

Automotive Aerodynamic Design Exploration Employing New Optimization Methodology Based on CFD

2010-01-0513

Published
04/12/2010

Kenichi Ando and Akio Takamura
Honda R&D Co., Ltd. Automobile R&D Center

Isao Saito
PSG Co., Ltd

Copyright © 2010 SAE International

ABSTRACT

Optimization methodology employing CFD for the aerodynamic design of automotive car styling is presented. The optimization process consists of three stages: Design of Experiments (DOE), Response Surface Modeling (RSM), and optimization algorithm execution. RSM requires a number of CFD calculations in order to ensure its accuracy, making it difficult to apply the RSM to aerodynamic design optimization. In order to resolve this issue, Adaptive Multi Stage RSM (AMS-RSM) was conceived. This method provided the response surface its required accuracy and robustness. The optimization process was realized by constructing an automatic optimization system consisting of software.

NOMENCLATURE

N_s	Sampling number
CD_{CFD}	Value of CD calculated by CFD
CD_{RSM}	Value of CD predicted by RSM

S	RBF approximation
a_i	Expansion coefficients
Φ_i	Basis function
R	Non-negative real-valued function
$\ \cdot \ $	Euclidean norm
c	Function spread parameter

INTRODUCTION

In the past few decades, a number of environmentally friendly technologies in the automotive industry, e.g., high-efficiency engines, low-rolling-resistance tires, lightweight materials, have been developed. Automotive styling is also regarded as an important factor in resolving environmental issues by reducing drag force, which results in high fuel efficiency. Automotive aerodynamicists, therefore, try to

obtain improved car styling in terms of the coefficient of drag, i.e., CD.

In conventional parametric studies of automotive aerodynamics, car shape is varied by CAD, calculation meshes are generated, and CFD calculations are performed. As a consequence, a huge amount of time is consumed. Mesh morphing techniques are, hence, employed in order to make models parametrically and consequently, working time can be reduced^[1,2,3].

A difficulty in parametric study can expand as the number of design parameters increases since they might have an effect on each other. Consequently, a large amount of CFD calculations are required so as to understand the behavior of aerodynamics in the design space. If the behavior is non-linear, then the difficulty can further expand. A marked increase in CFD calculations is, however, not always practical due to there being limits on computational power availability. This is considered one reason for aerodynamic optimization, based on CFD, not having been widely adopted to date in aerodynamic design development. An aerodynamic optimization system that seeks better CD values using a reasonable amount of CFD calculation is desired.

This paper demonstrates an efficient automotive aerodynamic optimization process and automatic system based on CFD. The optimization process consists of three stages, DOE, RSM and Optimization. In addition, AMS-RSM is introduced in order to find optimal CD values more efficiently. So as to realize the optimization flow, the CFD solver, mesh morphing and optimization software were systematically integrated and, consequently, the optimal CD values are obtained automatically.

Firstly, it is shown that the optimization methodology was devised by a 5-parameter study and secondly, the devised methodology was tested using a more intricate practical case, that is, a 12-parameter study. Lastly, AMS-RSM is explained.

OPTIMIZATION METHODOLOGY

The flow of the optimization (Figure 1) can be summarized as follows;

1. Prepare a base model and generate meshes
2. Determine CFD calculation sampling points by DOE
3. Create car models for each sampling point by morphing
4. Calculate CD values for the models by CFD
5. Create a response surface using the CFD results
6. Obtain the optimal CD values by optimization algorithm on the RSM

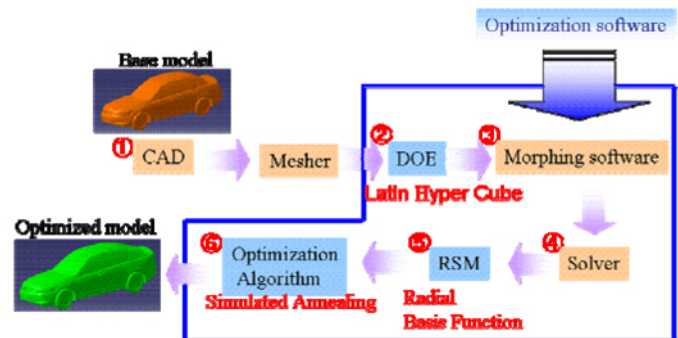


Fig. 1. Schematic of the optimization flow

The nucleus of the optimization process, i.e., DOE, RSM and optimization algorithm were determined from the accuracy and amount of CFD calculations involved. The accuracy is defined as the difference between the obtained optimal CD value by RSM and one by CFD. Here, a 5-parameter problem shown in TABLE 1 and Figure 2 was studied.

