Aerodynamics Design for Automotive Shape based on Approximate Optimization Algorithm

Lin-lin WU*, Yu FU, Xiao-bing BU, Xiang-rong LI and Feng-ling GAO
CAE Performance Division, Vehicle Crash Testing and Research Department, CATARC Automotive Test Center (Tianjin) Co., Ltd, Tianjin, China
*Corresponding author

Keywords: Automotive shape, Parameterization, Surrogate model, Optimization algorithm.

Abstract. Since it is difficult to find the optimal solution directly by the traditional CFD optimization method due to its strong dependence on the designer’s experience, an automatic aerodynamic optimization design platform for automotive shape was built based on mesh deformation technology, surrogate model and optimization algorithm in this paper. A parameterized model of an automotive was established. Latin hypercube method was adopted to select sample points. The drag coefficients corresponding to sample points were calculated by CFD simulation, whereby the influence of each parameter on drag coefficient was obtained. By comparing the calculation time, optimization effect and optimization accuracy of 9 combinations of surrogate models and optimization algorithms, the combination of RBF model and NLQPL algorithm was selected as the optimal one which is the most appropriate for the aerodynamic optimization design for automotive shape.

Introduction

Considering the increase of fuel consumption evaluation index and the requirement of driving range of new energy automotive, it has become an important means to reduce drag coefficient by CFD technology. The traditional CFD optimization method based on trial and error has a strong dependence on the designer’s experience. Although a relatively better design can be found, it is difficult to find the optimal solution directly and efficiently. Besides, in order to make CFD technology drive the aerodynamic optimization design for automotive shape effectively and accurately, it is still necessary to improve the optimization accuracy, shorten the optimization cycle and realize the automation of the optimization process, otherwise it can’t meet the requirements of the actual automotive development [1].

Baysal O proposed the optimization method of aerodynamic shape as early as 1999, and pointed out that the use of automated tools would effectively shorten the product development cycle [2]. Ando K and Ribaldone E realized the parametric design for the shape and parts of automotive based on the approximate optimization algorithm [3,4]. Wang Kunyang optimized the top box of passenger car based on Kriging model and genetic algorithm [5]. By combining surrogate model and optimization algorithm, Wang Yu studied aerodynamic optimization of automotive shape [6]. As described in the above researches, the calculation time has been shortened and the optimization accuracy has been improved. However, which combination of surrogate model and optimization algorithm is more appropriate for the aerodynamic optimization of automotive shape remains to be studied. In addition, due to the continuous development of mesh deformation technology, surrogate model and optimization algorithm, as well as the continuous progress of hardware resources, it is possible to make the parametric design apply to the aerodynamic optimization design of automotive shape automatically and efficiently [7].

This paper builds the aerodynamics automatic optimization design platform of automotive shape based on the mesh deformation technology, surrogate model and optimization algorithm. Based on this platform, by comparing the calculation time, optimization effect and optimization accuracy of the combination of different surrogate models and optimization algorithms, the optimal combination
which is the most suitable for the aerodynamic optimization design of the automotive shape within the acceptable range of the project is obtained.

**Automatic Optimization Design Platform**

It is necessary to build an automatic optimization design platform to find the optimal solution of automotive shape. The platform integrates the functions of shape deformation, CFD simulation and optimization into a unified framework, and automatically calls each software according to the logic sequence in the optimization design process by writing script files. The optimization design process is shown in Fig. 1.

![Optimization design process](image)

**Figure 1.** Optimize design process.

**Parametric Modeling**

There are many parameters involved in the process of aerodynamic optimization of automotive shape. They have different influence on drag coefficient. Usually, sensitivity analysis and engineering experience are needed to select parameters that have great influence on drag coefficient [8]. In the early modeling stage, the large camber angle is mainly selected as the optimization parameter, while in the later modeling stage, the local characteristic parameter is mainly selected.

Taking a SUV simple model as an example, five angles are selected as optimization parameters, as shown in Fig. 2. The variation range of each parameter is given in Table 1. The parametric model is built in the deformation software. The deformation area is determined by building the control body, and the deformation of the corresponding area is completed by moving the control points.

