SAE International

Automotive Aerodynamic Design Exploration Employing New Optimization Methodology Based on CFD

2010-01-0513
Published
04/12/2010

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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

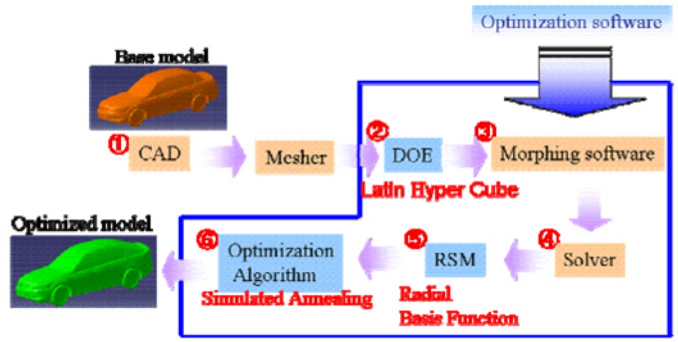

Fig. 1. Schematic of the optimization flow

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

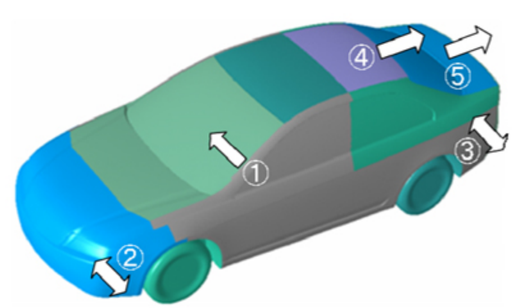

Fig. 2. Five-parameter

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;

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

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.

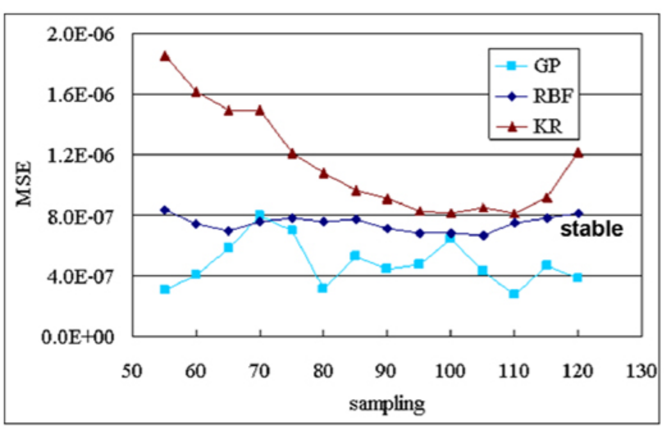

Fig. 3. MSE for samplings

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.