TABLE 1. Five-parameter study

Design parameter	Deformation
1. A-pillar	Inward translation
2. Fr-bumper	Inward/outward expansion
3. Rr-side	Inward/outward expansion
4. Rr-window	Rearward translation of window-top
5. Trunk-length	Rearward extension

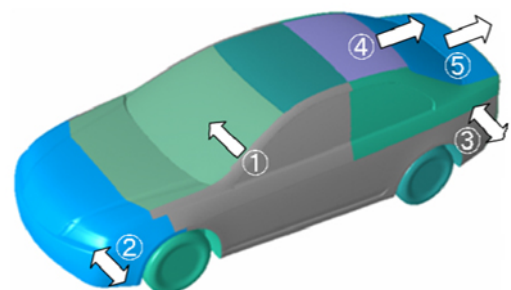


Fig. 2. Five-parameter

1. DOE

A Latin Hypercube (LHC) sampling was adopted in our optimization system. LHC is the DOE by which the design space can be filled up uniformly with the small number of sampling points. Full factorial and reduced factorial samplings are often employed in other engineering fields[4,5,6]. However, for automotive aerodynamic design optimization, CFD calculations take an enormous amount of time, especially for a multi-parametric problem. This is the reason why LHC was chosen for our optimization system.

2. RSM

The accuracy of the response surface is significant since optimal CD values are searched on the response surface via an optimization algorithm. The relationship between CD and design parameters is not always linear, and therefore, RSM that is adapted to non-linear behavior should be employed.

Here, three types of the RSM were compared with each other, i.e., Radial Basis Function (RBF), Gaussian process (GP), and Kriging (KR). Fig. 3 shows the tendency of the mean square error (MSE) for the number of samplings. It is desirable for MSE to be small and constant for a sampling number. MSE is given as follows;

$$MSE = \left(\frac{1}{N_s} \right) \sum_{i=1}^{N_s} \left\{ (CD_{CFD}(x_i) - CD_{RSM}(x_i))^2 \right\} \quad (1)$$

Kriging shows large MSE values for the small number of samplings and Gaussian processes show oscillation, which means over-fitting of the response surface with the sampling points. On the other hand, the RBF method shows low values of the MSE and is not influenced by the number of samplings. The RBF method, consequently, seems to be satisfactory for this aerodynamic problem.

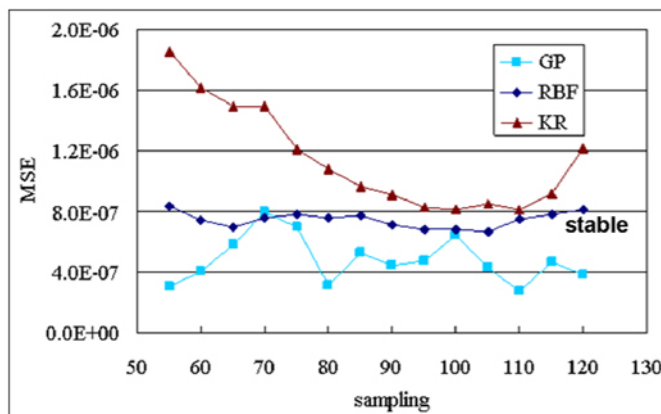


Fig. 3. MSE for samplings

The RBF has some different forms for basis functions, which include Gaussian, Hardy's multiquadrics, inverse multiquadrics, Duchon's spline, and Wendland's CSRBF [7]. The shape change of the response surface resulting in fluctuations in the optimal CD values for the sampling numbers should be avoided as much as possible by employing an appropriate RBF. In order to examine the shape change of the response surface, the trend of the optimum value of each design parameter was investigated for RBFs (Fig. 4). It is obvious that Hardy's multiquadrics interpolation produced practically the same optimum values, i.e., almost the same response surface, for the number of samplings. That means the Hardy's multiquadrics has more robustness compared with other RBFs. Hardy's multiquadrics interpolation was, as a result, adopted for our optimization system.