![Optimization parameters of automotive shape](image)

**Figure 2.** Optimization parameters of automotive shape.

| Parameter | Variation range       |
|-----------|-----------------------|
| Angle1    | 0° ~ 8.8°             |
| Angle2    | 2.9° ~ 11.3°          |
| Angle3    | 31.0° ~ 38.8°         |
| Angle4    | 38.8° ~ 58.0°         |
| Angle5    | 0° ~ 21.8°            |

**Table 1.** The variation range of each parameter.
CFD model and Calculation Settings

Governing Equation

The essence of computational fluid dynamics is to calculate the governing equations of hydrodynamics under the condition of following the basic conservation law. The governing equations of hydrodynamics include mass conservation equation, momentum conservation equation and energy conservation equation, which are expressed as follows [9]:

(1) Mass conservation equation

\[ \frac{\partial \rho}{\partial t} + \frac{\partial (\rho u)}{\partial x} + \frac{\partial (\rho v)}{\partial y} + \frac{\partial (\rho w)}{\partial z} = 0 \]  

here, \( \rho \) is the density, \( t \) is the time, \( u, v, w \) are the three components of the velocity vector.

(2) Momentum conservation equation

\[ \frac{\partial (\rho u)}{\partial t} + \text{div}(\rho uu) = \text{div}(\mu \text{grad}u) + \frac{\partial p}{\partial x} + S_u \]  

\[ \frac{\partial (\rho v)}{\partial t} + \text{div}(\rho vv) = \text{div}(\mu \text{grad}v) + \frac{\partial p}{\partial y} + S_v \]  

\[ \frac{\partial (\rho w)}{\partial t} + \text{div}(\rho ww) = \text{div}(\mu \text{grad}w) + \frac{\partial p}{\partial z} + S_w \]  

here, \( \mu \) is the dynamic viscosity of the fluid, \( p \) is the static pressure of the flow field in this area. \( S_u, S_v, S_w \) are the generalized source term of momentum in the direction of coordinate axis \( x, y, z \) under the rectangular coordinate system.

(3) Energy conservation equation

\[ \frac{\partial (\rho T)}{\partial t} + \text{div}(\rho u T) = \text{div} \left( \frac{k}{C_p} \text{grad} T \right) + \frac{\partial p v}{\partial y} + S_r \]  

here, \( C_p \) is the specific heat capacity of the fluid, \( k \) is the heat transfer coefficient of the fluid, \( T \) is the temperature of the fluid, \( S_r \) is the amount of internal energy increase caused by the heat source and the energy value of mechanical energy converted to internal energy caused by the viscous force.

Neglecting the influence of heat exchange on the flow field, only the mass and energy conservation equations are solved within the range of accuracy error.

Mesh Model

The unstructured mesh and prism mesh are combined to divide the mesh. The densified frame is set in the local area of the body and the rear area of the automotive to improve the local mesh density. In order to shorten the calculation time, the half of the SUV model is used for calculation. In the calculation domain, the distance between the head and the entrance is 3 times of the model length, the distance between the tail and the exit is 6 times of the model length, the width is 5 times of the model width and the height is 5 times of the model height. Finally, the number of surface mesh is 0.45 million, the number of volume mesh is 6.5 million, the number of boundary layer is 10, and the mesh on the symmetry plan is shown in Fig. 3.
Boundary Condition Setting

Assuming that the problem is a three-dimensional, steady-state and constant density problem. The separation algorithm and Realizable $k-\varepsilon$ turbulence model are selected. The number of iteration steps is set to 5000. The parameter settings of boundary conditions are illustrated in Table 2.

![Figure 3. Mesh on the symmetry plane.](image)

Table 2. Boundary conditions setting.

| Position | Type of boundary | Type of wall   | Value  |
|----------|------------------|---------------|--------|
| Inlet    | Velocity Inlet   | /             | 120km/h|
| Outlet   | Pressure Outlet  | /             | 0Pa    |
| Slip     | Wall             | Slip          | /      |
| No-slip  | Wall             | No-slip       | 120km/h|
| Side     | Wall             | Slip          | /      |
| Sym      | Symmetry Plane   | /             | /      |
| Body     | Wall             | No-slip       | /      |

Analysis of Optimization Results

DOE

Reasonable and efficient DOE is the key to improve the fitting accuracy of agent model. For DOE methods, the Latin hypercube method is favored by experts and scholars since it can show the characteristics of all design spaces with fewer sample points. Consequently, Latin hypercube method is used here to select 50 sample points.

The CFD calculation of DOE matrix is carried out automatically in the automatic optimization design platform. When the CPU cores is 16 and the memory is 20GB, it takes about 7 hours to calculate a sample point and 15 days for a round of optimization analysis. And the optimization cycle will be shortened with the increase of CPU cores. However, the cycle of updating CAS data is about 25 days. Therefore, it can meet the requirements of engineering development cycle.

