^{(k)}\right)^2 & x_1^{(k)} & x_2^{(k)} & \cdots & x_{n-1}^{(k)} & x_n^{(k)} \\ \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & & \vdots & \\ 1 & x_1^{(m)} & \cdots & x_n^{(m)} & \left(x_1^{(m)}\right)^2 & \cdots & \left(x_n^{(m)}\right)^2 & x_1^{(m)} & x_2^{(m)} & \cdots & x_{n-1}^{(m)} & x_n^{(m)} \end{bmatrix} \tag{5.1}$$

where $\boldsymbol{X}$ is a matrix of order $m \times p$ ($p = (n+1)(n+2)/2$), $\boldsymbol{y} = (y^{(1)}, y^{(2)}, \ldots, y^{(m)})^{\mathrm{T}}$ and $\boldsymbol{\varepsilon} = (\varepsilon^{(1)}, \varepsilon^{(2)}, \ldots, \varepsilon^{(m)})^{\mathrm{T}}$, respectively. From Eqs. (5) and (5.1), it should be noted that the number of unknown coefficients $\boldsymbol{\alpha}$ is $(n+1)(n+2)/2$, thus, to estimate these parameters, an equal or more number of experiment runs (i.e. $m \geqslant p$) are needed. The coefficient vector $\boldsymbol{\alpha}$ is estimated by the ordinary least-squares estimator [26] which are given by

$$\boldsymbol{\alpha} = (\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X})^{-1}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{y} \tag{6}$$

2.2. Design of experiment and model validation

2.2.1. Faced central composite design

Design of experiment is a collection and arrangement of experimental runs designed to gain the information most relevant to the