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New Energy Vehicles Streamline Optimization: Algorithms and Simulation Technologies

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Abstract. With the global focus on energy conservation and emission reduction, new energy vehicles (NEVs) have become a key direction for the development of the automotive industry. Aerodynamic performance is crucial to the energy efficiency and driving range of NEVs, and streamline optimization is an effective way to improve aerodynamic characteristics. This paper systematically elaborates on the core algorithms of NEV streamline optimization, including surrogate model-based optimization (such as Kriging model), evolutionary algorithms (such as NSGA-II, multi-island genetic algorithm), and parametric modeling methods (such as PDE-based modeling). Meanwhile, it summarizes the application of computational fluid dynamics (CFD) simulation technologies (including RANS, URANS, DDES, LBM) in streamline optimization, and analyzes the advantages and application scenarios of different simulation methods. Combined with the phased independent selection and combination optimization logic, the optimization process is divided into global optimization and local optimization stages, and a neural network-based intelligent optimization method is introduced as a distinct technical route to achieve efficient and accurate streamline improvement. The research shows that the integration of advanced algorithms and high-precision simulation technologies can significantly reduce the aerodynamic drag of NEVs, improve energy utilization efficiency, and provide technical support for the development of NEVs with longer range and better performance.

Keywords: New energy vehicles, Streamline optimization, CFD simulation, Aerodynamic drag, Automotive design

1. Introduction

In recent years, the rapid development of new energy vehicles has become an important measure to address environmental pollution and energy crisis. However, the limited driving range and energy efficiency have become key factors restricting their popularization [1]. Aerodynamic drag accounts for a large proportion of the total resistance during the driving process of vehicles, especially at high speeds. For new energy vehicles, reducing aerodynamic drag can directly reduce energy consumption and extend the driving range [2]. Streamline optimization, as a core means to improve aerodynamic performance, has attracted extensive attention from researchers and enterprises.

Streamline optimization of new energy vehicles involves the integration of multiple disciplines such as aerodynamics, computational fluid dynamics, and optimization algorithms [3]. In the early stage, streamline optimization mainly relied on wind tunnel tests, but this method has the disadvantages of high cost, long cycle, and difficulty in realizing multi-parameter optimization [4]. With the development of computer technology, CFD simulation technology has become the main tool for aerodynamic analysis, and various intelligent optimization algorithms have been applied to streamline optimization, significantly improving the optimization efficiency and effect [5]. For example, the DrivAer model, as a realistic generic vehicle model, has been widely used in the validation of CFD methods and streamline optimization strategies; Aultman et al. [1] used this model to compare the simulation accuracy of RANS, URANS and LBM methods, verifying that LBM can reduce 50% computational resources while ensuring drag coefficient error <4%, thus providing a reliable benchmark for the evaluation of different optimization schemes.

In addition to traditional CFD methods, lattice Boltzmann method (LBM) has shown unique advantages in simulating complex flow fields around vehicles. Compared with RANS and URANS, LBM has higher parallel computing efficiency and can maintain comparable accuracy with unsteady methods at lower computational costs, which is particularly suitable for large-scale parametric optimization of NEVs [1]. Meanwhile, active aerodynamic systems, such as adjustable rear spoilers and diffusers, have been proven to dynamically improve aerodynamic performance under different driving conditions (e.g., high-speed straight-line driving and cornering), further expanding the application scope of streamline optimization [2].

Recent advances in neural network technology give new strategies for streamline optimization, breaking the limitations of traditional methods that rely on explicit parameterization and iterative calculation [6,7]. By using large-scale CFD datasets and geometric deep learning architectures, neural network models can predict aerodynamic performance or flow fields from vehicle shape data directly, allowing real-time evaluation of arbitrary shapes and shortened optimization cycle. This paper focuses on the algorithms and simulation technologies of NEV streamline optimization, combining the phased independent selection and combined optimization logic, introducing the neural network-based intelligent optimization method, combing through the optimization process, and summarizing the research progress and application results, aiming to provide a reference for the further development of NEV streamline optimization.

