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Title

Interactive optimization of fluidic injection for single expansion ramp nozzle based on a modified autoencoder

Authors

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Abstract

The single expansion ramp nozzle (SERN) is an important component for wide-speed-range aerospace vehicles [1]. It generates most of the engine thrust and is also critical to the vehicle's pitching moment[2]. During acceleration, the nozzle will suffer poor performance due to overexpansion under off-design conditions. The fluidic injection is one of the most promising solutions to it thanks to its efficiency, robustness, and capability to integrate with the engine's secondary air system[3]. Research has been carried out to discover how the injection parameters affect nozzle performance since early this century[3]-[6], but until now, there is hardly a practical way to optimize these parameters given the baseline model and flight envelope. The major bottleneck is the large computation consumption for obtaining the injection effect under different flight conditions and injection parameters.

The present paper introduces a fast and precise way to predict and optimize nozzle injection flowfields via a modified autoencoder based on deep convolution neural network. For each flight condition, it takes a CFD-simulated nozzle flowfield without injection as input, and can predict the flowfields after adding the fluidic injection with any parameters. The gradients of injection parameters to nozzle performance are also cheaply obtained through the networks. With the gradients, the autoencoder is coupled with an optimizer to find the best combination of injection parameters for the given flight conditions.

The proposed method can give a merely immediate result compared to CFD-based optimization, which makes it possible to optimize nozzle performance within the whole flight envelope. It differs from previous machine-learning-based optimization in that it introduces flowfields without injection as a reference for predicting the flowfields with injections. It not only enhances the accuracy of predicting results as verified in the previous study[7], but also grants the method transferability to different optimization problems even when trained on a limited dataset. In addition, the new method provides designers access to the flowfield in the nozzle during the optimization, and the predicted thermal field can assist in the design of the cooling system as well.

The autoencoder is trained on a database including 7500 flowfields of different flight conditions and injection parameters, and the average prediction error on the test dataset for the axial thrust coefficients is 0.10%. Then, the optimization method is examined on a SERN model aiming to cruise at Mach 4. Eleven off-design flight conditions are selected inside the flight envelope. The intensities, locations, angles, and temperatures of the injections at these flight conditions are optimized to maximize the axial thrust. The results are validated with CFD and the average axial thrust coefficient of these conditions turns out to be raised by 0.34%.

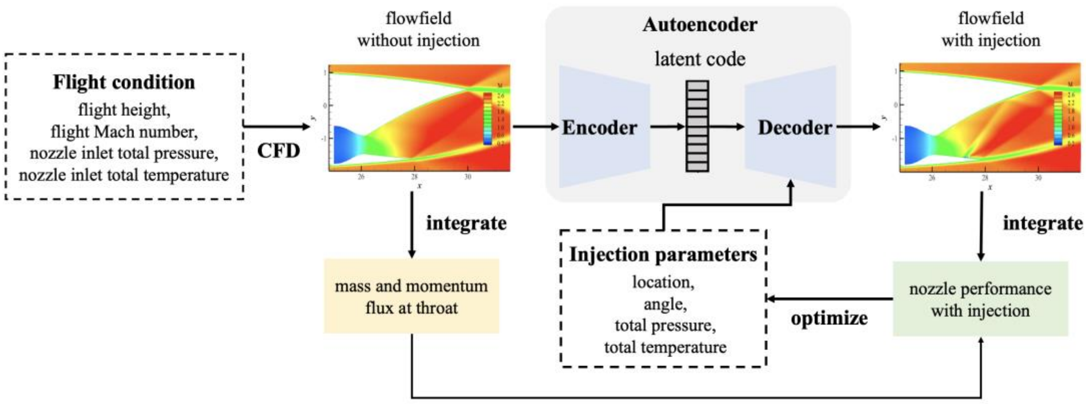

Fig. 1 The architecture of the optimization method

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