The determination method of supplement training condition for neural network model fusing real data and virtual data

Songsong Lu*†[1], Yingjie Shi[1], and Rui Bao[1]

[1]National Key Laboratory of Strength and Structural Integrity, School of Aeronautic Science and Engineering, Beihang University – China

Abstract

Real calibration tests can obtain high accuracy data, but data amount is limited due to costs. Virtual simulations can obtain rich enough data to cover each required application range, but data accuracy is lower. To achieve win-win results, many researchers investigated how to take fully advantages of real-calibration-tests data and virtual-simulation data in training of neural network (NN) model. Various real-virtual fusion neural network (FNN) models with high predicted accuracy in wider application range were therefore putforwad. However, these FNN models are difficult to be applied in engineering field. It is because their prediction errors for some conditions in required application range is relatively low (stated as lower cognitive (LC) conditions) and these LC conditions are hard to be identified without conducting corresponding comparative tests.
To address above issue, investigations were conducted in this research with scale-down aircraft wing strain-load FNN model serving as research object. A method coarsely identifying LC conditions of FNN model without conducting extra real calibration tests was established first. In this method, various sub-learners are embedded into the FNN model to obtain various predicted results for one condition; variance of predicted results corresponding to different sub-learners are calculated and conditions with higher calculated variance value were classified as LC conditions. This coarse method was verified by comparative study, where a significant LC condition with around 46% error is identified as its remarkable higher (over 7 times) variance than that of other conditions with error below 5%.

This coarse method was then further developed into an improved method, which can accurately identify LC conditions not ensuring a specified accuracy requirement. This improvement was achieved by microperturbation training on FNN model with various embedded sub-learners, especially by taking fully advantages of different evolution characterization of variance for different types of conditions at early stage of microperturbation training (the variance decreases for LC conditions but increases for other conditions with the increase of iteration steps). The procedure of this method is listed as follows: 1) using the virtual simulation data at a specific condition to train the FNN model with microperturbation; 2) adjusting the number of iteration steps of micropertubation training to obtain the smallest percentage of conditions with decreased variance; 3) determining conditions with decreased variance at this iteration step as most remarkable LC conditions; 4) excluding these most

*Speaker

†Corresponding author: 11523@buaa.edu.cn

significantly LC conditions from all predicted conditions and calculated variance of each remaining condition; 5) checking whether these variance ensures the specified predicition accuracy requirement and repeat the step 1)-4) until these variance ensuring the specified requirement; 6) determining all excluded significant LC conditions as the identified LC conditions not ensuring the specified predicition accuracy requirement.
The improved LC condition identifying method in this research is meaningful. Conducting supplementary tests under these conditions and retraining the FNN model after adding these supplementary data in training dataset will helps to effectively improve both accuracy and application range of FNN model.