Meta Model and Optimization Method for Automobile Styling and Aerodynamic Perfor Mance Development in Early Design Stage

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Abstract: Aerodynamic drag consists in most of the resistance of automobile when driving on high speed, which has a dramatic impact on the range of electric vehicle. The three dimensional unsteady and turbulent wake flow of automobile largely determines the aerodynamic performance of the vehicle especially drag, which has a tightly correlation with vehicle styling. The styling of automobile can be descripted by parameter. Parameters including length, width, height, radius and angle of the geometry details, which have an overall description of the whole vehicle styling. Styling parameters of a fastback sedan was modified by morphing technique resulting in a set of styling data. The aerodynamic drag of these stylings was achieved by high accurate CFD simulation. The kriging model was used to figure out how the styling parameters determine the aerodynamic drag. Meta models have been established, which expounds the drag sensitivity of styling parameter. Both how one single parameter influencing on aerodynamic drag and the synergistic effects of two parameters on the aerodynamic drag are exhibited. Results shows the ability of meta models to figure out the aerodynamic sensitivity of styling parameters and the meta models can also be used to guide the design of aerodynamics. The simplex method was employed to perform the optimization in the given design space, and the smallest Cd value was picked out.

Key words: aerodynamics, styling parameters, optimization, meta model, kriging model, simplex method

Introduction

The electrification and intellectualization of the automobile industry have put forward new challenges and requirements for energy conservation and emission reduction. Reducing air resistance through low wind resistance modeling design to achieve energy conservation and emission reduction is an important research content of automobile aerodynamics. Research shows that about 80% of CO_2 is emitted during the vehicle life cycle, and energy consumption can be reduced by 5% ~ 8% for every 10% reduction in wind resistance. Reducing wind resistance is of great significance for energy saving and carbon emission reduction of vehicles. In Europe, the United States, Japan, Korea and other developed countries and regions, automotive aerodynamics is fully developed, coupled with the development of automotive power system and intelligent driving technology to provide greater design space for automotive aerodynamic modeling, the international mass production of three-box car wind resistance coefficient (Cd) has reached the lowest 0.2 level. Chinese automobile aerodynamic research started late, the huge improvement has been received recent years and it is in the process of catching up. For example, the newly launched ET7 model of NIO has a high level of wind resistance coefficient of 0.208.

Automotive air resistance is closely related to styling design. In the traditional wind resistance development process, aerodynamic engineers and styling design teams need to go through a long period of design and verification development process. The efficiency of wind resistance development is low, the cost is high and the quality is not high, and some problems of wind resistance development are difficult to be found in the initial design process of styling. However, in the later stage of styling design, it is difficult to change or the cost of change is too high, which leads to the increase of project development cost and slows down the development progress, and has an adverse impact on the design of vehicle development cycle and acceleration of update iteration. Vehicle electrification and intellectualization provide more design space for modeling, but also pose challenges for wind resistance development. Wind resistance development and modeling design are more closely related in the early design stage of vehicle design. Therefore, collaborative design solutions for wind resistance development and modeling design in the early stage of vehicle design are urgently needed. This solution can quickly identify the key design features and design parameters related to aerodynamics in modeling design, quickly gives the aerodynamic sensitivity and design suggestions direction, can identify the wind resistance development risk in the conceptual design stage of the product, and lays the foundation of low wind resistance modeling design.

At present, the main technical means and tools for automotive wind resistance development include wind tunnel testing and computational fluid dynamics simulation analysis (CFD). Generally, wind tunnel testing needs to be carried out in the middle and late stage of modeling design with relatively fixed styling style. In this stage, the overall modeling is relatively fixed and the range of changes is limited, and CFD analysis is also carried out in the same stage. Therefore, the existing wind tunnel test and CFD simulation analysis tools cannot be involved in the early stage of modeling design, and the design style in the early stage of modeling cannot fully considers the aerodynamic performance. The existing development technical means are more to update and verify the details of modeling design, and the relatively fixed modeling style limits the level of aerodynamic performance. Therefore, the development of automotive aerodynamics and modeling needs design tools that can be involved in advance in the early design stage to assist modeling designers and aerodynamic engineers to fully consider the relationship between modeling and aerodynamic performance in the conceptual design stage of the product and develop low wind resistance modelling.