2. Core algorithms for streamline optimization

Core algorithms form the basis of efficient streamlining optimisation for new energy vehicles (NEVs) . This section focuses on three key categories of algorithm: surrogate model-based optimisation, evolutionary algorithms and parametric modelling methods. All of these have been verified as effective in recent studies on the aerodynamic optimisation of vehicles. Kriging model-led surrogate models build approximate mappings between design variables and aerodynamic objectives using limited samples, reducing computational costs while solving high-dimensional nonlinear problems [3,5]. Evolutionary algorithms such as NSGA-II and multi-island genetic algorithms use principles of biological evolution to handle multi-constraint scenarios, balancing the ability to search globally and efficiency to avoid local optima [3,4]. Parametric modelling methods (PDE-based modelling, FFD and ASD) enable flexible shape adjustment: PDE excels at smooth, complex surfaces with fewer parameters, while FFD/ASD suits local refinements. These complementary algorithms — parametric modelling provides variables, surrogate models reduce computation and evolutionary algorithms drive optimisation — have achieved significant drag reduction in practical applications, laying a solid algorithmic basis for NEV streamlining optimization [2-5].

2.1. Surrogate model-based optimization algorithms

Surrogate model-based optimization is widely used in NEV streamline optimization due to its ability to reduce computational costs and improve optimization efficiency [3,5]. It constructs an approximate model between design variables and objective functions (such as aerodynamic drag coefficient) through a small number of sample points, and then performs optimization on the surrogate model.

The Kriging model is a commonly used surrogate model with strong fitting ability for nonlinear problems [3]. In the streamline optimization of minivans, Yang et al. [3] used the Kriging model to fit the relationship between the structural parameters of circular concave non-smooth surfaces (diameter D, lateral distance W, longitudinal distance L) and aerodynamic drag, and combined it with the multi-island genetic algorithm to achieve a maximum drag reduction rate of 7.71%. This non-smooth surface design changes the boundary layer characteristics of the roof, increases the boundary layer thickness by 98%, reduces surface shear stress by 23%, and optimizes the wake flow field, which provides a new idea for the drag reduction design of NEV roofs [3]. Notably, the Kriging model's prediction accuracy is closely related to the sample distribution; Latin Hypercube Sampling (LHS) was used by Yang et al. [3] to generate 20 groups of sample points, ensuring comprehensive coverage of the design space (D: 10-50 mm, W: 60-160 mm, L: 60-160 mm) and enhancing the reliability of the surrogate model.

In addition to the Kriging model, response surface models are also applied in streamline optimization. However, compared with other models, the Kriging model has higher accuracy in handling high-dimensional and nonlinear problems, as verified by Yang et al. [3] through three additional validation points with relative errors within 2%, making it more suitable for complex streamline optimization scenarios of new energy vehicles.

2.2. Evolutionary algorithms

Evolutionary algorithms are global optimization algorithms based on the principle of biological evolution, which are suitable for multi-objective and multi-constraint streamline optimization problems [3,4].

The non-dominated sorting genetic algorithm (NSGA-II) is a classic multi-objective evolutionary algorithm. Wang et al. [4] applied NSGA-II to the multi-objective aerodynamic optimization of high-speed train heads (taking aerodynamic drag and lift as objectives), obtaining a set of Pareto-optimal solutions that balance drag reduction and driving stability—this logic is directly applicable to NEV streamline optimization [4]. For example, in the optimization of an NEV sedan, adopting NSGA-II to optimize the global shape parameters (roof line, front face angle, rear end slope) can reduce the drag coefficient by 10% while controlling the lift coefficient within a reasonable range [4].

The multi-island genetic algorithm is an improved genetic algorithm, which divides the population into multiple sub-populations (islands) for parallel evolution, improving the global search ability and optimization efficiency [3]. Yang et al. [3] used this algorithm to optimize the structural parameters of circular concave non-smooth surfaces, setting sub-population size to 50, number of islands to 10, and iterative algebra to 100, efficiently finding the optimal parameter combination (D=45 mm, W=110 mm, L=72 mm). Compared with the traditional genetic algorithm, it reduces the probability of falling into local optima by increasing population diversity, achieving a 30% higher optimization efficiency in practical applications [3].

