Computers & Fluids 90 (2014) 123–132

Contents lists available at ScienceDirect

Computers & Fluids

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

Multi-objective aero acoustic optimization of rear end in a simplified car model by using hybrid Robust Parameter Design, Artificial Neural Networks and Genetic Algorithm methods

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ARTICLE INFO

Article history:
Received 16 April 2013
Received in revised form 22 November 2013
Accepted 26 November 2013
Available online 4 December 2013

Keywords:
Computational Fluid Dynamics
Drag coefficient
Aerodynamic noise
Taguchi method
Neural Networks
Multi-Objective Genetic Algorithm

ABSTRACT

In this paper, optimization of rear end of a simplified car model is performed considering aerodynamic and acoustic objectives. Slant angle, rear box angle, boat tail angle, and rear box length are considered as main variables of the rear end. For numerical simulation of flow around the model and studying aerodynamic noise, realizable turbulent model and broad band noise model are used, respectively. Simulation results are validated by the experimental results reported in the literature. To reduce number of simulations to reach optimum values of parameters, Taguchi method has been used. The results of Taguchi are in good agreement with simulation results. Then, the results of Taguchi have been used to obtain a relation between parameters and objectives employing Artificial Neural Networks. Optimization of the model has been conducted by the Neural Network and Multi Objective Genetic Algorithm methods. Finally, flow around the optimized model has been studied by numerical simulation and results have been reported.
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1. Introduction

While driving, air flowing around the vehicle leads to drag and lift forces and aerodynamic noise. Significant efforts have been made to study flow around vehicles to optimize the shape to improve drawbacks of drag and aerodynamic noise. Krajnovic [1] used Response Surface Method (RSM) for aerodynamic optimization of flow around a train. Global optimization of drag coefficient and crosswind stability was obtained by application of Genetic Algorithm on polynomials of response surface methodology. Parussini et al. [2] implemented Multi-Objective Genetic Algorithm for designing airfoils considering performance and stability objectives. The number of simulations was reduced utilizing a response surface based on statistics. Chiba et al. [3] reported Multi-objective design optimization of a two-dimensional shielding effect for reduction of aircraft engine fan noise. The Kriging-based response surface model was applied to reduce the optimization cost. Tang et al. [4] used Taguchi Robust Design Method for dealing with aerodynamic shape optimization problems with uncertain operating conditions.

Thompson et al. [5] optimized drag and ventilation characteristics of small livestock trailers by performing CFD simulations for combinations of design variables defined by an Optimal Latin Hypercube Design of Experiments. Hai-jun and Ya-feng [6] utilized Artificial Neural Networks (ANN) trained by a relatively small number of CFD simulations for aerodynamic optimization. It was found that ANN approximation reduces cost of computations. Beigmoradi and Ramezani [7] performed drag minimization of a simplified car model, in which Robust Parameter Design (RPD) was found to be the appropriate method for finding optimum level of parameters in CFD problems.

In this work, a simplified vehicle model with four parameters, namely slant angle, rear box length, rear box angle, and boat tail angle is studied. Each parameter is considered in five levels and in order to reduce cost of computations, Taguchi method based on the Robust Parameter Design is used. A neural network is trained by Taguchi results to estimate the relation between objectives and parameters. Finally, Multi-Objective Genetic Algorithm is applied to optimize the model. Fig. 1 shows the aerodynamic and acoustic optimization process implemented in this research.

2. Background theory

2.1. Fluid flow equations

In this paper, flow around the model is considered to be three dimensional and incompressible. Therefore, Navier–Stokes

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0045-7930/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.compfluid.2013.11.026

Nomenclature

ANN	Artificial Neural Networks
GA	Genetic Algorithm
DOE	Design of Experiment
CFD	Computational Fluid Dynamics
RPD	Robust Parameter Design
RANS	Reynolds Averaged Navier – Stokes
SNR	Signal to Noise Ratio
MSD	mean square deviations
u	x-component of velocity vector (m/s)
v	y-component of velocity vector(m/s)
w	z-component of velocity vector (m/s)
p	static pressure
B_X, B_Y, B_Z	body forces
k	Turbulence Kinetic Energy
C_k	creation of Turbulence Kinetic Energy due to the mean velocity gradients
C_b	creation of Turbulence Kinetic Energy Due to Buoyancy
Q_m	portion of the fluctuating dilatation
l	length scale (m)
a_0	speed of sound (m/s)
P_A	total acoustic power (w)
P_{ref}	reference acoustic power
C_d	drag coefficient
F_d	total drag forces
A	projected area
u_∞	upstream bulk velocity
R_p	parameter range

Greek abbreviations

ρ	density of air
ε	Turbulence Dissipation Rate
τ	Shear Stress
μ_t	eddy viscosity
σ_k	Turbulent Prandtl Number for k
σ_s	Turbulent Prandtl Number for ε

