Set-Based Design Method for Vehicle Reliability Development Using Bayesian Active Learning

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In the development of automotive bodies, lightweight and reliability are required, and accurate estimation of loads applied to the body is essential. In developing multipurpose-platform vehicles, set-based design methods are used for input load estimation. For estimating reliability input loads, methods for searching maximum values are needed when creating the Response Surface Model (RSM). For RSM applied to multipurpose-platform vehicles, it is required to extract local maxima within the range of each vehicle configuration, rather than the entire variable range. To obtain such RSM, we developed a sampling method that improves the acquisition function of Bayesian Active Learning (BAL).

The suspension, which has a large influence on the Body input load, includes highly nonlinear elements such as the bump stopper shown in Fig. 1, causing the Body input load response to exhibit local peaks. Exploring such response fields with LHS(Latin Hypercube Sampling) can fail to capture these local peaks, resulting in reduced accuracy(Fig. 2).

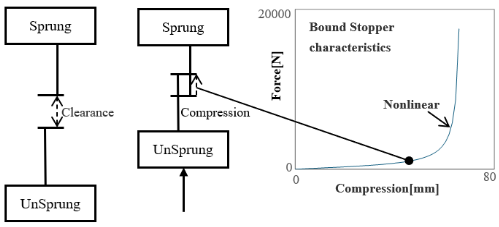

Fig. 1 Bump Stopper: Nonlinear Element in the Suspension Model

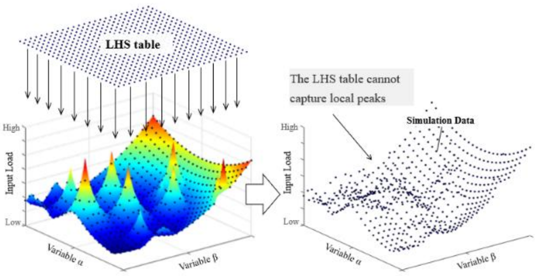

Fig. 2 Issues in LHS-Based Training Data Creation

To address this issue, it is necessary to extract a dataset that captures local peaks after sampling with LHS and add complementary samples. In this paper, we adopt active learning, select BAL as the specific method, and present an improved BAL. In BAL, Gaussian Process Regression (GPR) is used as the regression model constructed from training data $\boldsymbol{\mathcal{D}} = \{(\boldsymbol{x}_i, \boldsymbol{y}_i)\}_{i=1}^{n}$ (design points and their test results), providing not only the predictive mean $\mu(\boldsymbol{x})$ but also the variance $\sigma^2(\boldsymbol{x})$.Acquisition functions that depend on $\mu(\boldsymbol{x})$ and $\sigma(\boldsymbol{x})$ are then evaluated and maximized to search for candidate points expected to improve the response; in the improved BAL, the acquisition function shown in Eq. (1) is also employed.

$$\boldsymbol{a}_0(\boldsymbol{x}) = \tilde{\mu}^{\alpha}(\boldsymbol{x}) \times \tilde{\sigma}^{\beta}(\boldsymbol{x}), \tag{1}$$

$\tilde{\mu}$ and $\tilde{\sigma}$ are the predictive mean and standard deviation normalized to [0,1], respectively, and α and β are scale factors. Eq. (1) places greater weight on candidate points with both large predicted mean and large predicted standard deviation; therefore, unexplored regions with large values are likely to be near local peaks(Fig. 3). Solving the following optimization problem yields candidate points in the vicinity of local peaks.

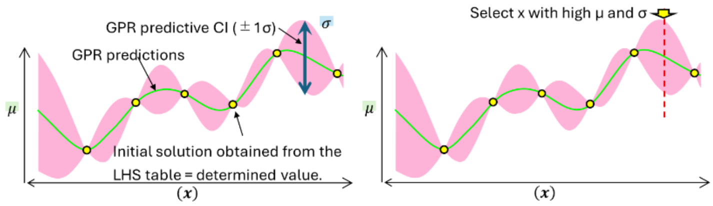

Fig. 3 Schematic behavior of the improved BAL

$$\boldsymbol{x}_{new} = \underset{x \in \mathcal{X}}{\operatorname{argmax}}\, \boldsymbol{a}_0(\boldsymbol{x})\,. \tag{2}$$

Fig. 4 shows actual vs. RSM-predicted input loads for the LHS-only and LHS + improved BAL cases, and Table 1 (RMSE/mean) provides quantitative support for the observed improvement.

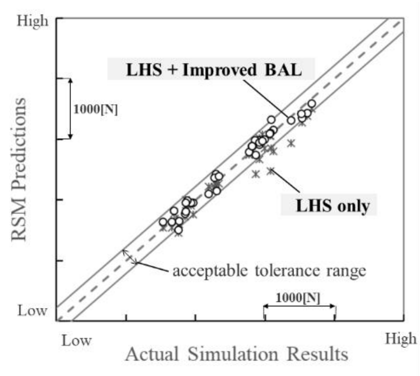

Fig. 4 Comparison of RSM Predictions and Actual Simulation

Table 1 Error of RSM Predictions vs. Actual Results

	RSME/mean
LHS	3.8%
LHS+Impruved BAL	1.5%

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