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Development of AI-based Bush Characteristics Prediction Model for R&H Simulation Modeling Efficiency

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This paper presents an automated AI-based modeling approach for bushing component characteristics in vehicle development. Traditional vehicle development requires component characteristic modeling through complex mathematical functions and equivalent substitution models. However, conventional lumped-mass parameter approaches present significant limitations: inconsistent frequency-dependent dynamic stiffness representation, poor transient response simulation for varying displacements, and heavy dependence on engineer expertise. This study proposes an AI-driven modeling technique that automates the entire bushing characteristic prediction process using deep learning, reducing development time while ensuring consistency and accuracy.

The conventional workflow—requiring characteristic formulation, linearization, and equivalentization—was restructured to leverage AI algorithms. The revised process requires CAE engineers only to collect raw bushing data; subsequent preprocessing, model training, and FMU generation occur automatically. Training data preparation involves outlier handling of static characteristics time-series displacement-force data (29,889 samples) and frequency-domain to time-domain conversion of dynamic characteristics across six amplitude levels (174,820 samples). The total training dataset comprised 203,709 samples, which were restructured for parallel MLP and Bi-GRU network inputs.

A parallel architecture combining MLP network for capturing nonlinear displacement-force relationships and Bidirectional GRU for learning temporal dependencies and hysteresis behavior was employed. The hybrid approach effectively represents both displacement-amplitude-induced nonlinearity and frequency-dependent nonlinearity of bushing characteristics. The MLP branch handles the static nonlinear mapping between displacement and force, while the Bi-GRU branch captures the hysteresis effects and dynamic behavior variations across different excitation frequencies. Among candidate algorithms including LSTM, GRU, and bidirectional variants, the MLP + Bi-GRU combination demonstrated superior performance in representing hysteresis behavior while maintaining sensitivity to both small and large amplitude variations.

The combined model achieved static and dynamic stiffness prediction accuracy exceeding 90% across frequencies and amplitudes, with excellent correlation in hysteresis behavior representation. Workload reduction analysis demonstrated significant practical improvements: the conventional equivalent model-based approach required 2.5–5.5 man-days per vehicle model, while the AI-based method required only 0.5–1.0 man-days, achieving a reduction of 2–4.5 man-days per vehicle (60–80% reduction). Real-world validation in engine mount tuning demonstrated automated generation of bushing model variants, integration with ADAMS/CAR for co-simulation, and identification of optimal dynamic stiffness characteristics for ride comfort.

The proposed AI-based bushing modeling method successfully automates component characteristic prediction while maintaining high accuracy exceeding 90%. By eliminating dependency on engineer expertise and reducing man-day requirements by 60–80%, this approach provides substantial practical value in automotive development. The integrated GUI tool enables seamless FMU generation for commercial software integration, democratizing bushing modeling across engineering teams. The methodology demonstrates that parallel configuration of MLP and Bi-GRU networks is effective for representing both displacement-amplitude-induced and frequency-dependent nonlinearity, establishing a foundation for future enhancements incorporating physics-informed neural networks.

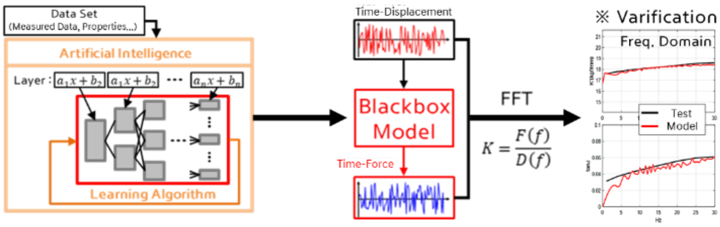

Fig. 2 Component Characteristic Modeling Process Using an AI Model.

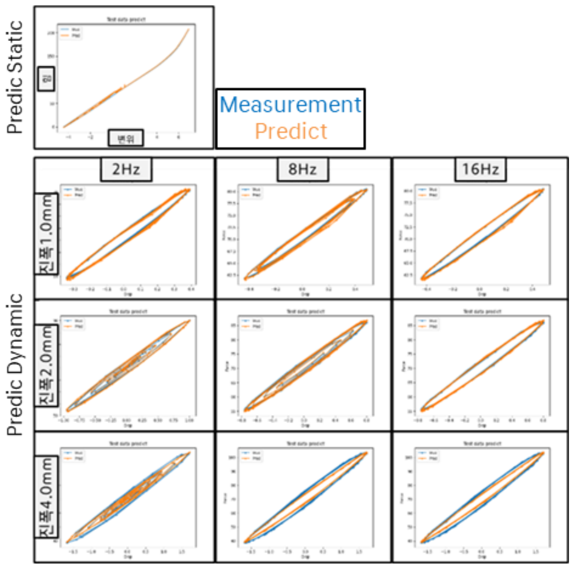

Fig. 1 Prediction Performance of the Final AI Model for Bushing Static and Dynamic Stiffness.