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[3-B-04] High-Precision Surrogate Method Based on Fusion Strategy for High-Speed Vehicles Aerodynamic Optimization

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Keywords: High-Precision Surrogate Model, Fusion Strategy, Aerodynamic Optimization

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High-Precision Surrogate Method Based on Fusion Strategy for High-Speed Vehicles Aerodynamic Optimization

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Abstract: To address the intricate challenges in optimizing the aerodynamic shape of high-speed vehicles, this study introduces a high-precision surrogate model method based on fusion strategy. Firstly, to meet the demands of the surrogate optimization strategy for a large number of high-precision samples, a method for constructing aerodynamic samples based on data fusion correction is presented. By correcting the calculation results of a large number of low-precision grids with the results of a small number of high-precision grids as a reference, this method improves data accuracy and significantly reduces the time required for sample calculations. This provides a more efficient and reliable means of establishing samples for high-precision surrogate models. Secondly, a double-stage fusion surrogate model is constructed, which can achieve a more accurate regression modeling of aerodynamic relationships, and improving the accuracy and reliability of the surrogate model under the same prediction samples, with an *MAE* of only 0.63%. Combining the DFS with GA and applying it to drag reduction optimization in high-speed vehicles, the resulting optimal model reduces drag coefficient by 9.27% compared to the base model. This result confirms the feasibility of the surrogate model based on the fusion strategy, providing a more accurate and efficient method for aerodynamic shape optimization in high-speed vehicles.

Keywords: Fusion strategy; Surrogate Model; High-speed vehicle; Aerodynamic optimization.

1 Introduction

High-speed vehicles occupy crucial position in the field of aerospace technology [1,2]. The aerodynamic shape design and configuration research of these vehicles are key issues in the development of the entire system, forming the basis for subsequent control, trajectory, and propulsion system designs [4-6]. One of the core tasks of aerodynamic design is the evaluation of the aerodynamic characteristics of high-speed vehicles. Accurate aerodynamic analysis can better support subsequent optimization designs. The use of surrogate models for predicting aerodynamic performance has been widely studied. However, compared to traditional aircraft [7,8], high-speed vehicles exhibit more pronounced nonlinearities, coupling effects, and uncertainties in the aerodynamic performance [9,10]. These characteristics impose higher accuracy requirements on surrogate models. If the surrogate model is not properly constructed, the final optimization results may deviate significantly from the actual global optimum. Additionally, the stability margins and design flexibility of high-speed vehicles are much smaller than those of aircraft [11,12]. As a result, the number of shape design variables increases, leading to a rise in sample size and accurate computation time, which extends the design cycle.

Variable-fidelity surrogate models present an effective strategy for the optimization process. By integrating low-fidelity sample data to aid in the construction of surrogate models, it is possible to attain higher global accuracy with a reduced number of high-fidelity samples. This method significantly enhances optimization efficiency. For instance, Chang et al. [13] proposed using the multiplicative scaling method to locally approximate high-fidelity analysis results with low-fidelity models, and Alexandrov et al. [14] combined this approach with the trust region method. Robinson et al. [15] introduced an improved space mapping method, successfully applying it to the variable-fidelity aerodynamic optimization of wings and flapping wings.

Variable-fidelity models based on Co-Kriging and Hierarchical-Kriging (HK) models are widely used. The Co-Kriging model was first applied to aerospace engineering design by Forrester [16,17] and Kuya et al. [18]. Subsequent studies have extensively explored Co-Kriging, for instance, by concentrating on simplifying the calculation of the Co-Kriging model's correlation function [19,20], or by integrating gradient information [21,22] as low-cost auxiliary data to enhance modeling efficiency. Han [23] proposed a simpler and more practical Hierarchical-Kriging (HK) model by sequentially building low- and high-fidelity Kriging models. In this model, the predicted values from the low-fidelity model were directly used as the global trend function in the high-fidelity model. This approach addressed the robustness and efficiency issues of Co-Kriging models and avoided the difficulty of calculating cross-covariances in Co-Kriging.

