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# OPTIMIZED LSTM NEURAL NETWORKS VIA NEURAL ARCHITECTURE SEARCH FOR PREDICTING DAMAGE EVOLUTION IN COMPOSITE LAMINATES

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## ABSTRACT

This work explores the use of Long Short-Term Memory (LSTM) recurrent neural networks for predicting highly nonlinear delamination growth patterns in tapered laminates subjected to quasi-static loading excitation. Recently, deep neural networks (DNNs) have transformed the modeling and design of composite structures by enhancing predictions of nonlinear behaviors, structural responses, and failure mechanisms. However, while DNNs offer significant flexibility, they are constrained by their need for fixed-dimensional vector inputs and outputs, which limits their applicability for sequence-dependent problems where input lengths vary [1]. In contrast, LSTMs overcome this limitation by utilizing a recurrent architecture tailored for sequential data, allowing them to retain long-term information through memory cells and gating mechanisms. In this study, high-fidelity FEM analysis provides the sequential degradation data for LSTM training. To achieve optimal performance without relying on manually designed neural network architectures, we employ a state-of-the-art Neural Architecture Search (NAS) framework enhanced by Bayesian Optimization (BO) [2]. BO enables systematic exploration and optimization over the space of network architectures and hyperparameters, allowing us to identify configurations that maximize model accuracy and efficiency. By automating the selection process, BO ensures that the resulting LSTM model is specifically tailored to capture the complex, history-dependent nature of delamination growth. Our results reveal that LSTMs can accurately predict delamination growth in near real-time, offering significant efficiency improvement over FEM simulations. These findings validate the potential of LSTM models as robust metamodels, promising new real-time predictive capabilities for composite material analysis and design. This foundational study also underscores the value of NAS in deep learning for complex material damage prediction, advancing the design of LSTM-based models.

## REFERENCES

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