Mechanical Engineering Doctoral Defense

Uncertainty Quantification and Prognostics using Bayesian Statistics and Machine Learning

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Abstract

The uncertainty quantification is critical for engineering design and analysis. Determining appropriate ways of dealing with uncertainties has been a constant challenge in engineering. Statistical methods provide a powerful aid to describe and understand uncertainties. Among all the statistics methods, this work focuses on applying Bayesian methods and machine learning in uncertainty quantification and prognostics. The main engineering filed on which this study focuses is mechanical properties of materials, both static and fatigue. This work can be summarized in the following items: First, to maintain the safety of vintage pipelines requires the accurate estimation of the strength. The objective is to predict the reliability-based strength using nondestructive multimodality surface information. Bayesian model averaging (BMA) is implemented for fusing multimodality non-destructive testing results for gas pipeline strength estimation. Several incremental improvements are proposed in the algorithm implementation. Second, the objective is to develop a statistical uncertainty quantification method for fatigue stress-life (S-N) curves with sparse data. Hierarchical Bayesian data augmentation (HBDA) is proposed to integrate the hierarchical Bayesian modelling (HBM) and Bayesian data augmentation (BDA) to deal with sparse data problem for fatigue S-N curves. The third objective is to develop a physics-guided machine learning model to overcome the limitations existing in parametric regression models and classical machine learning models for fatigue data analysis. A Probabilistic Physics-guided Neural Network (PPgNN) is proposed for probabilistic fatigue S-N curve estimation. This model is further developed for problems with missing data and arbitrary output distribution. Fourth, multi-fidelity modeling combines advantages of low- and high-fidelity models to achieve a required accuracy at a reasonable computation cost. The fourth objective is to develop a neural network approach for multi-fidelity modeling by learning the correlation relation between low- and high-fidelity model. Finally, conclusions are drawn, and future work are outlined based on the current study.

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Zoom Link: https://asu.zoom.us/j/83166975910