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An approach to enhance the generalization capability of nonlinear aerodynamic reduced-order models

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ABSTRACT

A novel modeling approach for nonlinear aerodynamic reduced-order models (ROMs) is developed to enhance the generalization capability of current ROMs. The proposed method is called the "modeling with validation case" approach. Instead of the conventional modeling process through training and test cases, three types of cases, namely, training, validation, and test cases, are introduced. The validation case is used to find the best parameters (widths of hidden neurons) of the model, in order to enhance the generalization capability of the nonlinear aerodynamic ROMs. Searching for optimal parameters is accomplished by the particle swarm optimization (PSO) algorithm, obtaining the minimal mean squared error of the validation case. The approach is applied to a recursive radial basis function neural network aerodynamic model. Two examples of a NACA0012 airfoil pitching in transonic flow are presented to compare the proposed approach with the conventional modeling process. The aerodynamic model with the proposed approach shows high accuracy from small to large pitching amplitudes in the time domain. In the frequency domain, comparisons of the first-order Fourier series indicate that the dynamic characteristics at different reduced frequencies and amplitudes are well captured. The conventional modeling process shows equivalent accuracy at large amplitudes but fails to predict the dynamic linear behavior at small amplitudes. Compared with the conventional modeling process, the proposed approach can capture both linear and nonlinear characteristics.

1. Introduction

Computational fluid dynamics (CFD) enables the high-fidelity simulations of linear or nonlinear flow physics. However, the CFD solver is inappropriate for certain aeroelastic analysis, design optimization, or other applications because of expensive computational costs. An alternative scheme is adopted to establish a properly designed reduced-order model (ROM) with high accuracy. ROMs can represent an aerodynamic system and predict the aerodynamic loads. The advantages of ROMs lie in reducing computational cost and allowing for a wide range of analysis on certain coupled problems combined with other analytical tools.

Once a ROM is obtained after evaluation, the expensive computational cost of the CFD solver can be avoided and ROM techniques can be used to achieve aeroelastic analysis or aerodynamic load prediction. The overviews and applications of different ROMs are discussed by Zhang and Ye [1], Ghoreyshi et al. [2], and Lucia et al. [3]. Several typical ROMs applied at present include ROMs based on the proper orthogonal decomposition (POD) [4] or balanced POD (BPOD) [5], harmonic balance method [6] of unsteady aerodynamic forces, and ROMs based on the system identification methods (i.e., Volterra series [7], the autoregressive with exogenous input (ARX) model [8], surrogate-based recurrent framework (SBRF) [9], and neural networks [10–16]).

An aeroelastic system has nonlinearity because of many aspects. In general, aeroelastic nonlinearity mainly includes structural nonlinearity and aerodynamic nonlinearity. In this paper, the main topic is aerodynamic nonlinearity. Given a flow field at a small angle of attack and small perturbation, the flow varies slightly in a linear fashion with wing motion, which is usually defined as dynamic linear or static nonlinear aerodynamics. These problems can be represented by dynamic linear model, such as ARX and first-order Volterra series. However, for many transonic flows with large shock wave motions or at high angles of attack and considering the viscous effect, the unsteady aerodynamic loads show a strong nonlinearity. Thus, the dynamic linear models become essentially unsuitable. To deal with aerodynamic nonlinearity, many studies have been conducted. Glaz et al. [9] developed a type of SBRF referred to as a nonlinear autoregressive moving average with exogenous input model. By introducing the output feedback, the recurrent framework is constructed to predict the nonlinear aero-

