

Development of High-Speed Prediction System Using Surrogate Models for Motor Cooling CAE

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1. Introduction

Cooling technology is essential for motor miniaturization and reliability improvement. Fig.1 shows an oil-cooling model for CAE. In the design of the cooling structure, particle-based CAE, which is time-consuming, is often used to simulate coolant flow. However, with the expansion of electric vehicles, shortening development time becomes essential. Thus, faster cooling CAE is critical. This paper describes a fast computational method for motor cooling CAE.

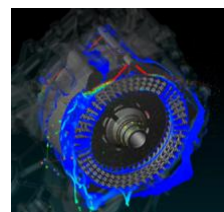


Fig.1 Motor cooling CAE

2. Methods

An overview of the acceleration method is shown in Fig.2. It includes of a preprocessing step, where CAE data are transformed to facilitate learning, a surrogate model that predicts flow using particle position coordinates, and a postprocessing step that calculates the wetted area, a cooling performance index, from the predicted particle positions.

Geodesic Convolutional Neural Network (GCNN) was employed as the machine learning method. This approach

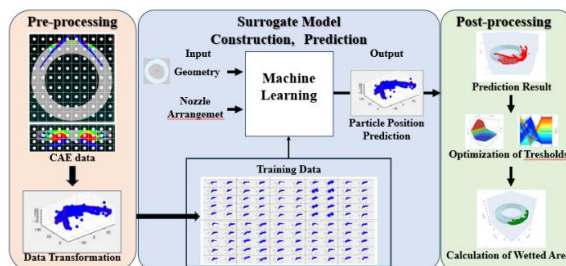


Fig.2 Overview of Surrogate Model Construction

was selected because it can extract geometric features, making it suitable for constructing surrogate models for complex geometries such as motors. The geometry is represented as a point cloud, and distances between particle nodes near the geometry and scattered particle nodes are calculated based on a Riemannian metric and used as weights. The network consists of a three-layer encoder and a two-layer decoder with 64 nodes and 50,000 epochs. The ReLU activation function is used.

The training data set consists of 40 cases for four different geometries, where 10 cases for each geometry are computed under steady-state conditions by uniformly sampling the nozzle angle, width, and position using the Latin hypercube method.

The prediction results for validation data within the interpolation range using the constructed surrogate model are shown in Fig.3. The distributions of the flow field and wetted area are generally in good agreement. While the main flow on the object surface that influences the wetted area is accurately predicted, scattered particles are considered to have been removed by thresholding due to their small values.

In addition, the prediction results of the wetted area for 10 validation datasets are shown in Fig.4. The mean absolute percentage error (MAPE) of the wetted area prediction is 5.1%, indicating good prediction accuracy.

The comparison of computation time is shown in Fig.5. By utilizing the proposed surrogate model, the computation time can be reduced by 95% compared with CAE, achieving significant time acceleration.

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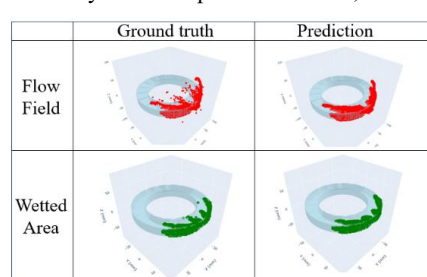


Fig.3 Prediction Results of Flow Field and Wetted Area

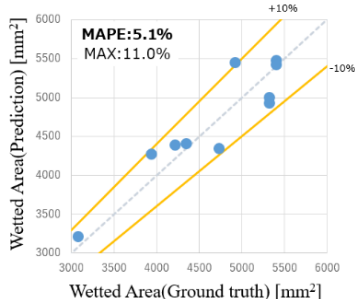


Fig.4 Prediction Accuracy of Wetted Area

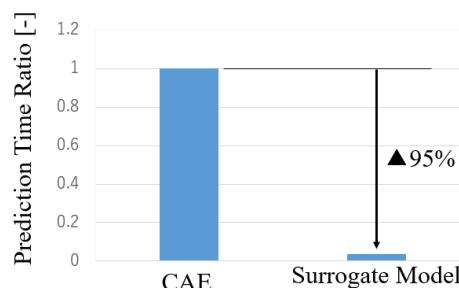


Fig.5 Comparison of Computation Time