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ENHANCING CRASHWORTHINESS OF LEGGED-TYPE LANDER HONEYCOMB BUFFERS UNDER LOW-VELOCITY IMPACTS THROUGH MACHINE LEARNING FRAMEWORK

Abstract

Machine Learning (ML) and Deep Learning (DL) techniques in Artificial Intelligence (AI) offer a compelling solution to the challenges inherent in traditional methods for analysing the crashworthiness of energy-absorbing structures. These challenges include high costs, prolonged computation times, and low accuracy. This study introduces an innovative framework that harnesses AI to streamline the design cycle for crashworthiness assessments of a legged-type lander honeycomb buffer energy absorber made of an aerospace grade aluminium alloy. The absorber serves as a foundational design concept for spacecraft landing footpads, with the goal of enhancing crashworthiness under low-velocity dynamic impact loads during landing phases. ML techniques are employed to predict the dynamic axial crushing response of this structural component. By treating the thickness, the number, and lengths of the edges of the honeycomb cells as parametric variables, a virtual Design Of Experiments (DOE) is used to generate both training and testing data, sampled through the Optimal Latin Hypercubic Sampling (OLHS) technique. Virtual impacting crash simulations of the structure are executed via Finite Element (FE) analysis, yielding force-displacement diagrams corresponding to sampled design variables, allowing for the training and validation of the ML models. To enhance the crashworthiness of the absorber, structural parameters serve as input data, while two distinct ML models are deployed to predict the time-series deceleration response (i.e., the energy-absorbing characteristic curve) of the structures: a standard multi-layer feedforward neural network (Multi-Layer Perceptron, MLP), and an advanced variant of recurrent neural network (Long-Short Term Memory, LSTM). The predictive accuracy of these models is compared with results obtained from FE analysis. Subsequently, a multi-objective optimization is conducted using Specific Energy Absorption (SEA) as the design objective, employing the NSGA-II genetic algorithm in conjunction with the ML-developed models. For demonstrative purposes, the geometry selected in this manner is then tested under conditions similar to those of a lunar lander through FE analysis. The primary objective of employing Machine Learning models is to significantly reduce computational requirements once the models are trained and validated, compared to conventional methodologies. Consequently, this machine learning framework provides engineers with an effective tool for accelerating the initial design exploration process and optimizing energy-absorbing structures. The framework developed and introduced in this research is intended to be applied to more complex geometries and applications in the future.