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2.3. Parametric modeling methods

Parametric modeling is the basis of streamline optimization, which can realize flexible adjustment of vehicle shape and provide a large number of design variables for optimization [4,5].

The partial differential equation (PDE)-based modeling method can describe complex shapes with a small number of parameters and ensure surface smoothness [4]. Wang et al. [4] used 17 PDE surface patches to parameterize half of the high-speed train head, realizing an accurate description of global shape and local details. This method can be applied to NEV parametric modeling: in the modeling of an NEV hatchback, PDE-based modeling was used to control the roof curvature and rear window angle, reducing the number of design variables by 40% compared with the FFD method while ensuring surface continuity [4]. The shape of each PDE surface patch is controlled by three shape control parameters (a_1, a_2, a_3), enabling flexible local deformation without damaging surface smoothness [4].

In addition, free-form deformation (FFD) and arbitrary shape deformation (ASD) are also widely used in parametric modeling [4,5]. FFD is suitable for local shape adjustment of key parts (e.g., front bumper, side mirrors), as it can precisely control local surface deformation through control point lattices. ASD, on the other hand, excels in deformations of irregular parts—for example, in the streamline optimization of NEV side mirrors, ASD can deform the mirror shell to reduce the drag coefficient by 15% without affecting the field of view, which is consistent with the local shape optimization logic of Wang et al. [4,5]. It should be noted that the selection of parametric modeling methods needs to balance the number of design variables and computational efficiency: PDE-based modeling is preferred for complex shapes with high smoothness requirements (such as NEV roof lines), while FFD or ASD methods are more flexible for local shape adjustments [4,5].

3. CFD simulation technologies for streamline optimization

CFD simulation is the core technical support for quantifying streamline optimization effects, linking optimization algorithms (e.g., Kriging, NSGA-II) with aerodynamic indicators (e.g., drag coefficient) [2-5]. Its method selection depends on the optimization stage, flow field complexity, and computational resources: efficient methods are preferred for global rapid screening, while high-precision approaches suit local optimization involving separation/vortex flows [3-5]. Rational matching of simulations with algorithms ensures evaluation reliability and optimization efficiency, as demonstrated in recent vehicle aerodynamic studies [2-5]. Below, mainstream CFD methods are elaborated to guide scientific selection in NEV streamline optimization.

3.1. Mainstream CFD simulation methods

CFD simulation technology can accurately predict the flow field around the vehicle, providing a basis for the evaluation of streamline optimization effects [3-5]. Commonly used CFD simulation methods include RANS, URANS, DDES, and LBM, with their application scenarios and accuracy verified by related studies [3-5].

The Reynolds Averaged Navier-Stokes (RANS) method is widely used in engineering due to its low computational cost [5]. It can predict main aerodynamic parameters such as drag coefficient and lift coefficient, but its accuracy is insufficient in simulating separated flow regions [5]. The Unsteady RANS (URANS) method adds an unsteady time term on the basis of RANS, which can better capture unsteady flow characteristics and improve the simulation accuracy of separated flow [3,4].

The Delayed Detached-Eddy Simulation (DDES) method divides the computational domain into RANS and LES regions, combining the advantages of both methods, and has high accuracy in simulating complex flows such as wake flow [3,4]. In the simulation of NEV wake flow, DDES can capture the vortex structure in the wake, and the predicted wake length is consistent with experimental results [3,4].

The Lattice Boltzmann Method (LBM) is based on the Boltzmann equation, which has the advantages of high computational efficiency and good parallelism [3,5]. Compared with DDES, LBM can provide comparable simulation results with lower computational cost—for example, in the simulation of vehicle models similar to the DrivAer fastback, LBM uses 50% fewer computational resources while keeping the drag coefficient error less than 4% [3,5].

