ABSTRACT
COMPUTATIONALLY INVESTIGATING FATIGUE PREDICTIONS OF NITINOL USING MULTI-FIDELITY MODELING AND MACHINE LEARNING

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Nitinol is a shape memory alloy that has many applications in the biomedical, aerospace, civil engineering, and automotive fields ranging from coronary stents to morphing wings on airplanes. Computational investigations into shape memory alloys are difficult to perform due to the complexity of models and their limitations in the theories they implement. Cyclic stress-strain response of superelastic Nitinol, a shape memory alloy, has unique characteristics due to the solid-to-solid reversible phase transformation from an austenite to a martensite phase that occurs to recover from large strains reaching 6%-8%. Some of the transformed martensite phase does not transform back upon unloading leading to a unique cyclic material response. Computational investigations into fatigue of Nitinol are difficult since there are two competing processes which occur during loading: plasticity formation and martensite transformation. Crystal plasticity material models are often used to study fatigue at the grain-scale, but they are computationally expensive to run making it difficult to obtain the number of simulations necessary to effectively investigate the driving forces behind fatigue crack nucleation in Nitinol. Some fatigue investigations using crystal plasticity material models use fatigue indicator parameters to determine the location in a microstructure where a crack is most likely to form, but there is currently no fatigue indicator parameter equation that is formulated for shape memory alloys.

The following work introduces a novel method for reducing the number of simulations required to calibrate the cyclic properties for models with many different inputs, such as crystal plasticity models. This work also utilizes a multi-fidelity modeling approach by using data extracted from finite element simulations to run a low-fidelity simulation. Low-fidelity simulations are less computationally expensive and less accurate than a high-fidelity finite element simulations, but they are a good estimate and make running a large number of simulations tractable. Using the multi-fidelity framework developed here, the crystal plasticity material model is calibrated with a Gaussian process-based Bayesian machine learning and optimization framework. This work takes a model calibrated using the aforementioned framework and provides some insight into the fundamental driving forces behind fatigue crack nucleation predictions in Nitinol.