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A k-NN-based active learning surrogate modeling technique for the simulation of composite laminated materials.

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ABSTRACT

The present study aims to develop a k-nearest neighbors (k-NN) based active learning methodology for the surrogate modeling of composite materials using sparse Gaussian process regression (SGPR) [1].

The proposed technique is a pool-based [2] methodology aiming to identify the most informative points from the pool dataset using a score estimation that consists of the bias plus the variance at each point. The points selected as the most informative are the ones with the highest score. The variance at each point is calculated by the SGPR surrogate model, while the bias is calculated as the weighted sum of the actual responses of the k-NN points from the initial training dataset. The weights are defined as a function of the normalized inverse distance of each pool point to its corresponding k-NN points.

The major goal of this study is to develop a robust and scalable active learning and surrogate modeling technique for the simulation of composite laminated materials, whose inputs and outputs are obtained from computationally expensive and complex finite element analyses [3].

Several benchmarks and real-word numerical examples are presented and compared to well-established active learning methods in the literature.

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