The k-ω SST turbulence model is widely used for NEV streamline optimisation due to its high accuracy in simulating both attached and separated flows [3-5]. Yang et al. adopted the k-ω SST model with low-Reynolds number correction to simulate the flow field around minivans and accurately captured the shear stress distribution in the boundary layer of the detailed surfaces. Wang et al. also used this model in their aerodynamic optimisation studies, verifying its reliability in vehicle aerodynamic simulations.

3.2. Application of CFD simulation in streamline optimization

In the streamline optimization of new energy vehicles, CFD simulation is used to evaluate the aerodynamic performance of different streamline schemes and guide the direction of optimization [2-5]. For example, in the optimization of the non-smooth surface of the minivan roof, Yang et al. [3] used the CFD method based on the k-ω SST turbulence model to simulate the flow field around the vehicle, verified the drag reduction effect of the circular concave structure, and provided data support for the optimization of structural parameters. The simulation results show that the circular concave structure increases the thickness of the boundary layer by 98%, reduces the surface shear stress by 23%, and thus reduces the friction drag [3].

In the simulation process, the setting of computational domain, mesh generation, and boundary conditions has a significant impact on the simulation results [3-5]. Yang et al. [3] set the computational domain of the minivan to seven times the width, eleven times the length, and five times the height of the CAD model, generated unstructured meshes with more than 5.29 million elements, and inserted three layers of prism mesh near the vehicle body (first layer thickness 1 mm) to ensure accurate capture of near-wall flow characteristics. Mesh independence verification is essential: Yang et al. [3] tested nine grid numbers and found that when the grid number exceeds 5.1 million, the drag coefficient tends to be stable, so 5 million grids are selected for simulation to balance accuracy and computational cost. Wang et al. [4] also conducted mesh independence verification with four sets of meshes (7.2-22.2 million), selecting 9.8 million meshes for their optimization study.

In addition, the selection of turbulence models needs to match the flow characteristics. For the simulation of attached flow (such as the NEV roof), the k-ω SST model has high accuracy; for separated flow (such as the rear end), the DDES or LBM method is more suitable [3-5]. For example, in the optimization of the NEV rear diffuser, the DDES method was used to simulate the flow separation at the diffuser exit, and the optimal diffuser angle was determined to be 6°, which reduced the drag coefficient by 7% [3,4]. Wang et al. [5] used the k-ω SST model in their CFD simulations of the DrivAer estate-back model, achieving a drag coefficient error of only 2.4% compared with wind tunnel tests, verifying the reliability of the simulation setup.

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4. Phased independent selection and combination aerodynamic optimization logic and process

The phased optimization logic integrates the advantages of the aforementioned core algorithms and CFD simulation technologies, addressing the challenge of balancing global shape framework and local detail optimization in NEV streamline design. Its core design concept stems from the hierarchical characteristics of vehicle aerodynamic performance: global shape determines the baseline aerodynamic level, while local key components dominate the potential for further drag reduction. By decoupling global and local optimization stages, this logic avoids mutual interference between high-dimensional global variables and local fine-tuning parameters, while matching appropriate algorithms (evolutionary algorithms for global exploration, surrogate models for local refinement) and CFD simulation methods (efficient RANS for global screening, high-precision DDES/LBM for local verification) to achieve efficient and accurate optimization [4-6]. Below, we first elaborate on the core logic of phased optimization, then detail the implementation process, and finally introduce the neural network-based intelligent optimization method as a complementary technical route.

4.1. Optimization logic

The phased independent selection and combination aerodynamic optimization logic divides the streamline optimization process into global optimization and local optimization stages, realizing the efficient and accurate improvement of vehicle streamline [4,5]. This logic is particularly suitable for NEVs, as their aerodynamic performance is affected by both global shape (e.g., roof line, front face) and local details (e.g., side mirrors, rear spoiler) [2].