At present, there are few researches on the early development of collaborative design tools for aerodynamics and modeling in China. Some vehicle enterprises have similar design tools, but the technical details and functions are not disclosed. Zheng Xin et al. [1] from Brilliance Automobile Group Holding Company developed a rapid modeling method for automotive wind resistance coefficient, which divides the vehicle modeling into different areas. The geometric weight of each modeling face affecting the wind resistance is obtained through simulation analysis. The prediction formula is established through multivariate primary model, and the change value of the wind resistance coefficient of the corresponding block is calculated according to the local change of the modeling. The updated wind resistance coefficient value can be obtained by combining with the basic wind resistance coefficient. This model has the function of wind resistance prediction in the early modeling design stage, but it does not give detailed prediction results and precision description, and lacks the adaptability description of different vehicle models. Japanese Honda Motor Company[2] developed a real-time aerodynamic design system, which can realize the sensitivity analysis of passenger car styling design and the implementation prediction function of wind resistance performance. The system includes approximate model, classification, feature extraction sensitivity analysis and data update, and integrates the wind resistance prediction function into CAD design software. By combining approximate models, classification, styling sensitivity analysis, and self-learning techniques to update the prediction accuracy, Honda applied the system to the development of several models. The system extracted styling features entirely from the perspective of geometric parameters to establish aerodynamic sensitivity models, without considering the relationship between parameters and aerodynamic performance development. Unable to identify key aerodynamic parameters related to styling design, lack of design guidance for styling designers and aerodynamic engineers. The British Motor Industry Research Association (MIRA)[3] developed a wind-resistance rating system, which was based on the data of 118 passenger vehicles tested in MIRA's full-scale wind tunnel. The system analyzed the correlation between modeling detail parameters and wind resistance. This method divided modeling into 9 regions and assigned a weight coefficient to each region. The regions with a large impact on wind resistance have a high weight coefficient, and the regions with a small impact on wind resistance have a small weight coefficient. The system divides the vehicle into different types. The system can guide designers to carry out aerodynamic performance design work by identifying the contribution of different areas of the modeling to wind resistance. The modeling design parameters of the system need to be selected and determined by the designer, which is highly subjective. Therefore, Carr et al. [4] integrated the system into CAD design software, so that the measurement of parameters can be more objective and the wind resistance coefficient can be predicted in real time in CAD software. However, this method still has two defects: firstly, the model ignores the correlation between different parameters in different areas of modeling or the same area; secondly, the model is built on limited experimental data, and the prediction beyond the existing design is not accurate.

To handle the non-linear characteristics of aerodynamic drag and styling parameters, the meta model was employed, such as kriging model or machine learning method. In the design space, optimization method such as simplex can be employed to find the minimum value of aerodynamic drag. In the following section, it's organized as: styling parameterization and aerodynamic database, methodology, simplex method, aerodynamic drag sensitivity of styling parameters, and pursuit for the smallest drag coefficient in the given design space. The discussion and conclusion will be given in the end of the paper.

1 Styling Parameterization and Aerodynamic Database

General experience from the car aerodynamics, modelling can be divided into the front of vehicle, the middle of the vehicle and the back of the vehicle. There are some important characteristics to have important influence on the wind resistance coefficient in each area. In the front part of the modeling, the front angle, the height of the front edge of the cover, the front angle of the cover, the front angle and the side angle of the car, etc. The middle of the vehicle includes the angle of the front window, the angle of the side window, the width and arc of the A-pillar, the arc of the front and back of the roof, the height of the front and back of the side skirt, and the position of the front and back of the side skirt in the x and y directions. The rear part of the modeling includes back inclination angle, trunk inclination angle, trunk rear along the height and x directions position, tail wing, flanks, rear maintenance inclination angle, rear maintenance separation features, etc. In the above important modeling features and areas, geometric features such as length, width, height, Angle and radian are defined to extract aerodynamic sensitive modeling design parameters. Based on the basic theory of automotive aerodynamics, the back inclination angle has an important influence on its aerodynamic characteristics. When the back inclination angle is 30 degrees, there will be resistance crisis and bistable phenomenon of outflow field, and the wind resistance deteriorates seriously. If the back inclination angle is less than 30 degrees, the air flow is attached to the back and forms an obvious C-pillar vortex. When the back inclination is greater than 30 degrees, the air flow separates from the back and the C-pillar vortex weakens or disappears. With the increase of the back inclination, the resistance coefficient gradually decreases and eventually becomes stable. Therefore, according to the back inclination, the styling styles are divided into fastback models, notchback models, estate back models and hatchback models. The uncertainty influence of strong nonlinear phenomenon caused by 30°back angle on wind resistance prediction has been distinguished and avoided.

Take the fastback sedan asan example, some parameters related closely with aerodynamic performance are picked out shown in Figure 1. θ1 refers to the slant angle of the front end of the enginehood, which has much influence on the flow attachment in this area. θ2 and θ3 refer to the slant angles of enginehood and windshield, and these two parameters define how fluid flows from front to the end of the vehicle. θ4 refers to the slant angle of the rear window, which defines the flow feature in the end. θ10 refers to the diffusing angle of the diffuser of the vehicle, which has much influence of the wake flow of the vehicle. θ8 refers to the slant of side window. w1 and w2 refers to the contraction distances of the front and end of vehicle body. h1, h2 and h6 refer to the high of front end of enginehood, front lip and end of trunk tail. h5 refers to the down deflection of the rear back, which is similar to parameter θ4 influencing flow feature in the rear back region.