Analysis of Sensitivity

Because of the high nonlinearity of the flow field around the automotive, the contribution of each parameter to the aerodynamic drag is different. The influence of each parameter on drag coefficient can provide some reference for the subsequent optimization. It can be seen from Fig. 4 that the sensitivity of Angle 5 is the highest and the sensitivity of Angle 4 is the lowest.
Comparison of the Accuracy of Surrogate Models

The surrogate model constructs the relationship between design variables and output response through mathematical methods such as interpolation, fitting and regression. Because of the characteristics of small amount of calculation and high speed of calculation, it is used to replace simulation calculation for optimization analysis in practical engineering. Therefore, the accuracy of surrogate model becomes one of the key factors that affect the accuracy of optimization.

Commonly used surrogate models include Response Surface Method (RSM) model, Radial Basis Function (RBF) model and Kriging model. Based on the DOE matrix, three kinds of surrogate models are constructed respectively. In order to find a more suitable surrogate model for this study, the accuracy of the three surrogate models is verified by the following methods:

1. Removing 5 sample points from the existing 50 sample points randomly and evenly, and the remaining 45 sample points are used to build the surrogate model;
2. Calculating the drag coefficient of the removed 5 sample points by the surrogate model;
3. Comparing the error between the calculated value of surrogate models and CFD model.

The comparison of the calculated value of the removed 5 sample points between CFD model and surrogate models is shown in Fig. 5. And the error of the calculated value of the removed 5 sample points between CFD model and surrogate models is shown in Table 3. From the above results, it is found that the accuracy of the RSM model is higher than that of the RBF model and Kriging model.
Table 3. Error of the calculated value between CFD model and surrogate models.

| Number | RSM model | RBF model | Kriging model |
|--------|-----------|-----------|---------------|
| 5      | 0.76%     | 1.24%     | 2.24%         |
| 12     | 0.91%     | 1.94%     | 2.83%         |
| 26     | 0.88%     | 1.59%     | 1.78%         |
| 39     | 0.69%     | 1.41%     | 2.45%         |
| 48     | 1.28%     | 2.01%     | 1.84%         |

Comparison of the Combinatorial Optimization Result

The optimization algorithm can be used to solve the problem to find the extremum in discrete state. The optimization based on surrogate model can help us to get the optimal solution quickly. There are many kinds of optimization algorithms, such as Adaptive Simulated Annealing (ASA) algorithm, Modified Method of Feasible Directions (MMFD) algorithm, NLPQLP-Sequential Quadratic Programming (NLPQLP) algorithm and etc. Because different surrogate models and optimization algorithms have different characteristics and applicability, according to the complexity of the research problem, there will be the corresponding optimal combination.

Using the above 3 surrogate models and 3 optimization algorithms, we can obtain 9 optimization combinations. The DOE matrix is optimized by the 9 optimization combinations respectively, and nine optimal solutions are obtained. Through the CFD simulation, the calculation values corresponding to the 9 optimal solutions are obtained. And then, the error between the optimal values and the simulation values of different optimization combinations is calculated. The optimization results of 9 optimization combinations are given in Table 4.

Table 4. The results of combination optimization.

| Optimization combination | Angle1 | Angle2 | Angle3 | Angle4 | Angle5 | Drag coefficient | Error |
|--------------------------|--------|--------|--------|--------|--------|------------------|-------|
| RSM+NLPOLP               | 8.8    | 11.3   | 31     | 38.8   | 0      | 0.3024           | 1.06% |
| RSM+MMFD                 | 8.8    | 11.3   | 31     | 38.8   | 0      | 0.3025           | 1.13% |
| RSM+ASA                  | 8.8    | 11.3   | 31     | 47.664 | 0      | 0.3024           | 1.08% |
| RBF+NLPOLP               | 0      | 11.3   | 31     | 47.664 | 0      | 0.2958           | 2.09% |
| RBF+MMFD                 | 8.8    | 11.3   | 31     | 39.990 | 0      | 0.2965           | 2.28% |
| RBF+ASA                  | 0      | 11.3   | 31     | 47.614 | 0      | 0.2958           | 2.10% |
| Kriging+NLPOLP           | 3.9144 | 10.9326| 32.2080| 42.5930| 1.9558 | 0.2961           | 2.86% |
| Kriging+MMFD             | 3.9569 | 11.1754| 32.6234| 47.8371| 1.8259 | 0.2966           | 2.96% |
| Kriging+ASA              | 3.9113 | 10.9340| 32.2089| 42.6765| 1.9558 | 0.2961           | 2.90% |