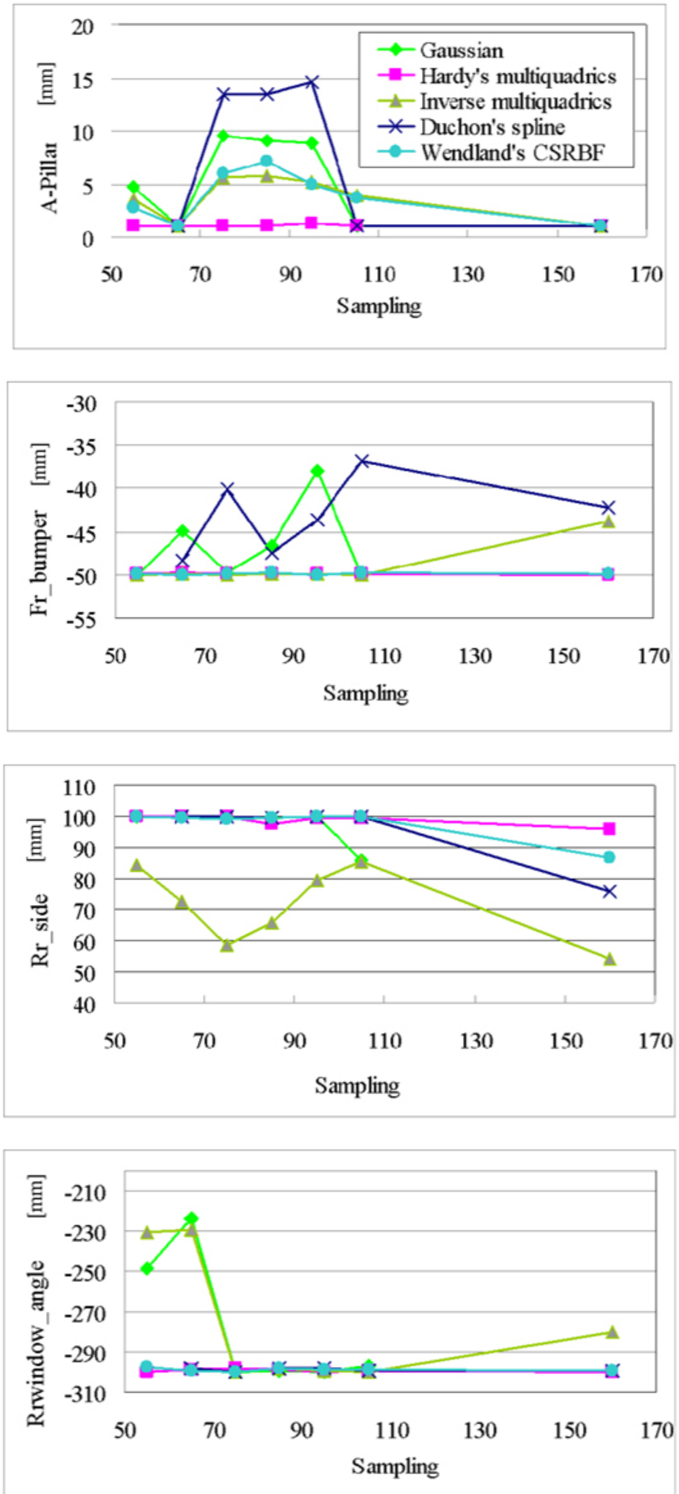

Fig. 4. Transition of optimal design parameter values for samplings

3. OPTIMIZATION ALGORITHM

The optimization algorithm is executed on the constructed response surface. If the shape of the response surface is simple, optimal CD values can be found without any difficulty. However, if the shape of the response surface is complicated, then some algorithms may not find the optimal CD values. One such case can be found when a response surface has some minima, i.e., a multi-modal problem.

The complexity of a problem, in general, grows as the number of design parameters increases and, as a result, the response surface can have some minima. Optimization algorithms should not fall into the local minima. Although there are many kinds of optimization algorithms, for example, Generic Algorithms (GAs), Simulated Annealing (SA), the Gradient Method, and the like[8,9], GAs and SA that do not fall into the local minima are appropriate and, in fact, both of them executed on the identical response surface gave almost the same optimal CD values. In our system, SA was, consequently, adopted. One of the reasons why it was selected is that setting algorithm parameters is less challenging than with GAs. Another is mentioned in the following chapter, AMS-RSM.

OPTIMIZATION SYSTEM

In this research, incompressible steady flow simulation is performed on RANS turbulence model, i.e., RNG $k-\varepsilon$ model by CFD-ACE. Runtime for one calculation is approximately five hours and some calculations could be executed simultaneously. SCULPTOR is employed for mesh morphing. The optimization process is controlled by modeFRONTIER.

In terms of mesh morphing, some logic was added to our system. CFD calculations can be diverged because of the generation of negative meshes by morphing. In order to solve such problems, an additional algorithm was composed that regenerates new meshes when negative meshes generate, and thereafter, executes CFD calculations. In addition, projected car frontal areas might be changed by deformation of the car shape, and accordingly, erroneous CD values could be calculated if the projected frontal area value is not corrected. In order to avoid this issue, the projected frontal area recalculation algorithm was also added to the optimization system.

APPLICATION TO A COMPLEX CASE

The deformation of a number of design parameters can be suggested in the early development phase. Accordingly, the optimization methodology and system must be constructed so as to cope with multi-parameter studies.

Here, a 12-parameter study shown in TABLE 2 and Fig. 5 was tested so as to ascertain that the optimization method contrived by the 5-parameter study can be applied to a more complicated problem.