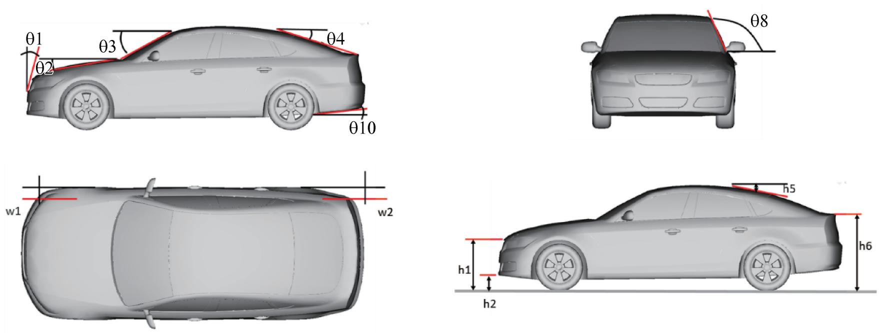

Figure 1 Styling parameters of fastback sedan related to aerodynamic performance.

Based on the modeling point cloud data, the CFD analysis numerical model of the vehicle outflow field was established, and the aerodynamic performance of the corresponding vehicle in the basic state was obtained through the analysis. The error correction of the simulation results was carried out by using the wind tunnel test results, and the corresponding relationship between the simulation model and the real vehicle wind tunnel test model was established. The parametric mathematical model of modeling design was established by using the mesh deformation technology. Define the styling design parameters in the digital model, and realize the styling parameterized design. Use the automatic mesh deformation technology to change the styling design style, and use the DOE algorithm to realize the space exploration design whose styling design parameters exceed the existing range of vehicle design. Through the extraction and measurement system of aerodynamic sensitive modeling design parameters and CFD analysis, the modeling design parameters and aerodynamic performance corresponding to the new modeling design were obtained, so as to realize the data enhancement of vehicle modeling and aerodynamic performance, and provide basic data support for wind resistance prediction.

2 Methodology

2.1 Kriging Model

Kriging method is a regression algorithm of modelling and prediction for stochastic field based on covariance function[5]. Kriging method is originally developed by Professor Daniel Krige, from Witwatersrand University of South Africa, especially from problems of gold extraction. For a given stochastic field descripted by the training data, $D:=\{(x_i,y_i):x_i\in\Omega\subset\mathbb{R}^M, y_i\in\mathbb{R}, i=1,\cdots,n\}$, kriging interpolation can be defined by

$$\hat{y}_0 = \sum_{i=1}^{n} \lambda_i y_i,$$

where, $\hat{y}_0$ is the prediction value of y_0, i. e. $y_0=f(x_0)$. λ_i is the weight coefficient. Kriging method tries to achieve the proper λ_i to make the $\hat{y}_0$ close to y_0 as much as possible, i. e. $min\ Var(\hat{y}_0-y_0)$, with unbiased estimation condition: $E(\hat{y}_0-y_0)=0$.

Kriging method adopts the following hypothesis for the prior:

1. $E[y]=c, Var[y]=\sigma^2$, i. e., the averaged and variance are the same for all points;

2. $Cov(x_i,x_j):=E[(y_i-c)(y_j-c)]=:C(\|x_i-x_j\|)$, the covariance only depends on the spatial separation between points.

As the unbiased estimation condition is defined by $E(\hat{y}_0-y_0)=0$, i. e. $E(\sum_{i=1}^{n}\lambda_i y_i-y_0)=0$. Considering $E[y]=c$, $\sum_{i=1}^{n}\lambda_i=1$. This is the constrain of λ_i.

Define the prediction deviation as

$$\begin{aligned} J &= Var(\hat{y}_0-y_0) = Var\left(\sum_{i=1}^{n}\lambda_i y_i - y_0\right) \\ &= Var\left(\sum_{i=1}^{n}\lambda_i y_i\right) - 2Cov\left(\sum_{i=1}^{n}\lambda_i y_i, y_0\right) + Cov(y_0,y_0) \end{aligned}$$

$$= \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j Cov(y_i,\ y_j) - 2\sum_{j=1}^{n}\lambda_i Cov(y_i,\ y_0) + Cov(y_0, y_0).$$

Note $C_{ij} = Cov(y_i, y_j)$, then, $J = \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j C_{ij} - 2\sum_{i=1}^{n}\lambda_i C_{i0} + C_{00}$.