To meet the requirements for surrogate model accuracy and sample size in high-speed vehicle optimization, this paper develops a high-precision surrogate method based on a fusion strategy. The fast aerodynamic modeling based on data fusion correction (DFC) is used to constructed the initial samples. A small amount of high-fidelity data is used to correct and merge a large amount of low-fidelity data, reducing sample construction time and enhancing design accuracy. The fusion surrogate (DFS) model strategy replaces the original model for analysis. The DFS model, composed of interpolation and regression surrogate models, integrates the advantages of both types, offering higher predictive accuracy than traditional surrogate models. Using the high-precision surrogate method based on the fusion strategy, combined with genetic algorithms, for drag reduction design of high-speed vehicles has yielded satisfactory results, demonstrating the strong engineering applicability of this method.

2. Simulation methods

2.1 Model design

The model used in this study is simplified on the X-33 vehicle [24], retaining only its canned fins and removing the body flaps and twin vertical tails, as shown in Figure 1. The parameters that need to be optimized are marked in the Figure 1 (Fixed bottom width W_2).

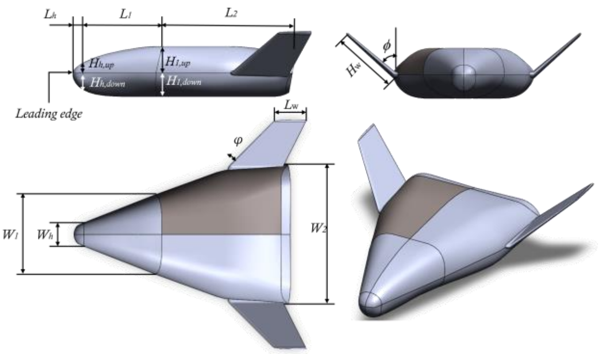


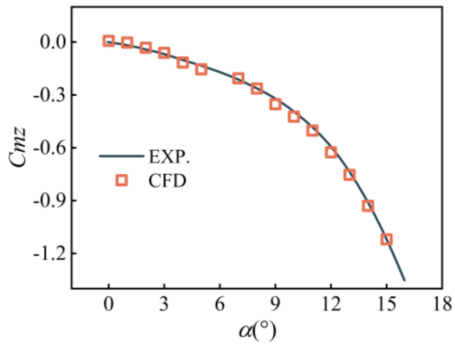
Figure 1: Model used in this study

2.2 Numerical method

The flow field calculation of the model uses the CFD method, and the finite volume method is used to discretize the flow control equation. The calculation of the flux and the viscous flux is realized by the AUSM+ format and the central difference format, respectively. The discrete equations are solved by implicit time advancement, and the turbulence model uses the Spalart-Allmaras (SA) model.

To verify the feasibility of the calculation method, it is verified in hypersonic condition. The hypersonic model selects the HB-2 model for the force test in the hypersonic wind tunnel (HWT) of JAXA [25]. As shown in the Figure 2, the calculated result is in good agreement with the experimental values, indicating that the numerical method has high analysis accuracy and can meet the optimization requirements.

(a) HB-2 model



(b) Pitching moment coefficient comparison

Figure 2: Pitching moment coefficient comparison between numerical aerodynamic coefficients and literature results

3 Surrogate Model based on Fusion Strategy

3.1 Fast Aerodynamic Modeling Based on Data Fusion Correction

The optimization design of high-speed vehicle requires a substantial number of initial aerodynamic samples. Given the challenges of limited computational resources and the extensive computational demands of three-dimensional model grids, this study adopts a data fusion correction (DFC) strategy to achieve a high-precision large sample dataset while conserving computational resources.

This strategy involves the fusion correction of data obtained from high- and low-fidelity sample points with varying grid densities. High-fidelity data typically necessitates more computational resources and time to process, whereas low-fidelity data, due to its lower resolution, can be processed more quickly. By using a small sample of high-fidelity aerodynamic data as the reference set, the accuracy of the large sample of low-fidelity aerodynamic data is elevated to the high-fidelity level. This method leverages the rapid processing capability of low-fidelity data to expedite the overall sample construction process, thereby saving significant computational time and resources without compromising data accuracy. In this study, a nested sample set of high- and low-fidelity sample points is used as the initial sample set, where high-fidelity sample points are a subset of low-fidelity sample points.