The shape of the response surface for the 12-parameter study is more complicated compared to the 5-parameter study and therefore, it seems to be difficult to predict optimal CD values within reasonable accuracy. Here, two methods were tested for the 12-parameter study. One was the method confirmed by the 5-parameter study, i.e., LHC+RBF+SA, and the other was one whose sampling was determined by a generic algorithm (GA). These methods are shown in TABLE 3. The base model CD value is 0.316.

TABLE 2. Twelve-parameter study

Design parameter	Deformation
1. Side body panel	Inward/outward expansion
2. Rr-bumper	Inward/outward expansion
3. C-pillar	Inward translation
4. Trunk length	Rearward extension
5. Fr-overhung	Forward extension
6. Cowl top	Upward/downward
7. Hood	Upward/downward translation
8. Roof	Upward/downward translation
9. Rr-window	Window top forward/rearward translation
10. Trunk-height	Upward trunk lid translation
11. Fr-window	Window top forward/rearward translation
12. Diffuser	Angle change

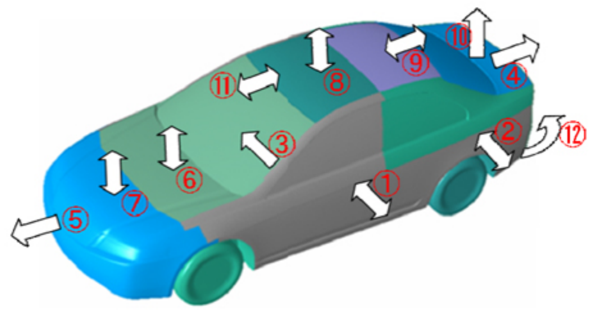

Fig. 5. Twelve-parameter

TABLE 3. Comparison of optimization methods

Method	DOE	RSM	Optimization Algorithm	Sampling No.
A	LHC	RBF	SA	164
B	LHC+ GA	RBF	SA	240

TABLE 4. Results of optimization

Method	CD_{RSM}	CD_{CFD}	Error
A	0.258	0.268	3.7%
B	0.256	0.278	7.9%

240 samplings of method B was obtained by the first 10 samplings and their 24 evolutions. i.e., 10 times 24 are equal to 240. In TABLE 4, CD_{RSM} denotes the optimum CD values predicted by the response surface and CD_{CFD} denotes the optimum CD values calculated by CFD. The CD_{CFD} values were calculated with the optimum design parameter values obtained from the optimization. Optimization process A offered a better result. The optimization method contrived by the 5-parameter study can be employed for more complicated parameter study.

However, the 3.7% accuracy of A might not be necessarily small, which was approximately equivalent to +/−0.010 of its CD values. This result came from the low accuracy of the response surface. The reason for the low accuracy lies in the fact that the number of samplings, 164, is not enough to create the response surface of the 12-parameter study, and hence, more samplings or another approximation method is required to construct the more accurate response surface so as to predict more errorless values of CD.

AMS-RSM

In general, the number of samplings should be increased as the number of design parameters grows in order to create a response surface within reasonable accuracy. It is, however, challenging to find the exact relationship between the number of samplings and design parameters.

The number of samplings seems to be influenced by multiple factors, e.g., the number of design parameters, sensitivity of them on CD, interaction among two or more of them, non-linear effect of them on CD. It is, however, impossible to know some of those factors before CFD calculations, and therefore, the required number of samplings is obscure. Under this situation, it is important to obtain reasonably optimal CD values regardless of the sampling number.

AMS-RSM makes it possible to dispose CFD sampling points efficiently. Reasonably optimal CD values could be, accordingly, searched for even if the sampling number is larger or smaller than the desired number. The concept of this method based on the idea that the optimum point is identical to one of some local minima, that is, finding local minima accurately leads to searching for the global optimum point accurately.

AMS-RSM creates response surfaces successively. The 1st response surface is constructed by sampling points all over the design space and complementing those points, and thereafter, a subsequent response surface is constructed by focusing additional sampling points on the periphery of the local minima of the 1st response surface (Fig. 6). As a result, the accuracy of the response surface around the local minima is improved and better CD values can be acquired. A detailed procedure of AMS-RSM is shown below.