Define thesemivariance $r_{ij} = \sigma^2 - C_{ij}$,

then,

$$J = \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j(\sigma^2 - r_{ij}) - 2\sum_{i=1}^{n}\lambda_i(\sigma^2 - r_{i0}) + \sigma^2 - r_{00}$$
$$= \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j\sigma^2 - \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j r_{ij} - 2\sum_{i=1}^{n}\lambda_i\sigma^2 + 2\sum_{i=1}^{n}\lambda_i r_{i0} + \sigma^2 - r_{00}.$$

Considering $\sum_{i=1}^{n}\lambda_i = 1$,

$$J = \sigma^2 - \sum_{i=1}^{n}\sum_{j=0}^{n}\lambda_i\lambda_j r_{ij} - 2\sigma^2 + 2\sum_{i=1}^{n}\lambda_i r_{i0} + \sigma^2 - r_{00}$$
$$= 2\sum_{i=1}^{n}\lambda_i r_{i0} - \sum_{i=1}^{n}\sum_{j=0}^{n}\lambda_i\lambda_j r_{ij} - r_{00}.$$

As J is the function of λ_i, to find the minimum value of J set the derivative of J to λ_i as zero i. e.,

$$\frac{\partial J}{\partial \lambda_i} = 0, i = 1, 2, \cdots, n.$$

At the same time the constraint condition $\sum_{i=1}^{n}\lambda_i = 1$ should be satisfied. So, the problem impressed by the last equation converts to an optimization problem with constraint condition. Using Lagrange multiplier method, the newly constructed objective function should be defined as, $J + 2\phi\left(\sum_{i=1}^{n}\lambda_i - 1\right)$, where ϕ is the Lagrange multiplier. The problem turns to make the new objective function to the minimum value by optimizing the set of parameters: ϕ, λ_1, λ_2, $\cdots$, λ_n, *i. e.*,

$$\begin{cases} \dfrac{\partial\left(J + 2\phi\left(\sum_{i=1}^{n}\lambda_i - 1\right)\right)}{\partial\lambda_k} = 0; k = 1, 2, \cdots, n \\ \dfrac{J + 2\phi\left(\sum_{i=1}^{n}\lambda_i - 1\right)}{\partial\phi} = 0 \end{cases}$$

$$\begin{cases} \dfrac{\partial\left(2\sum_{i=1}^{n}\lambda_i r_{i0} - \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j r_{ij} - r_{00} + 2\phi\left(\sum_{i=1}^{n}\lambda_i - 1\right)\right)}{\partial\lambda_k} = 0; k = 1, 2, \cdots, n \\ \dfrac{\partial\left(2\sum_{i=1}^{n}\lambda_i r_{i0} - \sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j r_{ij} - r_{00} + 2\phi\left(\sum_{i=1}^{n}\lambda_i - 1\right)\right)}{\partial\phi} = 0 \end{cases}$$

$$\begin{cases} 2r_{k0} - \sum_{j=1}^{n}(r_{kj} + r_{jk})\lambda_j + 2\phi = 0; k = 1, 2, \cdots, n \\ \sum_{i=1}^{n}\lambda_i = 1 \end{cases}$$

Considering $C_{ij} = C_{ji}$ *and* $r_{ij} = r_{ji}$,

then,

$$\begin{cases} r_{k0} - \sum_{j=1}^{n} r_{kj}\lambda_j + \phi = 0; k = 1, 2, \cdots, n \\ \sum_{i=1}^{n}\lambda_i = 1 \end{cases}.$$

Rewrite the equation above in linear system of equations as:

$$\begin{cases} r_{11}\lambda_1 + r_{12}\lambda_2 + \cdots + r_{1n}\lambda_n - \phi = r_{10} \\ r_{21}\lambda_1 + r_{22}\lambda_2 + \cdots + r_{2n}\lambda_n - \phi = r_{20} \\ \cdots \\ r_{n1}\lambda_1 + r_{n2}\lambda_2 + \cdots + r_{nn}\lambda_n - \phi = r_{n0} \\ \lambda_1 + \lambda_2 + \cdots + \lambda_n = 1 \end{cases}.$$

Noted as matrix:

$$\begin{bmatrix} r_{11}\, r_{12} \ldots r_{1n} & 1 \\ r_{21}\, r_{22} \cdots r_{2n} & 1 \\ \cdots\cdots\cdots\cdots & \\ r_{n1}\, r_{n2} \cdots r_{nn} & 1 \\ 1\ \ 1 \cdots 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \cdots \\ \lambda_n \\ -\phi \end{bmatrix} = \begin{bmatrix} r_{10} \\ r_{20} \\ \cdots \\ r_{n0} \\ 1 \end{bmatrix}.$$

By knowing the semivariance function r_{ij}, the set of parameters of kriging can be calculated. The semivariance function can also be defined as $r_{ij} = \frac{1}{2}E[(y_i - y_j)^2]$. The distance between two points in the random field D can be defined as $d_{ij} = \sqrt{x_i^2 - x_j^2}$. According to the first law of geography, near things are more related to each other. Kriging method supposes that the semivariance function is only related to the distance between points in space. This relationship can be linear, quadratic, exponent, logarithmic and so on, and can be descripted by curve fitting. The relationship between semivariance and distance in this paper is fitted by Gaussian function.

2.2 Simplex Method

Simplex method is a multi-variable function minimization method proposed by J. A. Nelder and R. Mead in 1965, also called Nelder-Mead method[6,7]. For an n variables function, the n+1 dimensional simplex was constructed, and a series of geometrical operations, including reflection, expansion, contraction and shrink, were employed to trend to the minimum value. All these geometrical operations trend to move the vertices to the minimum value, so also called downhill simplex method. Simplex method is also suitable for optimization with Response Surface Model (RMS). Simplex method does not need the derivates of the optimized model. Although, simplex method does not have high efficiency, but is a good choose for RSM models with small computational burden.