The DFC for aerodynamic datasets can be expressed as:

$$y_{\mathrm{Fu}}(x) = \rho(x) + \delta(x) \tag{1}$$

where $y_{\mathrm{Fu}}(x)$ represents the fused data, $\rho(x)$ is the regression model between the low-fidelity aerodynamic data $y_{\mathrm{Lo}}(x)$ and the high-fidelity aerodynamic data $y_{\mathrm{H}}(x)$, and $\delta(x)$ is the deviation model between $\rho(x)$ and $y_{\mathrm{H}}(x)$.

The DFC not only merges data of different fidelities but also integrates different surrogate models. First, a regression model $\rho(x)$ for low-fidelity data $y_{\mathrm{Lo}}(x)$) is established based on the high-fidelity training sample set (Eq.(2)). Through multiple training iterations, it ensures that the high- and low-fidelity data are on the same scale and share the same overall trend. Then, at the high-fidelity $y_{\mathrm{H}}(x)$ sample points, the deviation between the high-fidelity aerodynamic data $y_{\mathrm{H}}(x)$ and the regression model of the low-fidelity aerodynamic data $\rho(x)$ is calculated. An interpolation model for this deviation $\delta(x)$ is then established to more accurately estimate the intermediate values (Eq.(3)).

$$\rho(x) = \sum(\alpha_i - \alpha_i^*) y_{\mathrm{Lo}}(x) + b \tag{2}$$

$$\delta(x) = \beta_\delta + Z_\delta(x) \tag{3}$$

where $(\alpha_i - \alpha_i^*)$ represents the support vectors, b is the offset, β_δ is the mathematical expectation of the Gaussian random process $\delta(x)$, and $Z_\delta(x)$ is the Gaussian random process with a mean of 0 and a variance of σ_δ^2 .

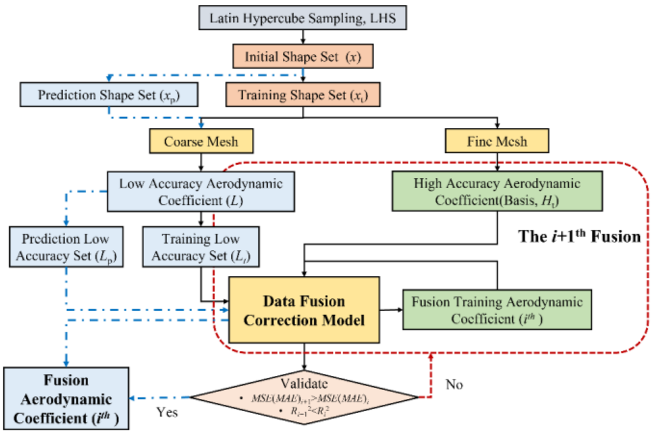
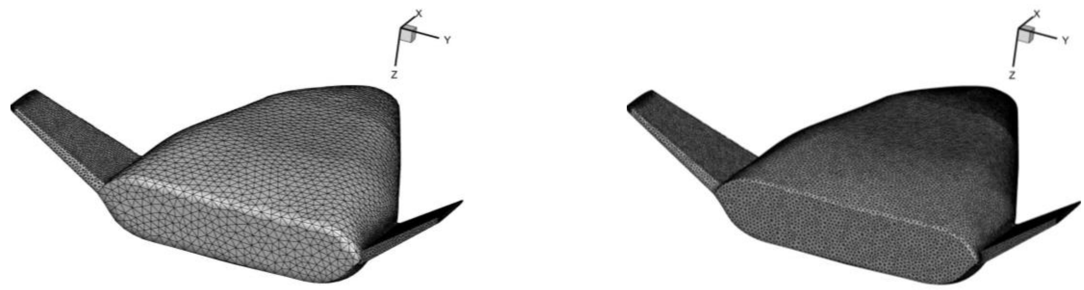


Figure 3: Fast Aerodynamic Modeling Based on Data Fusion Correction

Figure 4 shows the different precision grid models of the base model. The coarse mesh has 310,389 grid points, while the fine mesh has 1,847,219 grid points, with the computation time for the fine mesh being five times that of the coarse mesh. Using the Latin Hypercube Sampling method [14], 160 sample points are selected within the design space. All samples are constructed with the low-fidelity grid, and 40 of these samples are randomly chosen to construct high-fidelity models. The remaining 120 low-fidelity samples are designated for subsequent fusion correction.



