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Research on Thermal-Fluid Optimization of Racing Vehicle Powertrain Based on CFD and Data-Driven Approaches

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ABSTRACT

The main causes of racing power are high power density and compact structure, which can easily face the risk of thermal runaway under extreme working conditions. Traditional methods that rely solely on CFD (Computational Fluid Dynamics) simulation or empirical design have limitations such as high computational costs and insufficient dynamic response. This study proposes an optimization framework that combines CFD and data-driven methods to obtain multiple physical field details of the flow temperature field through CFD. By combining machine learning, a high-precision surrogate model is constructed to achieve rapid prediction and global optimization of thermal flow parameters. The innovation lies in building a layered optimization strategy that integrates data and physics, significantly reducing computational resource consumption while improving dynamic adaptability. On a theoretical level, it reveals the mechanism by which interdisciplinary integration enhances thermal management efficiency; At the engineering level, it provides an efficient and robust optimization method for the design of racing thermal systems, which has important application value.

1. Introduction

In the field of racing, the powertrain, as the core component, has high power density and compact structural design, making thermal management a key challenge to ensure performance and reliability. Under extreme working conditions, a sudden increase in local heat flux density can easily lead to thermal runaway, resulting in component failure or even system paralysis. Traditional optimization methods or relying on empirical design are difficult to accurately capture the dynamic characteristics of complex thermal flows; Or relying solely on CFD (Computational Fluid Dynamics) simulation, although it can provide multiple physical details of the flow field temperature field, the computational cost is high and the real-time performance is insufficient, especially in dynamic working conditions where optimization efficiency is limited. At the same time, data-driven methods rely on the proxy modeling capabilities of machine learning models such as neural networks and support vector machines to efficiently mine high-dimensional data patterns, but lack physical mechanism constraints. Therefore, interdisciplinary integration has become an inevitable choice to break through bottlenecks: CFD provides physical field benchmarks and constraints for data-driven methods, while data-driven methods improve computational efficiency through dimensionality reduction algorithms and real-time optimization strategies. The synergy of the two can significantly enhance the dynamic response capability and global optimization efficiency of powertrain thermal flow, providing theoretical support and engineering solutions for the design of racing car thermal management systems.

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2. The fundamental role of CFD in thermal flow analysis of powertrain

2.1 Basic Principles and Model Construction of CFD

CFD, as the core tool for thermal flow analysis of powertrains, plays a fundamental role in accurately modeling and efficiently solving complex physical fields. The core control equations include the mass conservation equation, momentum conservation equation, and energy conservation equation. The spatial domain is discretized using the finite volume method or finite element method, and transient or steady-state solutions are achieved by combining time advancement schemes. In terms of turbulence model selection, the RANS model simplifies turbulence pulsation through time averaging, has low computational cost, and is suitable for engineering coarse screening, but it is difficult to capture transient details; LES directly analyzes the structure of large-scale vortices and models small-scale vortices in a subgrid manner, which has higher accuracy but significantly increases computational resource consumption. In terms of multi physics field coupling, CFD achieves bidirectional data transfer of flow field temperature field structure field through fluid solid conjugate heat transfer method. For example, the high-temperature airflow generated by combustion in the engine cylinder heats the cylinder head through thermal convection and radiation, while the structural thermal stress feedback affects the boundary conditions of the flow field, forming a dynamic closed loop.

2.2 Analysis of Thermal Flow Characteristics of Powertrain

The thermal flow characteristics of the powertrain exhibit significant spatiotemporal non-uniformity and multi-scale coupling. In a typical heat source distribution, the transient high temperature released by combustion in the engine cylinder and the sustained high temperature of the exhaust system form the main heat load, while the coolant circulation takes away heat through forced convection, forming a complex heat flow network together. In terms of flow field structure, high-speed airflow forms a boundary layer near the wall, and its separation and reattachment effects significantly affect the local heat transfer coefficient. For example, flow separation on the surface of turbocharger blades can lead to a sudden increase in local heat flux density. The areas of thermal stress concentration are concentrated in the nose bridge area of the cylinder head, the turbocharger turbine disc, and the gear meshing surface of the gearbox. These areas are prone to thermal fatigue failure due to geometric changes or high stress cycles.

2.3 Challenges and improvement directions of CFD simulation

However, CFD simulation still faces multiple challenges. In terms of computational resource consumption, high-precision grids and transient simulations require extremely high hardware performance, resulting in a single simulation cycle lasting several weeks and making it difficult to support parametric optimization. The uncertainty of boundary conditions arises from the complexity of actual operating conditions, such as engine intake temperature, coolant flow rate, and other parameters that are significantly affected by the environment and operating conditions. However, idealized assumptions are often used in simulations, resulting in biased results. In addition, the powertrain involves multi-scale coupling from component level to system level, and traditional single scale models are difficult to balance local details and global efficiency. Therefore, it is necessary to develop cross scale modeling strategies to balance accuracy and efficiency.

3. Key Technologies of Data Driven Methods in Thermal Flow Optimization

3.1 Core advantages of data-driven methods

The data-driven approach provides a new path to break through traditional bottlenecks for optimizing thermal flow in powertrain systems by mining implicit patterns in high-dimensional data. Its core advantages are reflected in three aspects: facing the massive data generated by CFD simulation or experiments, machine learning algorithms can automatically extract key features and reveal nonlinear coupling relationships that are difficult to capture with traditional empirical formulas; Secondly, by constructing a proxy model to replace the time-consuming CFD calculations, data-driven methods can compress the analysis time of a single thermal flow from several hours to seconds, supporting real-time online parameter adjustment; Finally, by combining data augmentation techniques with transfer learning strategies, the model can quickly adapt to different racing car models or operating environments, significantly improving robustness, such as transferring from conventional track conditions to high-temperature desert or high-altitude scenarios.

