Dimensional analysis of metal fatigue life through deep neural networks

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Fatigue of materials refers to the changes of mechanical properties resulting from repeated loading. From aircraft to automobiles, fatigue has been a major cause of failure since these structures are subjected to cyclic loading. It has been suggested that nearly 90% of structures failures were caused by fatigue [1]. Therefore, understanding the mechanism of fatigue and predicting the fatigue life is of paramount importance to increase service life and avoid catastrophic failure of the structural components.

Ever since Wöhler proposed the stress amplitude-life (S-N) curves to characterize the metal fatigue behavior, most research has concentrated on predicting fatigue life using empirical equations, the coefficients of which are generally based on data obtained through exorbitant testing of each specific type of coupons. For instance, the well-known Basquin equation has been widely used to predict the fatigue life N_f using the stress measurements: $\frac{\Delta\sigma}{2} = \sigma_f^{'}\left(2N_f\right)^b$, where $\sigma_f^{'}$, b are all empirical coefficients that should be calibrated from experiments[2]. Although this method has shown to be very successful, it has several drawbacks. First of all, calibrating $\sigma_f^{'}$ and b requires large amount of data and such fatigue experiments are usually expensive. Second, no physics-related parameters are accounted for in the equation. Therefore, the parametric dependence of physical properties like modulus, surface roughness cannot be accounted for explicitly in the equation, which will greatly hinder the designing process.

Recently, some people have proposed physics-based models to predict metal fatigue life. Among them, Wu modified the Tanaka-Mura model by considering the inherent physical properties of the material, like surface energy and roughness [3]. This model shows promising results for low cycle fatigue lives of different metals without resorting to experimentation. However, the validation results for high cycle fatigue are still inaccurate. This might be attributed to several reasons. For example, this formulation doesn't consider many other material properties such as microstructural defects like void ratio. For a better understanding of the problem, dimensional analysis can be used to find the hidden complex relationship behind the veil.

In this project, a special type of deep neural network called DimensionNet will be used to find the universal equation for metal fatigue life prediction [4]. In DimensionNet, the input parameters are physical parameters related to the problem. After the first sub-neural network (scaling network), these parameters are automatically combined with each other to form several dimensionless quantities. Then in the deep neural network, the function f between the obtained dimensionless quantities and the outputs can be solved.

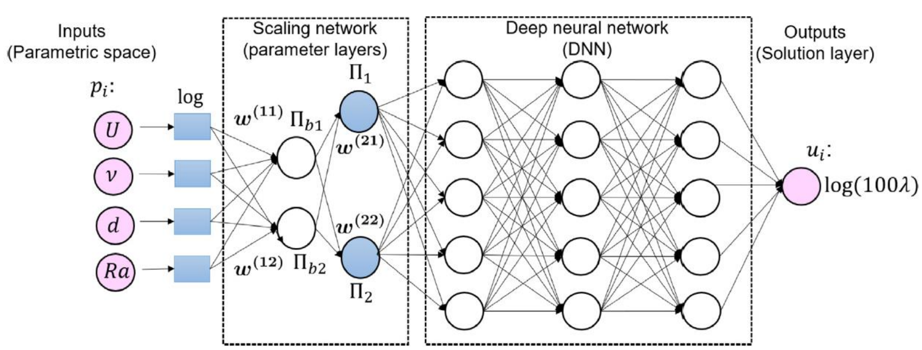

Fig. 1 Structure of the DimensionNet

The mechanistic data science (MDS) approach used in this project is summarized as follows:

1. In the data collection step, available data will be found on multiple research papers and databases.

2. In the reduced-order surrogate model step, the universal dimensionless function between dimensionless parameters and metal fatigue life will be generated from the collected data.

3. In the machine learning and regression step, a special type of deep neural network called DimensionNet will be used to find the internal relationship between physical parameters.

4. In the system and design step, with the obtained dimensionless function, the metal fatigue life can be predicted using a physics-based approach without doing extra fatigue experiments.

Reference

[1] Hummel, Rolf E. Understanding materials science: history, properties, applications. New York: Springer, 1998.

[2] Suresh, Subra. Fatigue of materials. Cambridge university press, 1998.

[3] Wu, Xijia. "On Tanaka‐Mura's fatigue crack nucleation model and validation." Fatigue & Fracture of Engineering Materials & Structures 41, no. 4 (2018): 894-899.

[4] Saha, Sourav, Zhengtao Gan, Lin Cheng, Jiaying Gao, Orion L. Kafka, Xiaoyu Xie, Hengyang Li, Mahsa Tajdari, H. Alicia Kim, and Wing Kam Liu. "Hierarchical Deep Learning Neural Network (HiDeNN): An artificial intelligence (AI) framework for computational science and engineering." Computer Methods in Applied Mechanics and Engineering 373 (2021): 113452.