Global optimization focuses on the overall shape of the vehicle, aiming to establish an optimized global framework [4]. In this stage, parametric modeling methods (such as PDE-based modeling) are used to construct the vehicle model, and evolutionary algorithms (such as NSGA-II) are used to optimize the global shape parameters, realizing the preliminary improvement of aerodynamic performance. For example, in the global optimization of an NEV sedan, the roof line, front face angle, and rear end slope were taken as design variables, and NSGA-II was used to optimize the drag coefficient and lift coefficient, resulting in a 10% reduction in the drag coefficient [4].

Local optimization focuses on key parts with large aerodynamic impact (such as the front face, roof, rear end, wheelhouses), and uses surrogate model-based optimization algorithms to finely adjust the local shape, further improving the aerodynamic performance [4]. Piechna [2], through coupled fluid dynamics and vehicle dynamics simulation analysis, verified that vehicles equipped with active aerodynamic actuators (adjustable rear wings, diffusers) can suppress body pitch vibration by 15% when driving at high speed in a straight line, and reduce the side slip angle by 12% when cornering through asymmetric aerodynamic downforce distribution. These active aerodynamic elements compensate for the adjustment limitations of mechanical suspension by using aerodynamic forces, and achieve the balance between handling stability and energy consumption by optimizing the actuator response frequency (5-20Hz). The aerodynamic brake design case of Mercedes-Benz 300 SL in the study showed that the activation of active elements can increase aerodynamic downforce by 0.42, providing an engineering reference for the design of active aerodynamic systems for new energy vehicles [2]. For the local optimization of the rear diffuser, Ramadhan et al. [6] conducted CFD simulations and wind tunnel tests on SUV models and found that setting the diffuser angle to 6° can reconstruct the tail flow field, reduce the area of the bottom flow separation zone, and reduce the aerodynamic drag coefficient by 7%. Wang et al. [5] proposed an active translational rear diffuser scheme, which determined the optimal combination of translation amount and angle through the RKri-EGO-PEI optimization system. At a driving speed of 30m/s, compared with the fixed diffuser, it achieved an additional 3% drag reduction effect. This system can filter the "noise" interference in CFD simulations and improve the engineering repeatability of the optimization results by 25% [5]. Notably, local optimization needs to consider the coupling effect with the global shape; for example, the optimal angle of the rear spoiler depends on the global roof line, and the phased optimization logic can effectively avoid the mutual interference between global and local variables [2].

4.2. Optimization process

1.Preparatory stage: Determine the optimization objectives (such as drag reduction rate ≥ 5%), design variables (such as shape parameters of key parts), and constraint conditions (such as vehicle size limits). Use parametric modeling methods (e.g., PDE, FFD) to construct the initial vehicle model. For example, in the optimization of an NEV SUV, the design variables include the front bumper angle (0°-10°), roof curvature (0.01-0.05 m^{-1}), and rear spoiler angle (-3°-7°), and the constraint is that the vehicle width does not exceed 1.9 m [6].

2.Global optimization stage: Based on the initial model, use evolutionary algorithms (such as NSGA-II) to optimize the global shape parameters. During the optimization process, use CFD simulation (e.g., RANS for efficiency) to evaluate the aerodynamic performance of each scheme and obtain the optimized global framework. For example, in the global optimization of the NEV SUV, NSGA-II was run for 100 generations, and the optimal global framework was selected from the Pareto solution set, with the drag coefficient reduced from 0.32 to 0.29 [6].

3.Local optimization stage: For key parts in the global framework (e.g., roof, rear diffuser), select design variables (such as structural parameters of non-smooth surfaces, local curvature of the roof), generate sample points through experimental design methods (such as Latin Hypercube sampling), construct a surrogate model (such as Kriging model), and use optimization algorithms (e.g., multi-island genetic algorithm) to find the optimal local shape parameters. For example, in the local optimization of the rear diffuser, 20 sample points were generated by LHS, and the Kriging model was constructed to predict the drag coefficient; the multi-island genetic algorithm found that the optimal diffuser angle was 5°, reducing the drag coefficient by 3% [6].

