

Powertrain Vibration Suppression via the Integration of Domain Randomization-Based Deep Reinforcement Learning Control and Model-Based Control

Heisei Yonezawa¹⁾ Ansei Yonezawa¹⁾ Itsuro Kajiwara¹⁾

1) Hokkaido University

KEY WORDS: Active vibration control, Deep reinforcement learning, Domain randomization, Model-based control

Automotive powertrain systems involve strong nonlinearities such as backlash and uncertainties in dynamic characteristics caused by variations in mass, damping, and operating conditions. These uncertainties may significantly degrade vibration suppression performance of controllers designed using a nominal model. Deep reinforcement learning (DRL) is promising for nonlinear control; however, policies trained in a single simulation environment may lack robustness against modeling errors and uncertainties.

To address this issue, this study applies a model-based controller (MBC)-assisted domain randomization (DR) framework to nonlinear powertrain vibration control. The MBC provides a baseline control action based on a nominal model, while the DRL policy compensates for nonlinearities, parameter variations, and modeling errors. Thus, the DRL agent does not need to learn the entire control action from scratch, which facilitates learning under widely randomized environments. Twin Delayed Deep Deterministic Policy Gradient (TD3) is employed as the learning algorithm, and long short-term memory (LSTM) networks are introduced into the actor and critic networks to utilize historical observations for inferring randomized environment dynamics. This study extends our previous framework by considering more diverse variations in powertrain dynamics and observation noise.

The proposed method is applied to active vibration control of a nonlinear powertrain model with backlash. During training, the vehicle body mass, actuator mass, damping coefficients, backlash size, and reference values are randomly sampled at the beginning of each episode. The physical parameters are varied within $\pm 50\%$ of their nominal values. In addition, noise corresponding to 5% of the observation signals is introduced into the training environment to improve robustness against measurement uncertainty. The DRL agent observes the controlled output, reference signal, tracking-error-related information, and control information generated by the MBC.

Figure 1 shows a representative simulation result under severe parameter variations. The DRL policies are statistically evaluated over five independently trained random seeds. Compared with the responses obtained using only the MBC and only the DRL controller, the proposed method suppresses transient vibration more effectively and achieves a response closer to the reference trajectory. The results indicate that DR provides robustness against variations in powertrain dynamics, while the MBC enables the learning-based controller to pursue improved vibration suppression without becoming excessively conservative.

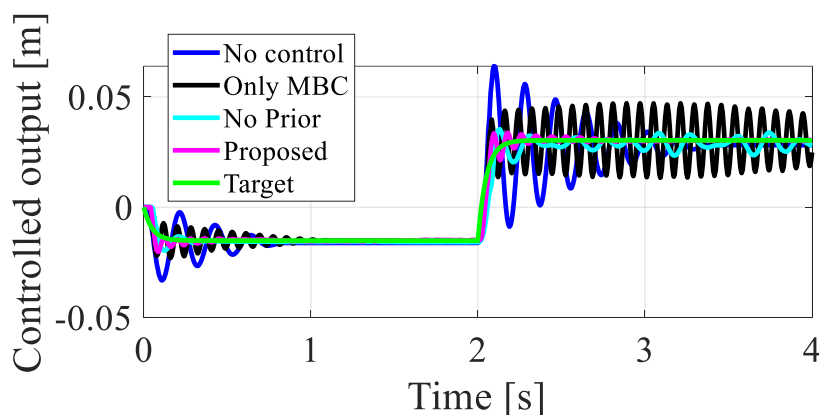


Fig.1 Simulation result over 5 seeds when M_B is the minimum, M_E is the minimum, C_D is the minimum, C_G is the maximum, C_C is minimum, $y_{0-2s}^r = y_{0-2s}^{rmin}$, $y_{2-4s}^r = y_{2-4s}^{rmax}$, and the size of backlash is the maximum.

This study applied an MBC-assisted DR framework using LSTM-based TD3 to nonlinear powertrain vibration control. Numerical simulations under diverse variations in powertrain dynamics and observation noise demonstrated that the complementary integration of MBC and DRL provides effective and robust vibration suppression.