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Reinforcement-Learning-Based Shape Optimization With Deep-Leaning-Based Effect Predictions: An Aerodynamic Optimization Method For Bluff Bodies

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Due to the complicated fluid-solid interference phenomenon, the aerodynamic characteristics of bluff bodies are difficult to be simply described in analytical formulas. Therefore, the aerodynamic optimization of bluff bodies is commonly inefficient. To solve this problem, numerous studies have tried to limit or avoid the appearance of man-in-the-loop (people actively intervene and manipulate the optimization process with experience). Following the same idea, the optimization process was conducted with machine learning in this paper. The novelties of the proposed method lie in two aspects. First, the reinforcement-learning technique was introduced because of its wonderful self-learning ability in unknown environments. Using reinforcement learning to automatically search for better shapes enables the optimization policy being continuously upgraded. Thus, the learnability is implanted into the optimization method guided by its decision-making experience instead of human experience. Second, a surrogate model based on deep learning techniques was used to accelerate the aerodynamic effect evaluations. The traditional numerical simulations (such as computational fluid dynamics) are replaced with a convolutional neural network model, which can fast and reliably predict the pressure distribution around different bluff bodies. The aerodynamic performance was calculated based on the predictions. To check the effectiveness of this hybrid method, validations were carried out from the view of methodology. First, the performance of the surrogate model was examined. Training data were collected from Reynolds-averaged Navier–Stokes (RANS) simulations of various polygons and circles. In comparison with the label results, the best model yields a mean relative pressure error of less than 5%, spanning a range of previously unseen geometrical shapes. Second, a numerical example was investigated on the optimization of hexagons with two axes of symmetry. The results showed that the method can securely find the global optimum solution after a series of attempts and learning. And its optimization policy becomes more effective and targeted throughout the learning process. The above two points demonstrate that the proposed method has an inspiring prospect for aerodynamic optimization of bluff bodies.