

A Self-Evolving Design Exploration System with Performance-Sensitivity-Guided Latent Space Expansion

Mikito Kawamura ¹⁾ Toshiki Terabe ¹⁾ Chika Kanba ¹⁾ Makoto Okawa ¹⁾ Takumi Sano ¹⁾

¹⁾ Toyota Motor Corporation 1 Toyota-cho, Toyota, Aichi, 471-8571 Japan

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The proposed method was validated using an engine bracket design problem considering thermal stress and noise-vibration (NV) performance. Correlation analysis identified the eighth principal component (PC8) as the most influential latent variable for thermal stress improvement. By generating retraining data through PC8 manipulation and performing retraining, the optimization process successfully expanded the Pareto front beyond the original search space. As a result, the best thermal stress value was improved from 164 MPa to 117 MPa, corresponding to a 28.7% reduction. These results demonstrate the effectiveness of performance-sensitivity-guided latent space expansion for discovering high-performance design solutions outside the original training data distribution.

To address this issue, the proposed method performs iterative retraining while expanding the latent design space toward directions expected to improve performance. First, optimization is conducted using a Graph Convolutional Network (GCN)-based surrogate model and an SDF-based generative shape model. The surrogate model predicts thermal stress and noise and vibration (NV) performance of an engine bracket, while the generative model represents shapes through latent variables using a DeepSDF-based autoencoder. Multi-objective optimization is performed using NSGA-II with the objectives of minimizing thermal stress and maximizing resonant frequency. Shape constraints are introduced to ensure manufacturability and assembly requirements.

The key contribution of this study is a performance-sensitivity-guided latent space expansion method. Latent variables obtained from the trained shape generation model are projected onto a lower-dimensional space using principal component analysis (PCA). Correlation coefficients between each principal component and performance metrics are then calculated. Principal components with strong correlations are regarded as important design directions and are manipulated toward expected performance improvement. New shapes generated from the modified latent variables are repaired, evaluated by CAE simulations, and added to the training dataset. The surrogate model and shape generation model are subsequently retrained using the expanded dataset. This process enables continuous expansion of the exploration space toward promising high-performance regions.

The proposed approach was validated using an engine bracket design problem. Correlation analysis revealed that the eighth principal component (PC8) showed the strongest relationship with thermal stress performance, with a correlation coefficient of -0.537 . By manipulating PC8, several newly generated designs achieved thermal stress values lower than the best result obtained in the initial optimization. After incorporating these designs into the retraining dataset and performing optimization again, the exploration region expanded significantly in the thermal stress improvement direction. The best thermal stress value improved from 164 MPa to 117 MPa, corresponding to a 28.7% improvement while maintaining the multi-objective optimization framework. Furthermore, the resulting Pareto front extended beyond that obtained in the initial optimization, demonstrating the effectiveness of the proposed method for discovering high-performance solutions outside the original training data distribution.

The results indicate that performance-sensitivity-guided latent space expansion is an effective strategy for overcoming the limitations of conventional surrogate-based optimization and generative design approaches. Future work will focus on nonlinear sensitivity evaluation methods and latent space expansion techniques that explicitly consider trade-offs among multiple performance objectives.

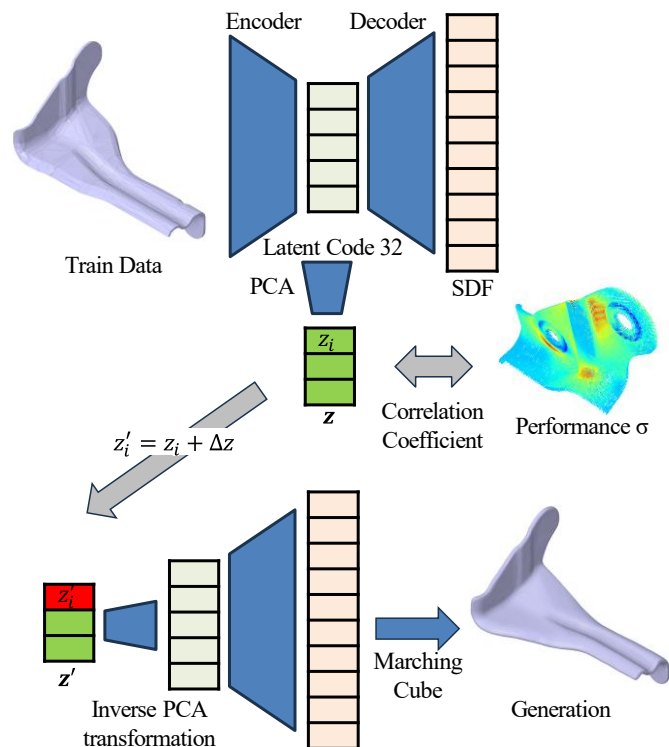


Fig. 1 Performance-Sensitivity-Guided Retraining Data Generation Method in Latent Space