(a) Coarse mesh (b) Fine mesh

Figure 4: Different grid models

As shown in Figure 5, there is a difference in magnitude between the low-fidelity and high-fidelity data before fusion. Even after normalizing the magnitudes, the trends of the low-fidelity data do not align with those of the high-fidelity data. After applying the DFC strategy, the fused data closely matches the high-fidelity results in both magnitude and trend, with a mean absolute error (MAE) of only 0.018. This demonstrates that the fusion strategy is effective and can be used for the initial samples in subsequent surrogate modeling.

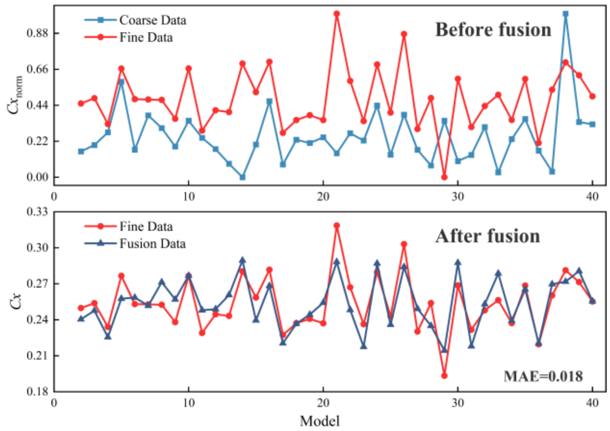


Figure 5: Drag coefficient before and after fusion

3.2 Double-stage Fusion Surrogate Model

For engineering optimization design problems, the surrogate model is not only required to have higher prediction accuracy but also needs to accurately reflect the fundamental characteristics of the original physical model to meet the requirements of optimization design. Considering the significant nonlinearity of hypersonic aerodynamic performance, this study constructs a double-stage fusion surrogate (DFS) model to predict the models' drag coefficient. The DFS is constructed from both regression surrogate model and interpolation surrogate model, integrating the advantages of both types. It has higher prediction accuracy and can more accurately reflect the changing characteristics of the original model [26].

The construction process of the DFS model is illustrated in Figure 5. Initially, a regression model $f_R(x)$ is employed to fit the overall distribution of the original aerodynamic sample $f(x)$, serving as the first-layer surrogate model. The $e_R(x) = f(x) - f_R(x)$, contains local characteristic information of the original model that the regression model itself cannot capture. Next, leveraging the precise fitting capabilities of the interpolation surrogate model, a second-layer surrogate model is constructed to model $e_{R,I}(x)$ to fit $e_R(x)$. The second-layer model is used to adjust the regression model, correcting the local information to obtain the DFS model.

In this study, the interpolation model and the regression model used are the Kriging model [27] and the BP neural network [28], respectively. The Kriging model is a typical representative of interpolation-type surrogate models, known for its flexibility and good adaptability to deterministic problems, though it performs poorly in large design space problems [29]. The BP neural network, on the other hand, excels in handling strong nonlinearity in large design spaces, albeit at the cost of substantial computational effort [29].

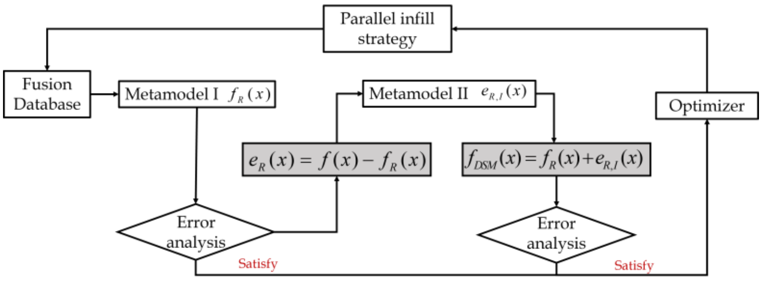
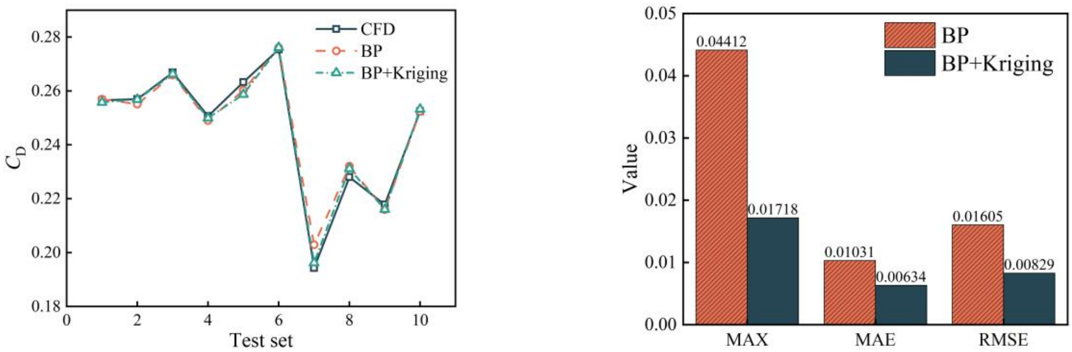