For a given unconstrained optimization problem,

min $f(x)$,

where f: R^n-> R is called the objective function and n is the dimension. The simplex is defined as the convex of n+1 vertices in n dimensions. We denote the vertices of the simplex as $x_1, x_2, \cdots, x_{n+1}$. By the iteration process including sorting the function values of the objective function and a series of geometric operations, the simplex method trends to move the vertices to the minimum value point. The algorithm can be organized as follows:

1) Sort. Evaluate the function values $f(x_i)$ of all the vertices of the simplex, and sort all $f(x_i)$ as $f(x_1) \leqslant f(x_2) \leqslant \cdots \leqslant f(x_n) \leqslant f(x_{n+1})$, where, $f(x_1)$ is the best vertex, $f(x_{n+1})$ is the worst vertex and $f(x_n)$ is the vertex next to the best one.

2) Reflection. Compute the reflection point x_r by $x_r = \bar{x} + \alpha(\bar{x} - x_{n+1})$. α is positive coefficient, where, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ is defined as the centroid of all the vertices except x_{n+1}. Evaluate $f_r = f(x_r)$. *If* $f_1 \leqslant f_r < f_n$, replace x_{n+1} with x_r.

3) Expansion. If $f_r < f_1$ then compute the expansion point x_e by $x_e = \bar{x} + \beta(x_r - \bar{x})$. β is a positive coefficient and larger than 1. Evaluate $f_e = f(x_e)$. *If* $f_e < f_r$, replace x_{n+1} with x_e; otherwise replace x_{n+1} with x_r.

4) Outside contraction. If $f_n \leqslant f_r < f_{n+1}$, compute the outside contraction point by $x_{oc} = \bar{x} + \gamma(x_r - \bar{x})$. γ is a positive coefficient and less than 1. Evaluate $f_{oc} = f(x_{oc})$. *If* $f_{oc} \leqslant f_r$, replace x_{n+1} with x_{oc}; otherwise go to step 6.

5) Inside contraction. If $f_r \geqslant f_{n+1}$, compute the inside contraction point x_{ic} by $x_{ic} = \bar{x} - \gamma(x_r - \bar{x})$. γ is a positive coefficient and less than 1. Evaluate $f_{ic} = f(x_{ic})$. If $f_{ic} < f_{n+1}$, replace x_{n+1} with x_{ic}; otherwise, go to step 6.

6) Shrink. For $2 \leqslant i \leqslant n+1$, define $x_i = x_1 + \delta(x_i - x_1)$. All vertices except x_1 shrink to x_1 to construct the new simplex geometry.

The simplex geometry in two-dimensional space can be shown below, and the geometrical operations can be illustrated as shown in the diagram.

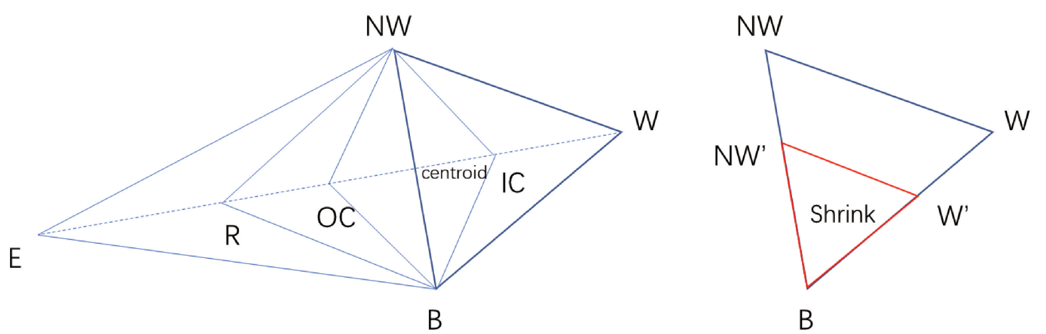

Figure 2 The diagram of geometrical operation of simplex in two-dimension. B best vertex, W worst vertex, NW vertex next to the worst one, R the reflection point, E the expansion point, OC the outside contraction, IC the inside contraction.