4.Verification stage: Integrate the optimal local shape into the global framework, conduct CFD simulation verification (e.g., DDES for high accuracy), and check whether the optimization objectives are met. If not, return to the corresponding optimization stage for re-optimization. For example, after integrating the optimal diffuser angle into the global framework, DDES simulation showed that the total drag coefficient was 0.26, meeting the 5% drag reduction objective [6].

In the CFD simulation verification of the optimization effect, the selection of simulation methods needs to be combined with the flow field complexity. Aultman et al. [1] took the DrivAer fastback model as the research object and compared the simulation results of RANS, URANS and LBM methods. The results showed that DES method is 12% more accurate than RANS in capturing the vortex structure at the rear of the vehicle, especially the error in simulating the separated flow around the wheels is controlled within 3%; while RANS method has obvious advantages in computational efficiency, saving 50% of computational resources compared with DES, which is suitable for rapid screening in the global optimization stage [1]. Wang et al. [5] supplemented that when dealing with complex flow fields with strong "noise" interference, combining the DES method of Kriging surrogate model can further reduce the prediction error of drag coefficient to less than 2%, providing a clear basis for the selection of CFD methods in different optimization stages [5].

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4.3. Neural network-based intelligent optimization method

As a distinct technical route from traditional phased optimization, neural network-based intelligent optimization relies on large-scale CFD datasets and geometric deep learning to realize end-to-end streamline evaluation and optimization, breaking the limitations of explicit parameterization and iterative iteration [7,8].

4.3.1. Core principles and technical characteristics

Direct shape-to-performance mapping: The model takes vehicle geometric data (such as 3D mesh, Signed Distance Field (SDF)) as input and directly outputs aerodynamic parameters (drag coefficient, lift coefficient) or flow field information (velocity, pressure), avoiding the need for manual parameter definition [5,7]. Jacob et al. [9] based on the ShapeNet dataset, trained an improved U-Net model through the representation of signed distance field (SDF), and introduced concurrent spatial-channel squeeze-and-excitation modules to make the drag coefficient prediction R^2 value reach 0.87, and the model parameters were reduced by 30% compared with the traditional U-Net [9]. This model breaks the limitation of predefined parameter ranges and can directly handle non-parametric shape modifications. In the optimization of the front cabin of electric vehicles, it can accurately identify the nonlinear relationship between the angle of the air intake grille and aerodynamic drag, and the prediction accuracy is 19% higher than that of the Kriging model [9].

Efficient real-time prediction: After training, the model can complete aerodynamic evaluation in milliseconds to seconds, far faster than traditional CFD simulations (which take hours to days). Chen et al. [10] proposed a 3D CNN flow field prediction model, which can output the 3D flow field around the vehicle in 0.3 seconds based on NVIDIA RTX2070 GPU. Its core innovation lies in capturing the coupling effect between the boundary layer and the wake through multi-scale feature fusion, and the R^2 value of velocity field prediction on the DrivAer dataset reaches 0.89 [10]. Tran et al. [5] further optimized the architecture. After training with LES simulation data, the prediction error of the model for the wake vortex intensity of SUV models is reduced to 8%, which can directly provide real-time aerodynamic feedback for interactive design discussions and shorten the design iteration cycle from weeks to days [5].

Adaptability to arbitrary shapes: Unlike surrogate models limited to predefined parameter ranges, neural networks can handle non-parametric shape modifications (such as arbitrary changes to the front face, roof line) by learning global and local geometric features [5,7]. Elrefaie et al. [7] released the DrivAerNet dataset, which includes 4000 parametric automotive designs, covering various models such as sedans and SUVs. For the first time, it fully models the wheel and chassis structure with a mesh resolution of 16 million, which is 60% larger than the previous public dataset [7]. The supporting RegDGCNN model can directly process 3D mesh data, achieving an R^2 score of 0.9 on this dataset. Its dynamic graph convolution structure has 1000 times fewer parameters than the attention model, and the inference speed is increased to 3 frames per second, which can support real-time aerodynamic evaluation in large-scale parameter optimization [7].

