

Multifidelity Assessment of Supersonic Wave Drag Prediction Methods for Axisymmetric Bodies

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Introduction

The prediction of supersonic wave drag is a crucial aspect of the design and optimization of aerodynamic bodies, particularly in high-speed flight applications such as supersonic aircraft and spacecraft. Accurate wave drag prediction is essential for assessing the performance, fuel efficiency, and overall aerodynamic characteristics of vehicles that travel at speeds greater than the speed of sound. Among various approaches used to predict wave drag, multifidelity methods have emerged as an effective way to balance accuracy with computational efficiency. These methods combine models of varying fidelity to provide a more comprehensive and reliable assessment of wave drag, while minimizing computational cost. The application of multifidelity methods to the prediction of supersonic wave drag for axisymmetric bodies provides an interesting case study in balancing the trade-offs between model accuracy and computational resources. Supersonic wave drag, also known as shock drag, arises due to the formation of shock waves around an object moving through a compressible fluid, such as air at supersonic speeds. As a supersonic body moves through the air, it generates shock waves that cause a discontinuous change in pressure, temperature, and velocity. These shock waves result in a resistance to motion, which is quantified as wave drag. The amount of wave drag depends on various factors, including the shape of the body, the Mach number (the ratio of the object's speed to the speed of sound), and the flow conditions around the body. For axisymmetric bodies, such as missiles, projectiles, and space launch vehicles, the analysis of wave drag involves considering the effects of shock wave interactions and the boundary layer behavior over the surface of the body.

Description

Accurate wave drag prediction for axisymmetric bodies involves solving the governing equations of fluid dynamics, typically the compressible Navier-Stokes equations, which describe the motion of a compressible fluid under the influence of external forces. However, solving these equations accurately and efficiently, particularly for supersonic flows, presents significant challenges. High-fidelity methods, such as Direct Numerical Simulation (DNS) and high-order Computational Fluid Dynamics (CFD) techniques, offer the most accurate results but are computationally expensive and time-consuming. On the other hand, lower-fidelity methods, such as potential flow theory, Euler equations, and panel methods, are computationally more efficient but tend to provide less accurate predictions of wave drag, especially in complex flow conditions. Multifidelity methods offer a way to leverage both high-fidelity and low-fidelity models to achieve a balance between accuracy and computational efficiency. These methods involve combining predictions from different models of varying fidelity and using them to improve the overall accuracy of the results. One common approach is to use a high-fidelity model

to obtain an accurate baseline solution and then use a lower-fidelity model to approximate the flow characteristics in regions where high accuracy is not required. By combining the results from multiple models, multifidelity methods can reduce the computational cost while still providing a reliable prediction of wave drag. This approach is particularly useful in practical applications where fast simulations are required, such as in the optimization of aerodynamic shapes, the assessment of design parameters, or the analysis of different flight conditions [1].

One important aspect of multifidelity methods is the use of surrogate models, which are simplified models that can quickly approximate the behavior of a more complex system. Surrogate models are typically built using data from high-fidelity simulations or experiments and are used to replace expensive simulations when a fast response is needed. The key idea behind surrogate models is to use a reduced set of input parameters to generate an approximate output that closely matches the results from the high-fidelity model. Common surrogate modeling techniques include polynomial regression, kriging, and radial basis functions. These models can be trained using a small number of high-fidelity simulations and can then be used to rapidly predict wave drag for a wide range of design variables. Another important component of multifidelity methods is the concept of model hierarchies, where different models of varying fidelity are used at different stages of the analysis. For example, a low-fidelity model might be used to perform an initial design optimization or to explore a large design space, while a higher-fidelity model is used to refine the design or assess critical flow regions with greater accuracy. This hierarchy of models allows for a more efficient exploration of the design space, as low-fidelity models can quickly identify promising design candidates, while high-fidelity models can be reserved for more detailed analysis of the most promising configurations. This approach is particularly useful when dealing with large-scale optimization problems, where the cost of running high-fidelity simulations for every design iteration would be prohibitive [2].

In the context of axisymmetric bodies, multifidelity methods can be applied to wave drag prediction by combining different levels of simulation fidelity. For example, a low-fidelity potential flow model might be used to estimate the shock wave locations and the initial drag forces, while a higher-fidelity CFD model might be used to capture the effects of shock-boundary layer interactions and more accurately predict the drag contribution from these effects. By using a combination of these models, researchers can improve the accuracy of wave drag predictions while minimizing the computational burden.

One of the key advantages of multifidelity methods is their ability to handle a wide range of flow conditions, including high-speed flows with complex shock wave interactions, which are common in supersonic flight. In addition, these methods allow for the incorporation of uncertainties in the modeling process. For example, in real-world applications, there may be uncertainties in the material properties, geometric details, and flow conditions. Multifidelity methods can be used to propagate these uncertainties through the simulation process, providing a more robust prediction of wave drag that accounts for potential variations in the design parameters or operating conditions. Recent advancements in multifidelity methods for wave drag prediction have focused on improving the accuracy of surrogate models and reducing the computational cost of high-fidelity simulations.

For example, researchers have explored the use of machine learning algorithms, such as neural networks and support vector machines, to build surrogate models that can quickly approximate the results of high-fidelity simulations. These machine learning models can be trained using a relatively small number of high-fidelity simulation results and then used to predict wave drag for a wide range of input parameters, including the geometry of the

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axisymmetric body, the Mach number, and the flow conditions. Another area of recent research is the development of hybrid multifidelity methods, which combine the strengths of different modeling approaches. For example, some researchers have combined panel methods with CFD simulations to achieve a more accurate prediction of wave drag. In these hybrid approaches, panel methods are used to quickly estimate the flow field around the body, while CFD simulations are used to capture the effects of complex shock interactions and boundary layer behavior. This combination of models allows for a more accurate prediction of wave drag while maintaining the computational efficiency of panel methods.

Conclusion

The application of multifidelity methods to supersonic wave drag prediction for axisymmetric bodies has shown significant promise in improving both the accuracy and efficiency of wave drag predictions. By combining high-fidelity and low-fidelity models, researchers can obtain more reliable results while reducing the computational resources required. This approach is particularly valuable for design optimization, where rapid assessments of wave drag are needed to evaluate the effects of design changes on vehicle performance. Moreover, multifidelity methods can be used to account for uncertainties in the modeling process and provide more robust predictions of wave drag under a variety of conditions. In conclusion, multifidelity methods offer a powerful and efficient approach to the prediction of supersonic wave drag for axisymmetric bodies. By combining high-fidelity and low-fidelity models, these methods can balance the trade-offs between computational cost and accuracy, providing reliable results for a wide range of design and flow conditions. The continued

development of surrogate models, machine learning techniques, and hybrid approaches will further enhance the capabilities of multifidelity methods and improve their applicability to complex aerodynamic analysis. As the demand for high-speed flight vehicles continues to grow, multifidelity methods will play a critical role in the design and optimization of supersonic vehicles, enabling faster, more efficient, and more accurate wave drag predictions.

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