3 Aerodynamic Drag Sensitivity of Styling Parameters

The metamodel established by kriging method shows the principle how the aerodynamic drag varies with parameters being adjusted. This principle is also called the sensitivity of styling parameter to the aerodynamic drag. Figure 3 shows the influence of an single parameter on aerodynamic drag coefficient. The current design value of styling parameter is marked on the sensitivity line. This result shows how one single styling parameter influents the Cd at current design state. The sensitivity of styling parameter to Cd can be classified into four basically types: monotone increasing, monotone decreasing, increasing followed by decreasing, and decreasing followed by increasing. For monotone increasing type of sensitivity, Cd increases with enlarging styling parameter in the design space such as h2. For monotone decreasing type of sensitivity, Cd decreases with enlarger styling parameter such as θ1. By enlarging the slant angle of the front of the engine hood, the flow in front of the vehicle can flow through the engine hood more smoothly. For increasing followed by decreasing type of sensitivity, Cd increases with enlarging the parameter, at a given design point the Cd reaches the maximum value, then the Cd will decrease with enlarging the parameter, such as h5, w1, w2, θ4. The contractive distances of the front and rear end of the vehicle body have same sensitivity type. Aerodynamic drag of the vehicle has maximum value in the given design space with varying the slant angle of rear window. For decreasing followed by increasing type sensitivity, there exists a minimum value of Cd in the given design space, such as h1, h6, θ2, θ3, θ8 and θ10.

Influence of two parameters on Cd can also be illustrated by 3D diagram shown in Figure 4. Among all 3D diagrams, ones with Cd gradient mainly dominates one single parameter direction, the parameter dominating the Cd gradient plays more important role on Cd than the other one, such as h1 vs h2 and θ8 vs w1. If Cd gradient behaves in all direction and there exists a minimum value, all these two parameters dominate the Cd in the design space, such as h6 vs θ10 and θ2 vs θ3, and the sensitivity of one single parameter behaves as decreasing followed by increasing. If the Cd gradient exits in the positive diagonal line, all these two parameters have the same sensitivity type and both dominate the Cd, such as h5 vs θ4 and w1 vs w2. If the Cd gradient exits in the negative diagonal line, these two parameters have the opposite sensitivity type and both dominate the Cd, such as θ1 vs θ2. In all 3D diagrams, if the Cd gradient exits in diagonal line or on all directions, these two parameters can influent each other. If the Cd gradient exists on one or two parameter directions, these two parameters do not influent each other in some extent.

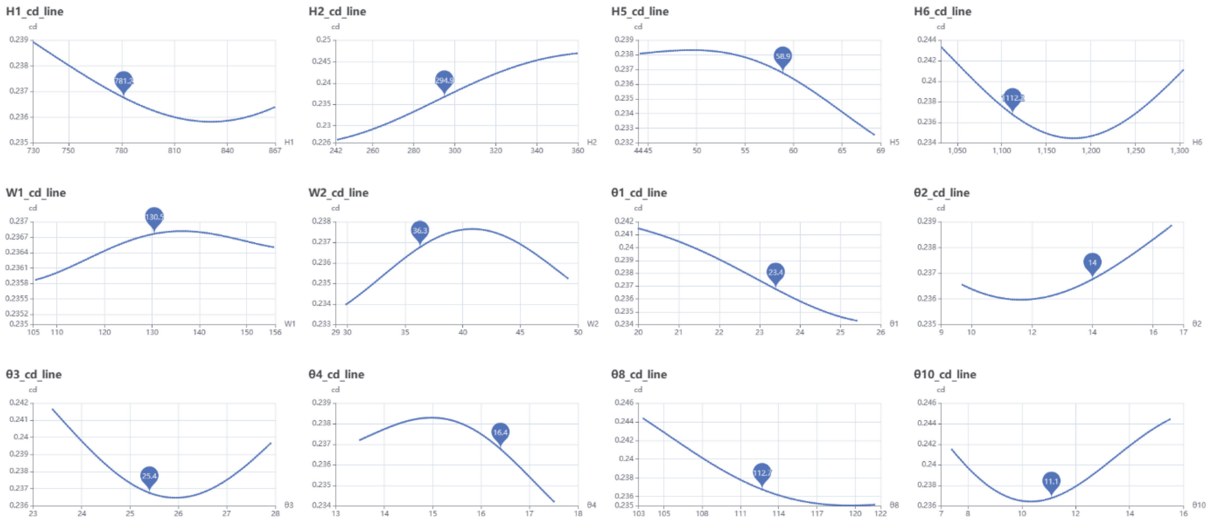

Figure 3 Influence of one single styling parameter on aerodynamic drag coefficient at initial design point.

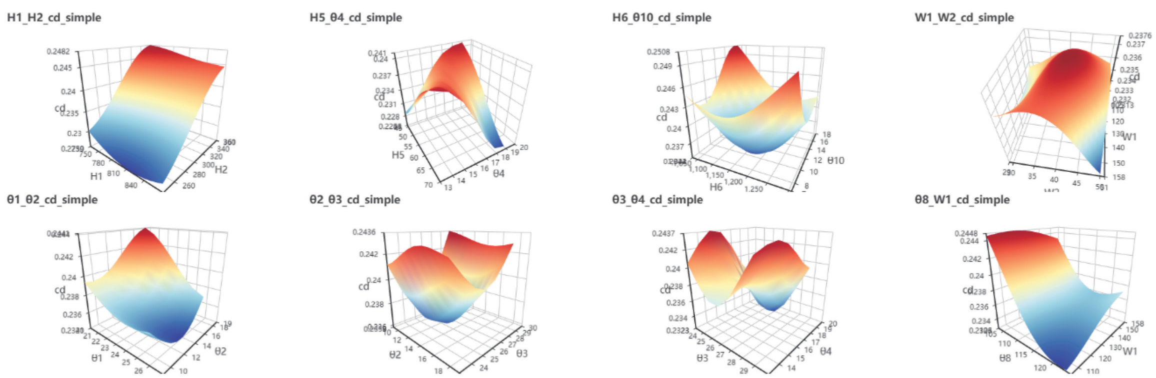

Figure 4 Influence of two styling parameters on aerodynamic drag coefficient at initial design point.