Figure 6: Flowchart of double-layer surrogate model

MAX (Max Absolute Error), *RMSE* (Root Mean Square Error, Eq.(4)) and *MAE* (Mean Absolute Error, Eq.(5)) are used to measure the prediction accuracy of the surrogate model. In Eq.(4)- Eq.(5), y_i is the true function value and $\hat{y}_i$ is the predicted value of the surrogate model. Figure 7 shows the comparison of *MAX*, *RMSE*, and *MAE* for each surrogate model. As shown in the Figure 7, in predicting the drag coefficient of high-speed vehicle, the errors of the DFS model are smaller than that of the BP neural network, regardless of the *MAX*, *MAE* or *RMSE*. This fully demonstrates that the DFS model has higher prediction accuracy than traditional surrogate models.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_i - \hat{y}_i\right)^2} \tag{4}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|\left(y_i - y_i\right)\right| \tag{5}$$



(a) Predicted value of drag coefficient (b) Prediction errors

Figure 7: Prediction results and errors of drag coefficient of different surrogate models

4 Optimization of high-speed vehicle

For achieving shape optimization, the genetic algorithm (GA) is used for optimization design of high-speed vehicle, which provides a richer selection space to find the optimal solution. As shown in Figure 8, during the optimization process, the data generation strategy based on data fusion correction and the double-stage fusion surrogate model are used to provide the initial population for optimization.

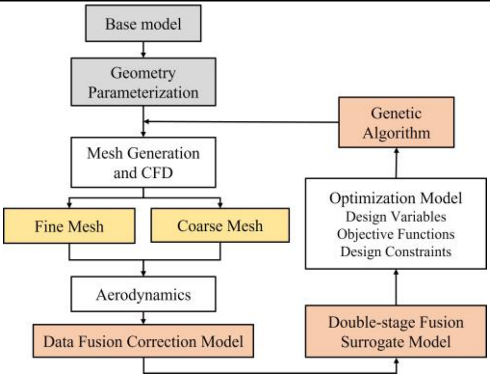


Figure 8: Optimization flowchart

The freestream condition is set at an altitude of H=40 km and a Mach number of 10. The optimization goal in this study is to minimize the drag coefficient of the model, with a constraint that geometric shape parameter variations are within a 5% threshold (Eq.(6)).

$$\begin{aligned} &\min \quad f_{obj} = C_D \\ &\text{s.t.} \quad 0.95x_{j,0} \le x_j \le 1.05x_{j,0} (j = 1, 2...14) \end{aligned} \tag{6}$$

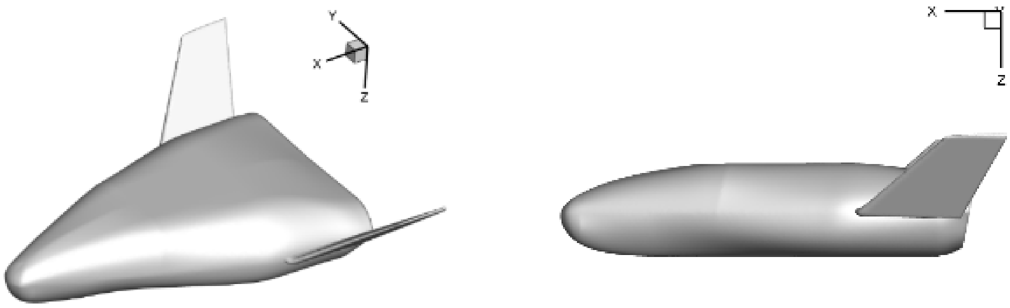
The optimal model illustrated in Figure 9b reveals notable distinctions, particularly in the wing sweep angle, sweepback angle, and a reduction in the nose position. Despite minimal alterations in the overall model length, an elongation is observed in the first cone's length, coupled with a reduction in thickness. From Figure 10, it can be seen that the opt model reduces the pressure at the trailing edge of the body, and the high-pressure area on the lower surface of the first cone moves backward. The drag coefficient of the optimized model experiences an 8.63% decrease compared to the base model, with a mere prediction error of 0.683%. These results confirm the reliability and effectiveness of the surrogate model based on fusion strategy employed in this study.