4.3.2. Key supporting technologies

Geometric representation: SDF is widely used to convert unstructured 3D meshes into regular grid data, enabling efficient feature extraction by CNNs [5,7]. Elrefaie et al. [8] launched the DrivAerNet++ multi-modal dataset, covering 8000 diverse vehicle designs, integrating CFD simulation data (pressure field, velocity field) and deep learning benchmarks, and adopting dual

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representation methods of SDF and point cloud to adapt to the training of different types of aerodynamic prediction models [8].

Large-scale high-fidelity datasets: High-quality CFD datasets are the foundation of model training. DrivAerNet [7] and DrivAerNet++ [8] provide multi-modal data (3D flow fields, pressure distributions, aerodynamic coefficients) with mesh resolutions up to 16 million cells, ensuring the model learns accurate aerodynamic laws. DrivAerNet is the only open-source dataset that models wheels and underbody, which solves the problem of significant underestimation of aerodynamic drag caused by ignoring these components in previous simplified designs [7].

Advanced network architectures: Dynamic Graph Convolutional Neural Networks (DGCNN) [7], 3D CNN [10] and U-Net [9] are the most common. RegDGCNN [7] dynamically updates the graph structure based on geometric features, effectively capturing local, flow-sensitive regions (such as wheelhouses and the rear wake.) The improved U-Net architecture [9] enhances the model's ability to extract key features through squeeze-and-excitation modules and improves its robustness to mesh differences through methods such as remeshing for data augmentation.

4.3.3. Application advantages in NEV streamline optimization

Shortening the design cycle: Designers can modify vehicle shapes freely and get real-time aerodynamic feedback, slashing the iteration cycle from weeks to days [5,8]. Leveraging the DrivAerNet++ dataset, models for various NEV types train rapidly, completing aerodynamic evaluations in seconds and boosting design exploration efficiency.

Handling complex shape modifications: Tailored to streamline optimization of different NEV categories (sedans, SUVs, hatchbacks), it accommodates new components like battery packs and lightweight materials [8]. In NEV lightweight design, DrivAerNet++-trained models predict both aerodynamic drag and structural strength, enhancing multi-objective optimization efficiency by 40%.

Combination with traditional methods: Serving as a pre-screening tool for phased optimization, it rapidly narrows the design space [7]. Followed by fine-tuning with surrogate models and evolutionary algorithms [5,7], for example, a 3D CNN model screens global shape schemes, while the Kriging model and multi-island genetic algorithm refine key parts, balancing optimization efficiency and accuracy [3,5,10].

5. Conclusion

Steamline optimization is an important way to improve the aerodynamic performance of new energy vehicles, and the integration of advanced algorithms and CFD simulation technologies is the key to realizing efficient optimization. Surrogate model-based optimization algorithms (such as Kriging), evolutionary algorithms (such as NSGA-II, multi-island genetic algorithm), and parametric modeling methods (such as PDE-based modeling) provide technical support for the phased optimization process, while RANS, URANS, DDES, LBM and other CFD simulation methods ensure the accurate evaluation of optimization effects. The neural network-based intelligent optimization method, as a distinct technical route, realizes end-to-end shape-to-performance mapping through large-scale datasets and deep learning architectures, significantly improving optimization efficiency and adaptability to arbitrary shapes.

In the future, with the development of artificial intelligence and big data technology, the streamline optimization of new energy vehicles will tend to be the integration of traditional algorithms and neural networks. It is expected to establish a hybrid optimization framework: use

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neural networks for rapid global exploration, and traditional methods for local fine-tuning, realizing the balance between efficiency and accuracy. At the same time, the combination of multi-disciplinary optimization (such as aerodynamics, structural mechanics, and aesthetics) and multi-fidelity datasets (RANS + DNS) will become an important research direction. For example, the integration of lightweight materials and streamline optimization can further reduce the energy consumption of NEVs, and the use of DrivAerNet++-like multi-modal datasets can improve the generalization ability of neural network models.

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