

Development of a Shape Optimization Framework Using AI-Based Shape Generation for Electric Water Pump Design and Its Practical Implementation Challenges

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As part of the development of an AI-driven design platform, a shape optimization method combining DeepSDF-based shape generation and a surrogate model was investigated for electric water pumps (EWP). Conventional parametric design methods limit the searchable design space because shape variations are restricted to predefined design variables. To overcome this limitation, DeepSDF was adopted to represent shapes in a latent space and generate diverse shapes beyond conventional parametric approaches.

DeepSDF was trained using flow-passage geometries accumulated through previous EWP development projects. During practical implementation, two major issues were identified: insufficient reconstruction accuracy for thin-walled and hollow structures, and poor interpretability of latent variables. In the initial reconstruction results, important blades disappeared, making the generated geometries unsuitable for performance evaluation (Fig. 1). To address this issue, the geometry was simplified by removing geometric regions that contribute minimally to pump performance. As a result, reconstruction accuracy was significantly improved, and CFD verification confirmed that the differences in pump head and efficiency between the original and reconstructed geometries remained within 5% (Fig. 2).

To improve the interpretability of the latent space, Principal Component Analysis (PCA) was applied to the latent variables. The resulting principal component space enabled continuous and interpretable control of shape variations, where geometric features such as blade curvature and pipe dimensions varied systematically with principal component values (Fig. 3). By inverse transformation from the principal component space to the latent space, arbitrary shapes corresponding to selected principal component values could be generated, enabling interpretable control of non-parametric shape generation.

A Gaussian Process surrogate model was constructed and applied to multi-objective optimization. The optimization results demonstrated the capability to generate promising design candidates not included in the training data. However, discrepancies between surrogate predictions and CFD validation results were observed in high-performance regions. Future work will focus on enhancing prediction accuracy through automated CAE-driven data generation and iterative model retraining toward the realization of an AI-driven design platform.