Based on the above results, the calculation time, optimization effect and optimization accuracy of nine optimization combinations are compared and analyzed. From the perspective of surrogate model, the optimization effect of the combination corresponding to RBF model is the largest, and that corresponding to RSM model is the smallest, but its optimization accuracy is the highest and the calculation time is the shortest. The optimization accuracy of the combinations corresponding to Kriging model is the lowest and the calculation time is the longest. From the perspective of optimization algorithm, the combination corresponding to MMFD algorithm has the smallest optimization effect and the lowest optimization accuracy. The optimization effect and optimization accuracy of the combination corresponding to NLPQLP algorithm and ASA algorithm differ very little, but the calculation time of the combination corresponding to ASA algorithm is significantly higher than that of other combinations. Therefore, the combination of RBF model and NLPQLP algorithm with the largest optimization effect but not the smallest optimization accuracy and the shortest calculation time is selected as the optimal combination, and its result is the final optimization result.
Comparison of the Optimization Results

The parameters and results of the initial model and the optimal model are compared as shown in Table 5. It can be seen from the results that the drag coefficient of the optimal model is 0.3021, which is 0.31.6 counts less than that of the initial model, and the optimization effect is nearly 10%. Outstanding effect of reducing drag coefficient is obtained.

Table 5. The parameters and results of the initial model and the optimal model.

| Model       | Angle1 | Angle2 | Angle3 | Angle4 | Angle5 | Drag coefficient |
|-------------|--------|--------|--------|--------|--------|------------------|
| Initial model | 6.5384 | 4.1012 | 38.358 | 53.616 | 5.6026 | 0.3337           |
| Optimal model | 0      | 11.3   | 31     | 47.664 | 0      | 0.3021           |

Conclusion

An aerodynamics automatic optimization design platform for automotive shape was systematically studied in this work, by which the optimal combination of surrogate model and optimization algorithms was compared investigated. From the results obtained, specific conclusions can be summarized, including:

(1) For this model, the sensitivity of the departure angle is the highest and the sensitivity of the rear windshield angle is the lowest. The result of the sensitivity can provide some reference for the subsequent optimization.

(2) When the number of sample points is the same, RBF model has the largest optimization effect. RSM model has the highest optimization accuracy and the shortest calculation time. NLPQLP algorithm and ASA algorithm have similar optimization effect and optimization accuracy, but the calculation time of ASA algorithm is significantly higher than NLPQLP algorithm.

(3) Considering the calculation time, optimization amplitude and optimization accuracy comprehensively, the combination of RBF model and NLPQLP algorithm is more suitable for the aerodynamic optimization of this model. And the optimization effect is nearly 10%. Whether it can also be suitable for the optimization of other models remains to be further studied.

(4) In order to balance the optimization amplitude, optimization accuracy and calculation time better, we can supplement appropriate number of sample points on the basis of DOE, but the method of supplementing sample points still needs further study.

Acknowledgement

This research was financially supported by the Research on common basic technology of CATARC Automotive Test Center (Tianjin) Co., Ltd, (NO. TJKY1920011 and NO. TJKY1920010).

References

[1] H. X. Zhang, Y. F. Qiu, L. B. Zhang, Surrogate model method for aerodynamics optimization on automobile configuration, Computer Aided Engineering, 3(2014) 6-11.
[2] O. Baysal, Aerodynamic Shape Optimization: Methods and Applications, SAE Technical Paper, 3(1999)1209-1212.
[3] K. Ando, A. Takamura, I. Saito, Automotive Aerodynamic Design Exploration Employing New Optimization Methodology Based on CFD, SAE Technical Paper, 4(2010)547-551.
[4] E. Ribaldone, I. D. Puri, F. Cogotti, et al, Optimizing the External Shape of Vehicles at the Concept Stage: Intergration of Aerodynamics and Ergonomics, SAE International Journal of Engines, 2(2011)2622-2628.
[5] K. Y. Wang. Study on the Influence of Roof Box on Aerodynamic Drag Reduction of Vehicle, Master Degree Dissertation of Jilin University, Changchun, 2019.
[6] Y. Wang, Optimization of Aerodynamic Drag Reduction for A Vehicle, Master Degree Dissertation of Tianjin University of Science & Technology, Tianjin, 2017.

[7] F. Wang, H. Zhu, Z. G. Yang, Aerodynamic Shape Optimization of Automotive Body Based on Approximation Model. Computer Aided Engineering, 6 (2016)34-41.

[8] X. Wang, X. F. Cao, F. Li, et al, Analysis of Parameter Sensitivity for Vehicle Fuel Economy, Proceedings of the 13th Shenyang Annual Scientific Conference (Science, industry, agriculture and medicine), 3(2016)45-52.

[9] Z. H. Han, J. Wang, X. P. Lan, An Example and Application of Fluent in Fluid Engineering Simulation. Beijing University of Technology Press, Beijing, 2005.