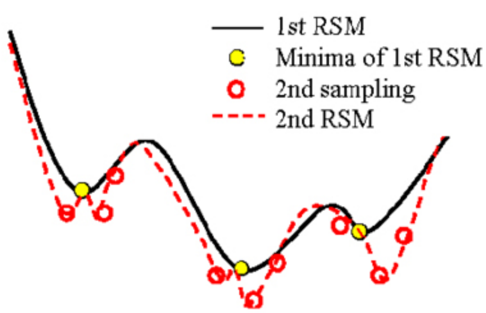

Fig. 6. Schematic diagram of AMS-RSM

PROCEDURE

1. Build the 1st response surface

The 1st response surface is created by the above-mentioned method, i.e., the LHC and Hardy's multiquadrics. The RBF approximation is as follows [10];

$$S(x) = \sum_{i=1}^{n} a_i \Phi_i(x) \tag{2}$$

The Hardy's multiquadrics applied here is;

$$\Phi_i(x) = R(\|x - x_i\|) \tag{3}$$

$$R(\|x - x_i\|) = \sqrt{c^2 + \|x - x_i\|^2} \tag{4}$$

2. Search for local minima

Time evolution of the SA optimization is governed by the temperature scheduler, namely “hot phase” and “cold phase.” During the hot phase, the better values are searched for in a broad region of the search space and thereafter, a rapid downhill convergence occurs according to the steepest descent heuristic algorithm during the cold phase (Fig. 7). During the hot phase, unfavorable transitions can be accepted according to a Boltzmann probability distribution.

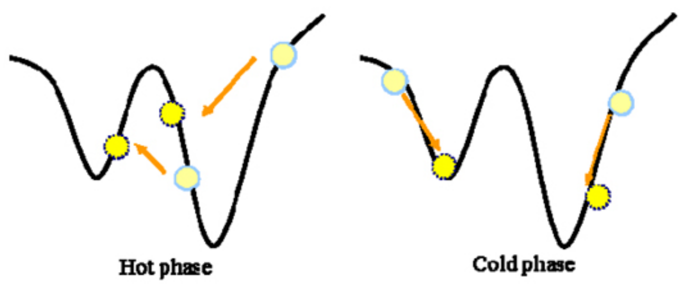

Fig. 7. Schematic diagram of SA optimization during the hot phase and cold phase

This characteristic of SA makes it possible for local minima to be searched by deliberately making the ratio of the hot phase zero.

Here, 9 points are generated on the 1st response surface and optimization is executed by SA without the hot phase. This setting consequently converged 9 points to each nearest local minimum. The SA algorithm searched for local minima most accurately compared with other algorithms, e.g., Broyden Fletcher Goldfarb Shanno (BFGS) method. GAs also can be used in order to search for local minima. However, the convergence of GAs is worse than that of SA algorithms because of the characteristics of genetic operators, e.g., selection and reproduction. This is also the reason why SA was adopted in our optimization system.

3. Add the 2nd sampling points

After the local minima and the global minimum on the 1st response surface are found, sampling points are added by LHC around them. Ten percent of the original range of each design parameter is set as a design parameter range for the 2nd sampling.

4. Calculate the 2nd sampling CD values

CFD calculation is executed for the 2nd sampling.

5. Build the 2nd response surface

The 2nd response surface is created using the calculation results of the 1st and 2nd samplings. A parameter of the spread of the Hardy's multiquadrics interpolation, c, in Eq. (4) should be appropriately changed so as to cope with non-uniformity between the 1st and 2nd samplings and retain accuracy of the 2nd response surface.

6. Search for the global minimum

An SA algorithm that includes the hot phase and the cold phase is executed on the 2nd response surface and the global optimal CD value is searched for. Once the global minimum is found, it is compared with the CD values for the 2nd sampling and the minimum for the 1st response surface.

The above procedure was tested for some sampling numbers in order to investigate the effect of the AMS-RSM and dependency on the sampling number. TABLE 5, Fig. 8 and Fig. 9 show the distribution of the total sampling, the comparison of the optimal CD values and accuracy between the existing RSM and AMS-RSM algorithms, respectively. The optimal CD values in Figs. 8, 9, 10 and 11 are the CFD values, i.e., CD_{CFD}, obtained with the optimum design parameter values by the RSM or AMS-RSM. In the present case, CD was improved for a wide range of sampling numbers by employing the AMS-RSM.