From the analysis above, the high non-linear characteristics of aerodynamics can be illustrated by the meta model of the aerodynamic drag coefficient. These high non-linear characteristics of aerodynamics make the development more difficult. The meta model established by kriging method can be used to separate or decompose the non-linear characteristics of all these parameters to guide the aerodynamic development.

4 Pursuit for the smallest Drag Coefficient in the Given Design Space

The meta model created by kriging method descripts the aerodynamic sensitivity of styling parameters in high dimension. From the view of one or two dimension, the relationship between aerodynamic performance and styling parameters is illustrated locally, such as using 2D line diagram and 3D diagram. By changing one parameter, the sensitivity of the other parameters also changes, which can be treated as non-linear characteristics. While, form the view of high dimension of meta model, the relationship between aerodynamic performance and styling parameters is certain, and there exists a minimum value of Cd. In this paper the simplex optimization method is employed to optimize the Cd of the fastback sedan in the given design space. Figure 5 shows the value of Cd decreasing in the optimization process. The maximum and minimum value of Cd refer to the worst and best design points in among all the vertices of the simplex geometry. The optimization almost converges after 200 iterations. The Cd decreases by 9.08% from 0.239 to 0.218. The remarkable Cd reduction implies that the combination of kriging model and simplex method can be used to provide optimization suggestion of Cd reduction by styling changing.

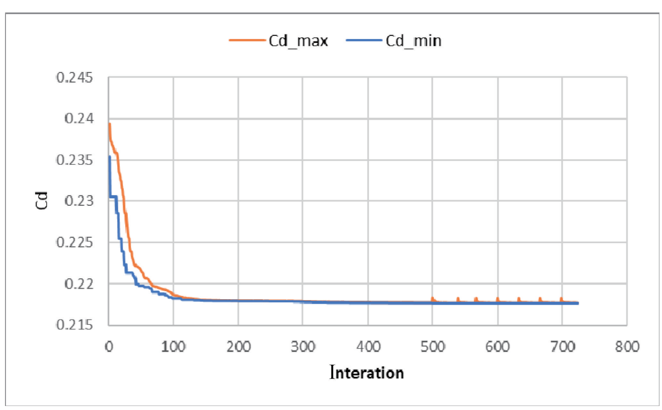

Figure 5 Cd decreasing with the iteration of simplex optimization.

As descripted above, the aerodynamic sensitivity of styling parameters changes with parameters change from the view of 2D and 3D diagram as shown in Figure 6 and Figure 7. At the optimizable design point all parameters are set at their optimizable value in the given design space, as shown in Figure 6. Some of the sensitivity types are monotone and the optimizable design point is at the lowest or highest value in the design space. Some of the sensitivity types are decreasing followed by increasing, and the minimum value of Cd exists in the middle of the design space.

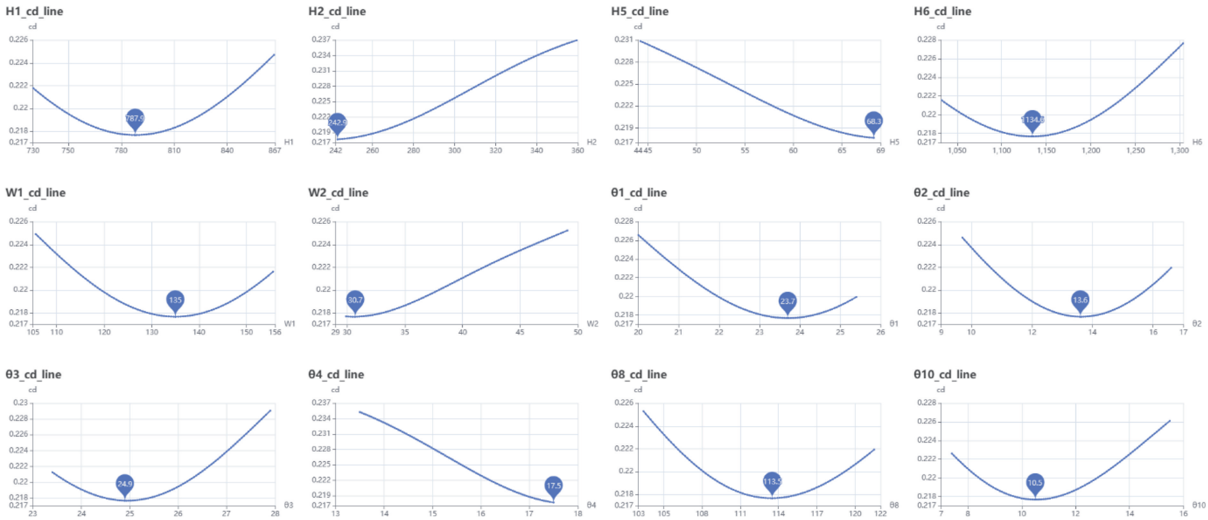

Figure 6　Influence of one single styling parameter on aerodynamic drag coefficient at optimum design point.

