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Physically Guided Neural Network Based on Transfer Learning (TL-PGNN) for Hypersonic Heat Flux Prediction

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Abstract. Hypersonic vehicles create high-temperature environments, thus causing air molecules to undergo chemical reactions. As a result, the nonlinearity of the mapping relationship between heat flux and inflow condition is strengthened. Accurately predicting the heat flux of real gases using machine learning methods relies on an amount of training data of real gas, but the computational cost is often unacceptable. To solve the issue stated, we propose a novel neural network named Physically Guided Neural Network based on Transfer Learning (TL-PGNN). We design a new network architecture to depict physical laws and use heat flow data of ideal gases to enhance the network's capability to depict heat flow from only a few real gas samples. Experiments of sphere demonstrate that, compared to ordinary DNN and PGNN, applying TL-PGNN decreases the mean L1 error by 72.66% and 24.53% on the test set, respectively.

AMS subject classifications: 76K05, 68T05

Key words: TL-PGNN, transfer learning, heat flux prediction, small datasets.

1 Introduction

When the flight vehicle is flying at hypersonic speed, the airflow and the fuselage surface undergo intense friction, and the air is compressed leading to a sharp rise in air temperature. The air and the fuselage surface produce a huge temperature difference. Part of the heat energy is transferred to the fuselage. This heating phenomenon is called aerodynamic heat. Aerodynamic heat causes the surface temperature of the airframe to rise

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sharply, affecting gas flow and structural protection [1–3]. Therefore, accurate prediction of the aerodynamic heat distribution at hypersonic speeds is essential for the optimization of the aerodynamic shape of the vehicle and the design of thermal protection [4]. Traditional aerodynamic heat prediction methods include numerical computation, approximate estimation, ground-based wind tunnel experiments, flight experiments, etc. However, they still face many difficulties in practical applications. High-fidelity numerical computation methods are widely used in the simulation of aerodynamic heat and a series of engineering computation software is integrated on this basis. A series of engineering calculation software, such as AEROHEAT, LATCH, and LARUA etc [5–7]., have been integrated to perform full-scale numerical simulation of the vehicle with high accuracy. But the numerical computation needs a lot of time and requires high-quality accurate mesh, which makes it difficult to optimize quickly in the design stage of the vehicle. In approximation methods, theoretical formulations are designed to provide reasonably accurate results quickly [8–10], most of which are based on Plandtl's boundary layer theory. For example, Fay and Riddle obtained a stagnant heat flux formulation under the equilibrium boundary layer assumption. Similar methods for stagnant heat flux prediction include the Kemp-Riddle method, the Lees method, the Scala method, and the Romig method [8–10]. Ground-based wind tunnel experiments can predict the aerodynamic heat distribution pattern relatively accurately, but there is a lack of aerodynamic/thermal correlation theories and correlation methods that can accurately reflect the hypersonic flow characteristics11. Flight experiments can specifically monitor the aerodynamic heat of the design conditions, but they are very costly and are limited by experimental cycle time [11–13].

In recent years, machine learning methods have advanced rapidly, achieving accurate prediction of previously unknown data using existing samples. These techniques have achieved excellent generalization performance and are widely used in various fields, including image recognition [14], natural language processing [15], partial differential equation solving [16], aerodynamic modelling [17], and scientific data prediction [18]. Machine learning has also been extensively used to analyze hypersonic heat. Gang Dai [19] has established a mapping relationship between wall heat fluxes and extreme temperature points of the grid. This allows for the accurate prediction of the heat fluxes corresponding to coarse grids on the wall-normal vectors. Ren Haijie [20] used flight test data and RANS test data to establish a relationship between the average strain/rotation rate tensor and the experimental heat flux. This relationship was then used to predict heat flux under various heat flow conditions. Schouler Marc [21] used both kriging and artificial neural networks to predict pressure and heat flux stagnation coefficients, along with pressure, friction, and heat flux coefficient distributions of re-entrant thinning segments of any aerodynamic profile. These methodologies address the problem from physical data to data algorithms, and finally to physical prediction. However, there is a weak correlation between physical data and physical prediction, and the resulting predictions lack physical interpretability. Besides, there are some interesting work using transfer learning in fluids science, which aims to solve unknown problems based on