TABLE 5. Distribution of AMS-RSM sampling numbers

Total sampling number	1st sampling	2nd sampling
280	240	40
320	280	40
360	320	40
400	360	40
440	400	40
480	440	40

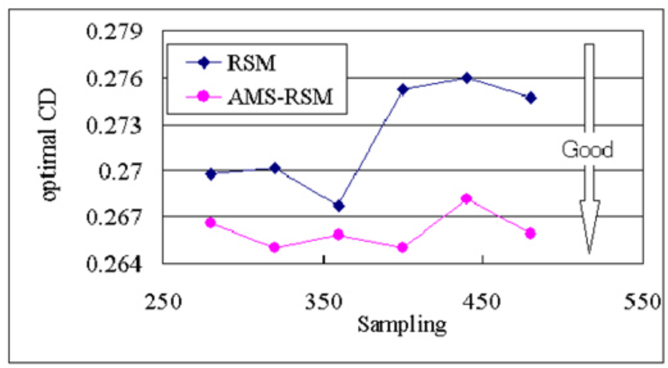

Fig. 8. Effect of AMS-RSM and robustness for the number of samplings

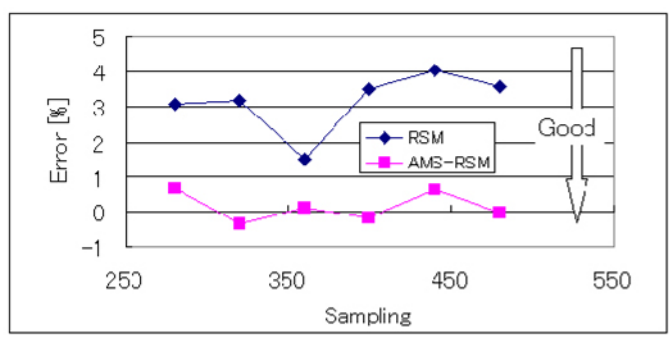

Fig. 9. Accuracy of AMS-RSM for the number of samplings

The existing RSM method shows the high dependency of the optimal CD on the number of samplings. Also, it shows that more samplings do not always result in the lower optimum CD value. This fact, generally, makes the parametric study difficult. The optimal CD found by the AMS-RSM, on the contrary, show the lower dependency on the number of samplings. This is significant since the desirable number of samplings is unknown unless the results of some sampling numbers are compared to each other. Even if the generated sampling numbers are not exactly desirable, reasonable CD values can be obtained by the AMS-RSM.

RSM depends on not only the sampling number but also the sampling pattern. The LHC sampling patterns can be regarded as quasi-random samplings and, therefore, they do not always give sampling patterns that result in good optimal CD values. The AMS-RSM is also a countermeasure against this kind of issue. Figures 10 and 11 demonstrate comparisons of the optimal CD values between two sampling patterns for the existing RSM and AMS-RSM respectively. One is the LHC sampling (A). The other pattern is set by replacing the samplings with the upper 3-percent CD values of all samplings by the samplings with ordinary CD values (B).