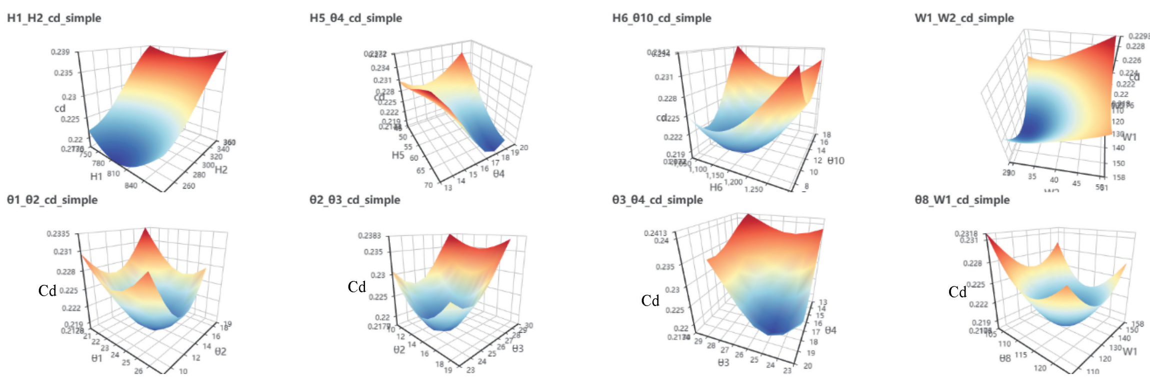

Figure 7　Influence of two styling parameters on aerodynamic drag coefficient at optimum design point.

5　Discussion

The aerodynamic design of automobile can be divided into four parts simply: aerodynamic shape, aerodynamic feature, aerodynamic device and aerodynamic algorithm. Vehicle whole sizes, styling parameters, and attachment option can be used to parameterize the aerodynamic design of vehicle. The combination of basic size model, styling parameters model, and attachment option model constructs the meta model of Cd prediction of automobile. Figure 8 shows the accuracy and error of this meta model. The Cd values of prediction are close to the experimental results, and the prediction error is less than 7%, which almost can be compared with CFD simulation. This meta model can be used to handle the definition of the target of the aerodynamic drag and the optimization in the early design stage of automobile.

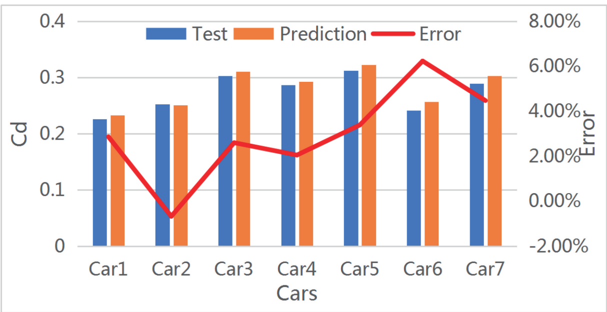

Figure 8　Accuracy and error of Cd prediction meta model.

6　Conclusion

Aerodynamic performance has tight relationship with vehicle styling, which can be descripted by styling parameters. To handle the non-linear characteristics of vehicle aerodynamics, the kriging method was employed to build a meta model to explore the aerodynamic sensitivity of styling parameters. Then the simplex optimization method was employed to find the minimum value of Cd in the given design space. Some conclusion can be given as：

1. The kriging model can be used to build the meat model to descript the relationship between styling parameters and aerodynamic performance. The aerodynamic sensitivity of one single parameter or two synergistic parameters can be illustrated by 2D line diagram or 3D diagram. This sensitivity results can be used to guide the aerodynamics design.

2. From the view of 2D line diagram or 3D diagram, parameters changing can influent the sensitivity of the other parameters, which is considered as the non-linear characteristic in this paper. While in high dimension including all the parameters, the relationship between styling parameters and aerodynamics is exact, and there exists the minimum value of Cd.

3. Simplex method has high efficiency on finding the minimum Cd value based on the meta model build by kriging model. A 9.08% Cd reduction has been received for the fastback sedan in this study. Simplex method is suit for optimizing the Cd performance based on meta model.

4. The combined model including vehicle basic size, styling parameters model, and attachment option model was established to set the development target and optimization of aerodynamic drag in the early stage. The prediction error is less than 7%, which almost can be compared with CFD simulation.

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