Table 1 Comparison of model shape parameters before and after optimization (Body)

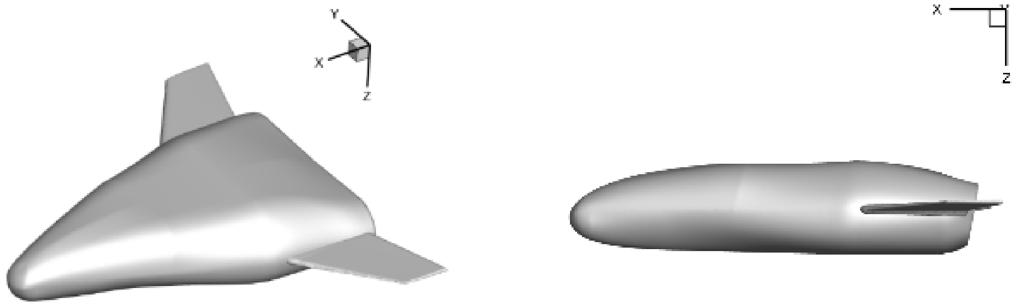
Model	L_h	L_1	L_2	$H_{h,up}$	$H_{h,dn}$	$H_{1,up}$	$H_{1,dn}$	W_h	W_1	LE
Base	0.901	7.168	11.815	0.899	2.123	2.395	1.505	7.265	2.110	0.00
Opt	0.946	7.526	11.224	0.854	2.017	2.275	1.429	7.628	2.216	0.20

Table 2 Comparison of model shape parameters before and after optimization (Wing)

Model	L_w	H_w	φ	ϕ
Base	2.963	6.998	54.077	0
Opt	2.815	6.648	51.373	-14.874



(a) Base model (C_D=0.2404)



(b) Optimal model(C_D=0.2197)

Figure 9: Different shapes of high-speed vehicle

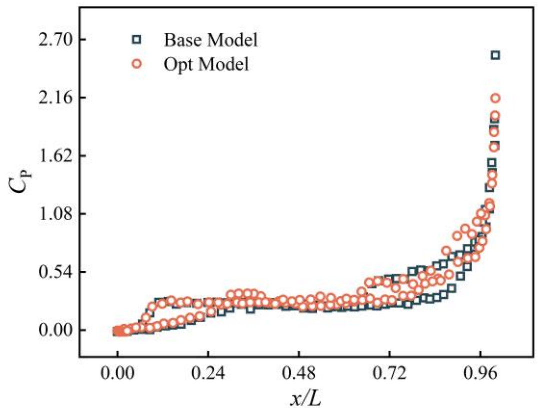


Figure 10: Comparison of XY-sectional pressure coefficient distribution

5. Conclusion

This paper proposes a high-precision surrogate method based on a fusion strategy for the aerodynamic shape optimization of high-speed vehicles. To address the challenge of increasing design samples for high-speed vehicles, a fast aerodynamic modeling based on data fusion correction (DFC) is established. This method uses a small amount of high-precision aerodynamic data to correct a large number of low-precision samples, significantly reducing the time required to create the initial sample set. Due to the nonlinear variations in hypersonic aerodynamics, which decrease the prediction accuracy of traditional surrogate models, a double-stage fusion surrogate model (DFS) combining regression and interpolation is developed, offering higher predictive accuracy across the entire design space. Utilizing a surrogate optimization strategy and genetic algorithm, the high-precision surrogate method is applied to the aerodynamic design of high-speed vehicles. The optimal model demonstrates an 8.63% drag coefficient reduction at hypersonic speeds compared to the base model. These results indicate that the proposed design method meets practical engineering design requirements and exhibits engineering applicability.

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