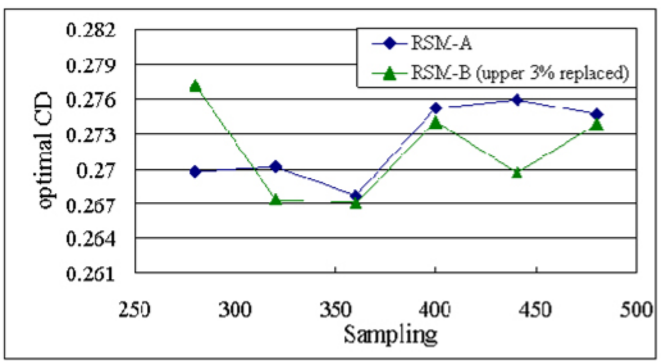

Fig. 10. Robustness of existing RSM for the two sampling patterns

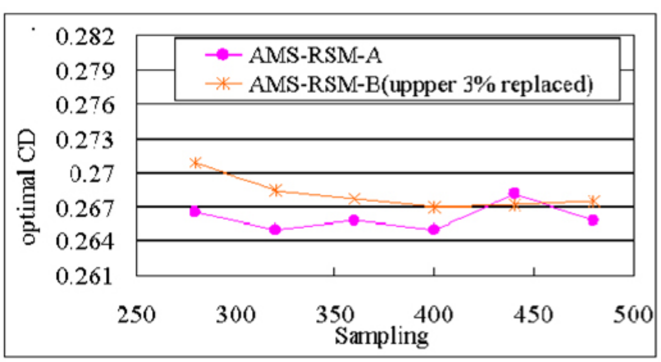

Fig. 11. Robustness of AMS-RSM for the two sampling patterns

Figure 10 shows that the optimal CD for the RSM-B fluctuates for the number of samplings similar to the RSM-A, i.e., it does not have robustness. Also, the optimal CD can change dramatically as the sampling pattern changes for the same sampling number. For example, the difference between the optimal CD values of the two sampling patterns is 0.007 for the 280 sampling.

On the other hand, Fig. 11 shows that the optimal CD values for the AMS-RSM-B is more stable, similar to the AMS-RSM-A, as compared to that for the RSM-A and RSM-B. Also, the difference between the optimal CD values of the two sampling patterns of the AMS-RSM is smaller compared to that of the RSM. This denotes the optimal CD obtained by AMS-RSM is not highly dependent on the sampling patterns, that is, the AMS-RSM supplies the optimization process with the robustness not only for the sampling number but also for the sampling pattern.

Figures 12 and 13 show the base and optimized model, and the flow around the models, respectively. The deformation of some design parameters, e.g., side body panel, Rr-bumper, C-pillar, had a strong effect on the CD values. On the other hand, the deformation of Fr-window angle, diffuser angle and roof had little effect. CD reduction was larger compared to the existing RSM method (Fig. 8) and the accuracy was also improved (Fig. 9), e.g., for the 320 sampling, +/−0.002 of its CD values. In this case, no account of design parameter constraints is taken, e.g., the rear window visibility, in order to test system potential although it is possible to execute the optimization under some constraints.

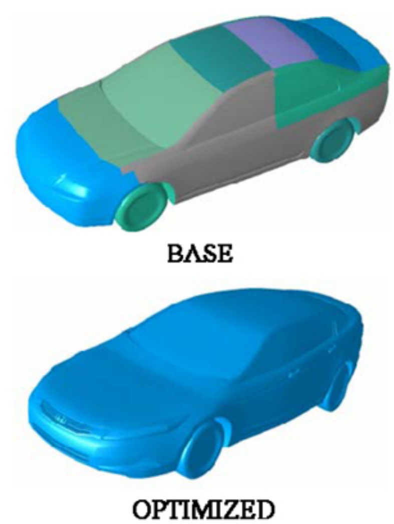

Fig. 12. Base and optimized model

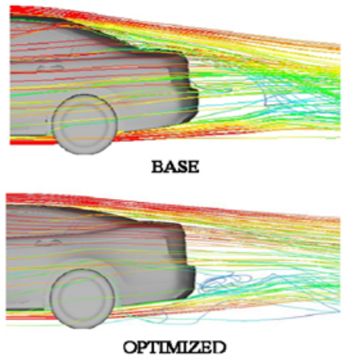

Fig. 13. Flow around the models

CONCLUSION

An optimization methodology for automotive aerodynamic design was contrived and an automatic system that includes a CFD solver, morphing software and optimization software was developed. The optimization process consists of three phases, i.e., LHC for DOE, RBF (Hardy's multiquadrics) for RSM, and SA for optimization. This process was refined by employing AMS-RSM methodology in order to cope with a more complicated parameter study. The AMS-RSM algorithm contributed to the following;

1. Searching for lower optimal CD
2. Supplying response surface accuracy
3. Supplying sampling number and sampling pattern robustness

As a result, aerodynamic design can be efficiently and precisely forwarded in aerodynamic development. Man hours are also effectively reduced as compared to conventional parametric studies. In our 12-parameter study, the optimum aerodynamic design was obtained within a week. Consequently, valuable guidance in how to advance aerodynamic design works was offered in the early development phase.

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