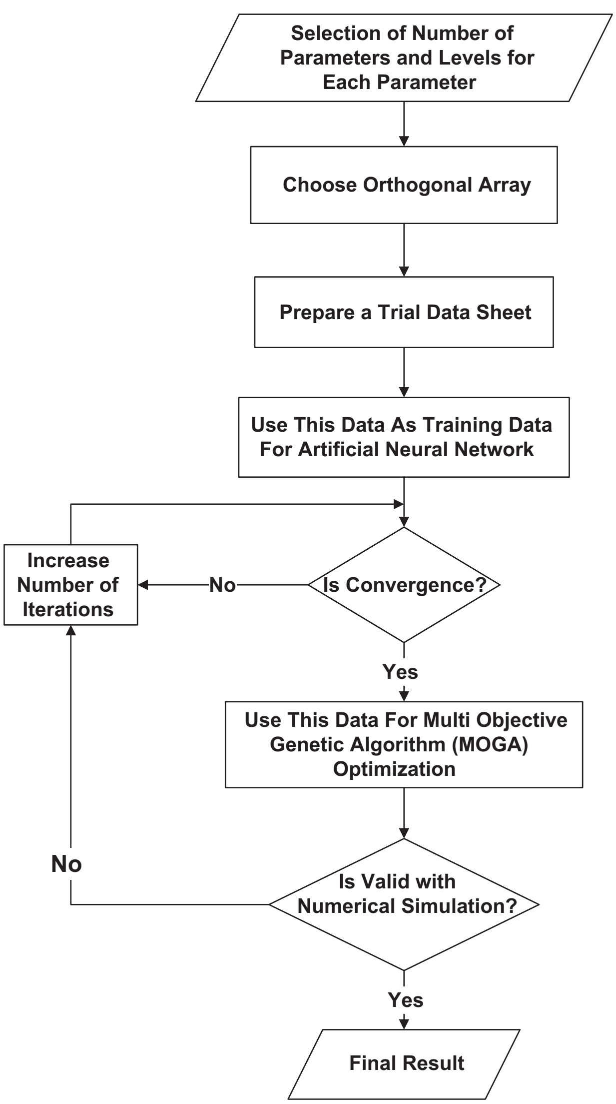

Fig. 1. Flowchart of aerodynamic and acoustic optimization process.

equations with a turbulence model are applied to solve the problem. Cartesian tensor form of Navier–Stokes equations can be written as follow:

$$\frac{\partial}{\partial x_i}(\rho u_i) = 0 \tag{1}$$

where ρ is density and u_i is velocity component in x_i direction. In turbulent flow, the solution variables in Navier–Stokes equations can be written as the sum of mean and fluctuating terms. The velocity components can be represented as Eq. (2).

$$u = \bar{u} + u', \quad v = \bar{v} + v', \quad w = \bar{w} + w' \tag{2}$$

where $\bar{u}, \bar{v}, \bar{w}$ and u', v', w' are the mean and fluctuating velocity components, respectively. In addition, pressure and other scalar quantities can be represented as follow:

$$\lambda = \bar{\lambda} + \lambda' \tag{3}$$

where λ represents a scalar quantity such as pressure.

Substituting Eqs. (2) and (3) into Navier–Stokes equations and taking a time average provides the ensemble-averaged momentum equations as in Eq. (4).

$$\frac{\partial}{\partial x_j}(\rho u_i u_j) = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j}\left[\mu\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} - \frac{2}{3}\delta_{ij}\frac{\partial u_i}{\partial x_i}\right)\right] + \frac{\partial}{\partial x_j}(-\rho\overline{u_i' u_j'}) \tag{4}$$

where δ_{ij} is Kronecker delta coefficient ($\delta_{ij} = 0$ if $i \neq j$, $\delta_{ij} = 1$ if $i = j$). Eq. (4) is called Reynolds-averaged Navier–Stokes (RANS) equations and $-\rho\overline{u_i' u_j'}$ term is Reynolds stresses.

The Boussinesq approach is a common method to relate the Reynolds stresses to the mean velocity gradients [8]. This approach can be written as Eq. (5).

$$-\rho\overline{u_i' u_j'} = \mu_t\left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i}\right) - \frac{2}{3}\left(\rho k + \mu_t\frac{\partial u_i}{\partial x_j}\right)\delta_{ij} \tag{5}$$

In the k–ε model, eddy viscosity, μ_t, is computed as a function of Turbulence Kinetic Energy, k, and Turbulence Dissipation Rate, ε, by solving two additional transport equations for k and ε. Transport equations for k and ε in the realizable k–ε are:

$$\frac{\partial}{\partial t}(\rho k) + \frac{\partial}{\partial x_i}(\rho k u_i) = \frac{\partial}{\partial x_i}\left[\left(\mu + \frac{\mu_t}{\sigma_k}\right)\frac{\partial k}{\partial x_j}\right] + C_k + C_b - \rho\varepsilon - Q_m \tag{6}$$

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