3.2 Key Algorithms and Model Selection

The selection of key algorithms and models directly affects the optimization effect. In dimensionality reduc-

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tion algorithms, principal component analysis extracts data principal components through linear transformation, which is suitable for flow field data with strong structure. However, autoencoders, with their nonlinear encoding ability, can more efficiently compress high-dimensional temperature field data; In terms of proxy models, Gaussian process regression characterizes data uncertainty through kernel functions and can maintain high accuracy even with small sample sizes, but the computational complexity increases cube wise with sample sizes. Radial basis function networks achieve fast prediction through local interpolation and are suitable for large-scale parameter optimization; In optimization algorithms, genetic algorithm simulates natural selection to achieve global search, which can avoid falling into local optima, while particle swarm optimization relies on the information sharing mechanism between particles to converge faster in continuous parameter optimization. The two are often combined to balance exploration and development capabilities.

3.3 Optimization Framework for Data Physical Fusion

The optimization framework of data physical fusion is the key to breaking through the limitations of a single method. In the hierarchical optimization strategy, CFD provides physical constraints, while data-driven models optimize the objective function based on constraint conditions; The dynamic weight allocation mechanism adjusts the optimization priority in real time according to the working conditions, for example, focusing on flow field uniformity to reduce wind resistance in high-speed straight road working conditions, and prioritizing the control of turbocharger temperature in uphill working conditions; The closed-loop feedback mechanism collects key parameters in real-time through sensors, calibrates and iterates with simulation results, forming a closed loop of “data acquisition model correction optimization decision-making”, significantly improving the credibility and engineering applicability of optimization results.

4. CFD and data-driven collaborative optimization methods

4.1 Construction of Multidisciplinary Modeling and Simulation Platform

The construction of a multidisciplinary modeling and simulation platform is the fundamental support for collaborative optimization. The platform adopts a modular design concept, which decouples and encapsulates the CFD solver, data preprocessing module, and optimization algorithm library. Each module achieves data interaction through standardized interfaces. For example, the temperature field and flow velocity field data output by the CFD module are converted into machine learning readable formats by the preprocessing module, and then input into the optimization algorithm library for parameter optimization. The optimization results are then fed back to the CFD module for verification, forming a closed loop. To meet the computational requirements of large-scale parameter scanning, the platform introduces a parallel computing architecture: on the one hand, it uses GPU to accelerate the matrix operation and iteration process in CFD solvers, reducing the single simulation time by more than 60%; On the other hand, by using a distributed computing framework to allocate simulation tasks with different parameter combinations to multiple nodes for parallel execution, the computational efficiency is significantly improved. For example, when optimizing the layout of cooling channels, the thermal performance of hundreds of geometric variants can be evaluated simultaneously.

4.2 Collaborative optimization process design

The collaborative optimization process design is divided into three stages: offline training, online prediction, and closed-loop verification. In the offline stage, CFD is used as the core to generate a training dataset: thousands of samples are collected in the parameter space through Latin hypercube sampling, and temperature field, flow field, and thermal stress distribution data are obtained through high-precision CFD simulation for each sample. A “parameter performance” mapping database covering all operating conditions is constructed. Based on this database, train a data-driven proxy model to compress the prediction time from hours in CFD to milliseconds while ensuring accuracy. In the online stage, sensors collect real-time current operating parameters, and the proxy model quickly predicts the optimal thermal management strategy and outputs it to the executing agency. In the verification phase, a small amount of CFD simulation is used to calibrate the bias of the proxy model, forming a closed-loop iterative mechanism of “data-driven rapid prediction - precise physical simulation verification” to ensure the credibility of the optimization results.

4.3 Uncertainty quantification and robustness optimization

Uncertainty quantification and robustness optimization are key to addressing the complexity of practical operating conditions. In terms of input parameter uncertainty, probability distribution modeling is used to describe the variation range of random variables such as material properties and boundary conditions, and a large number of virtual samples are generated through Monte Carlo simulation. In the sensitivity analysis of output results, the Sobel index is used to quantify the contribution of various parameters to thermal management performance and identify key influencing factors. The robust optimization objective focuses on maximizing the minimum thermal management performance within the parameter fluctuation range. For example, by optimizing the layout of the cooling channels, the highest temperature of the engine can still be below the safety threshold even when the coolant flow fluctuates by ± 10%, thereby significantly improving the reliability and adaptability of the system under complex operating conditions.

5. Conclusion and Prospect

This study proposes an optimization framework that combines CFD and data-driven collaboration, which significantly improves the dynamic response capability of thermal flow through interdisciplinary integration. The dual advantages of this method in reducing computational costs and improving optimization accuracy are verified. However, limited by the development cycle of racing cars, there is still a problem of single data collection scenarios in experimental verification, and the adaptability of the current model to extreme working conditions needs to be enhanced. Future research will focus on two major directions: first, building a digital twin of powertrain full lifecycle thermal management, integrating real-time sensor data and virtual simulation to achieve dynamic calibration; The second is to explore the application of deep reinforcement learning in adaptive thermal control, breaking through the rule dependence of traditional optimization algorithms through end-to-end strategy learning, and providing more intelligent and robust solutions for racing thermal management systems.

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