

Development of an AI Surrogate Model for Refrigeration Cycles with a Reliability Assessment Method

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In BEV development, thermal management systems are required to provide increasingly advanced functions to improve driving range, charging performance, cabin comfort, and battery durability. To support thermal management development, detailed CAE models integrating refrigerant circuits, coolant circuits, and vehicle systems have been developed. However, the high computational cost of detailed refrigeration-cycle simulations limits their application in large-scale virtual validation activities.

To address this issue, an AI surrogate model was developed based on simulation results generated by a detailed refrigeration-cycle CAE model. The surrogate model predicts refrigerant state variables using time-series operating conditions and control commands. An LSTM-based architecture was employed to capture dynamic behavior of the refrigeration cycle. Furthermore, Gaussian noise augmentation was introduced during training to mitigate error accumulation caused by autoregressive prediction.

The developed surrogate model achieved high prediction accuracy while significantly reducing computational cost. The mean absolute prediction errors for heat transfer rates and power consumption were below 0.1 kW (Fig.1), while computation speed was improved by approximately 1000 times compared with the detailed CAE model.

A key challenge of AI surrogate models is reliability when applied outside the training domain. To address this issue, a reliability assessment model based on a Variational Autoencoder (VAE) was developed. The model reconstructs multivariate time-series input data and calculates a reconstruction error, which is used as a reliability indicator. The relationship between reconstruction error and surrogate-model prediction error was evaluated using intentionally generated extrapolation cases.

The results showed a strong correlation between reconstruction error and surrogate-model prediction error, with a Pearson correlation coefficient of 0.89 (Fig.2). This indicates that reconstruction error can serve as an effective indicator of surrogate-model reliability. By running the surrogate-model and reliability assessment model simultaneously, a virtual validation environment capable of both high-speed simulation and reliability monitoring was established. When low-confidence situations are detected, the framework allows re-evaluation using the detailed CAE model.

As a result, comprehensive system-level validation became feasible while continuously monitoring surrogate-model reliability, enabling practical deployment of AI-based refrigeration-cycle models in BEV thermal-management development.

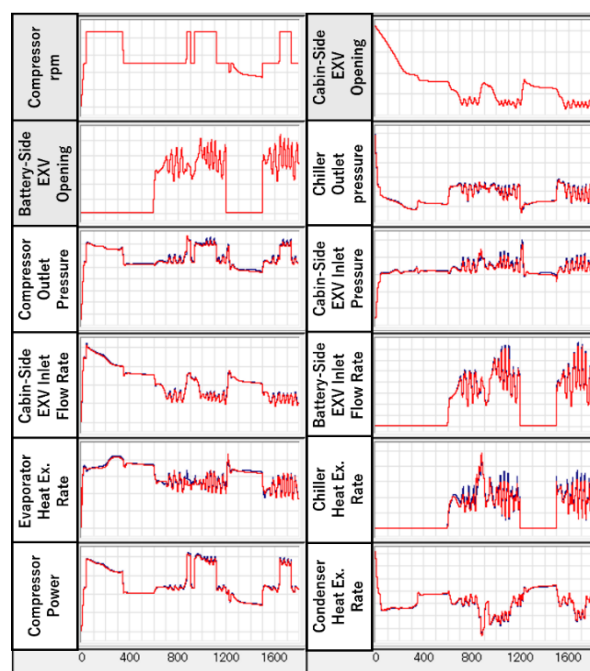


Fig.1 Time-Series Comparison of the AI Surrogate Model and the CAE Model

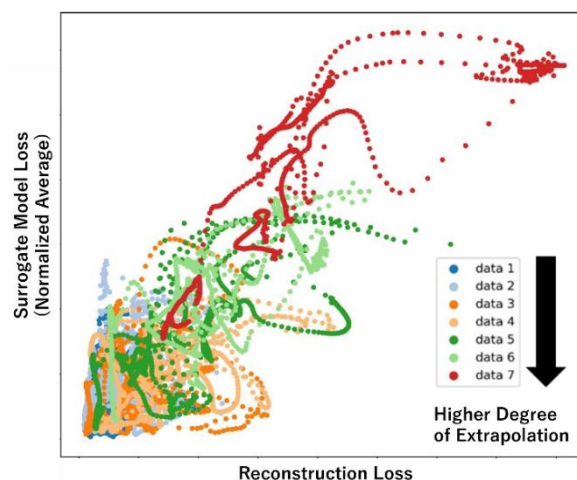


Fig.2 Correlation Between Surrogate Model Error and Reconstruction Error