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Nomenclature

A	relative amplitude of cases
a	the sound speed
b	the half chord length
C_l	lift coefficient
$C_{l(p)}$	lift coefficient at time instant p
C_m	moment coefficient
$C_{m(p)}$	moment coefficient at time instant p
c	the number of neurons in the hidden layer
c_1	local acceleration constants
c_2	global acceleration constants
D	dimension of sample space
DT	time step of CFD simulation
d	current iterative number
dS	surface element of control volume Ω
$\boldsymbol{E}^c(\boldsymbol{W}, \boldsymbol{V}_{grid})$	the inviscid flux vectors
$\boldsymbol{E}^v(\boldsymbol{W})$	the viscous flux vectors
$\boldsymbol{Gbest}_i^d$	the global best position
g	total iteration number
h	radial basis function
h_j	the output of the jth neuron in the hidden layer
h_p	the plunging displacement of the airfoil at time instant p
k	reduced frequency of pitching motion, $k = \omega b/V$
l	the dimension of output vector $\boldsymbol{y}$
m	input delay order of aerodynamic model
mse	mean squared error
N_T	number of training data points
$N(i)$	the set of face-neighbor cells of the ith cell
n	output delay order of aerodynamic model
$\boldsymbol{n}$	the outer unit normal vector to the boundary $\partial\Omega$
$\boldsymbol{S}_{im}$	the normal vector area of the face shared by the ith and the mth cells
$Size$	population of particles
s	the dimension of input vector $\boldsymbol{x}$
p	the time instant
$\boldsymbol{P}_i^d$	the local best position
Q_T	the source term of the S–A turbulence model
$\boldsymbol{R}_{source}$	the source term in URANS equation
RE	relative error
r_1	random numbers from 0 to 1
r_2	random numbers from 0 to 1
T	non-dimensional time
T_{CFD}	time cost of all CFD simulations
$T_{\mathrm{ROM+MV}}$	time cost of training the RRBFNN (PSO-Validation) model
t	real time
$t_{CFD(i)}$	the actual output of training case at ith data point
$\boldsymbol{u}_p$	input vector of aerodynamic model at time instant p
V	the flow velocity
$V_{\max}$	the maximum velocity
$\boldsymbol{V}_{grid}$	the velocity introduced by the moving grid
$\boldsymbol{V}_i^{d+1}$	the velocity of the ith particle at the $d+1$th iteration
$\boldsymbol{v}_j$	center vector of the jth neuron in the hidden layer
$\boldsymbol{W}$	the conservation vector
$w_{i,0}$	the bias of the ith output neuron
$w_{i,j}$	the weight that connects the jth hidden neuron to the ith output neuron
$\boldsymbol{X}_i^{d+1}$	the position of the ith particle at the $d+1$th iteration
$X_{\max}$	upper bound of width
$X_{\min}$	lower bound of width
$\boldsymbol{x}$	input vector of radial basis function neural network
$\boldsymbol{y}$	output vector of radial basis function neural network
y_i	the output of the ith neuron in the output layer
$y_i(\boldsymbol{X}_i)$	model output at ith data point of widths $\boldsymbol{X}_i$
$\mathbf{y}_{CFD}$	the actual output matrix given by CFD solver
$\mathbf{y}_{simu}$	the output of aerodynamic model
α_0	the maximum pitching amplitude
α_m	mean pitching angle of harmonic motion
θ_p	the pitching displacement of the airfoil at time instant p
Ω	control volume
Ω_i	the volume of the current ith grid cell
$\boldsymbol{\sigma}$	width matrix of radial basis function neural network
σ_j	the width of the jth neuron in the hidden layer
ω	the rotational velocity
ω_1	lower bound of the inertia weight
ω_2	upper bound of the inertia weight
$\omega(d+1)$	the inertia weight at the $d+1$th iteration

Abbreviations

modeling with validation case = a new modeling approach by training/validation/test cases
modeling without validation case = conventional modeling approach by training/test cases
PSO-Training = RRBFNN (PSO-Training) for short
PSO-RRBFNN = RRBFNN model with optimizing widths by PSO algorithm
PSO-Validation = RRBFNN (PSO-Validation) for short
RBFNN = radial basis function neural network
RRBFNN = recursive radial basis function neural network
RRBFNN (PSO-Training) = incorporating the conventional modeling approach in training PSO-RRBFNN, with the fitness function set as the mean squared error of training case
RRBFNN (PSO-Validation) = incorporating the novel modeling approach in training PSO-RRBFNN, with the fitness function set as the mean squared error of validation case

dynamic loads at fixed or time-varying free-stream Mach numbers. He et al. [17] applied the superposition principle to aerodynamic describing functions by constructing an equivalent linearized aerodynamic model in frequency domain. Results demonstrated that this method can solve several weak nonlinear problems in the transonic limit cycle oscillation (LCO) prediction. Moreover, many nonlinear aerodynamic models based on neural networks [10–16] have been developed.

Neural networks are effective tools for modeling a broad category of complex nonlinear systems, especially those systems in which mathematical models are difficult to obtain [18]. Marquez and Anderson [10] predicted unsteady transonic aerodynamic loads by using multilayer functions and by constructing a temporal neural network with discrete time and limited memory. The results of lift coefficients are much better than those of moment coefficients. Suresh et al. [11] predicted lift coefficients at high angles of attack. However, to validate the generalization capability, test cases under different pitching angles and reduced frequencies are also needed. Zhang et al. [12] introduced the output feedback on radial basis function (RBF) neural network (RBFNN) to describe unsteady phenomena, thus achieving a recursive RBFNN (RRBFNN) to identify aerodynamic loads. Ghoreyshi et al. [13] developed an aerodynamic model based on RBFNN for approximation of nonlinear unsteady aerodynamics. Given that the model inputs include