Assessment of multi-fidelity structural theories to train probabilistic machine learning for process-induced defects

ASSESSMENT OF MULTI-FIDELITY STRUCTURAL THEORIES TO TRAIN PROBABILISTIC MACHINE LEARNING FOR PROCESS-INDUCED DEFECTS

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Over the last few years, there has been growing interest in developing simulation tools to predict and mitigate Process-Induced Defects (PID) in composites [1, 2]. For instance, autoclave curing has complex multi-physics thermo-chemical-mechanical interactions, making developing reliable simulation tools challenging. One of the crucial features of virtual manufacturing is proper structural modeling, which is essential to detecting residual deformations and stresses [3]. The computational overhead of such models may be very high, hindering their application for large structures or optimization problems. Using surrogate models based on machine learning is promising to improve numerical efficiency and extend the application field of virtual manufacturing for composites [4].
This paper focuses on developing surrogate models based on the Gaussian Process Regression (GPR) to predict PID, such as spring-in angles. In a previous work [4], the authors used GPR to limit the need for experimental data by using numerical tools with variable fidelity. Figure 4 shows results from [4] concerning the effect of different training data sets on the GPR. The spring-in angle of all sequences of 0/90 orientation angles in an eight-layer composite was evaluated, with each sequence indicated by two lamination parameters computed through the classical lamination theory. The simulation data consisted of 1D, 2D, and 3D models. The proper choice of simulation data led to a significant improvement in the GPR with only a few experimental sets used.

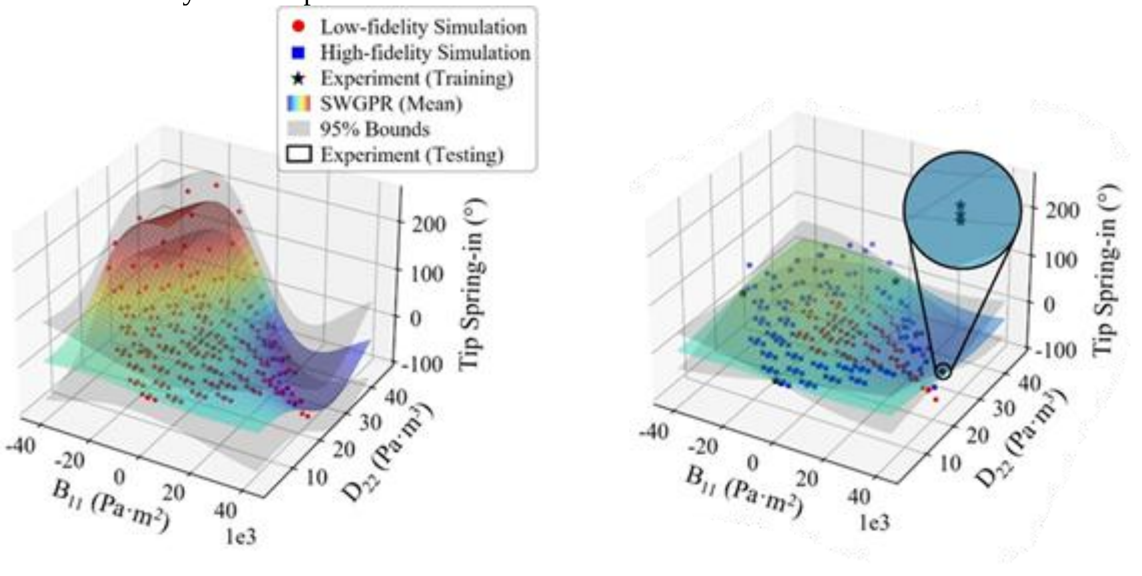

Figure 1: Spring-in angles from a GPR model and multifidelity models [4]

This work extends the findings from [4] by focusing on the fidelity of the simulation and its effects on

the GPR. The aim is to obtain guidelines to find the minimum number of high-fidelity models for proper and efficient training. The efficiency concerns two aspects: the efficiency in training the surrogate model, i.e., reducing the time and resources needed to build it, and the efficiency of the trained model in making predictions compared to high-fidelity virtual models or conducting experiments.
The multi-fidelity models are based on the Carrera Unified Formulation (CUF) [3], in which 1D structural theories with advanced kinematics can be obtained. Figure 2 shows two examples of theories: an Equivalent-Single Layer (ESL) with a linear distribution of the displacement field and a Layer-Wise (LW) with a piece-wise linear distribution. This work aims to systematically assess ESL and LW theories with variable expansion to minimize the computational cost required to train an accurate surrogate model, i.e., to improve the training efficiency by limiting the need for expensive high-fidelity data and obtaining reliable predictions by the GPR. The numerical cases evaluate composite parts' autoclave curing and residual deformations. Guidelines to improve the accuracy and efficiency of the method in predicting PID are drawn to provide a cost-effective and broadly applicable virtual tool for understanding and improving composites' design, development, and manufacturing.

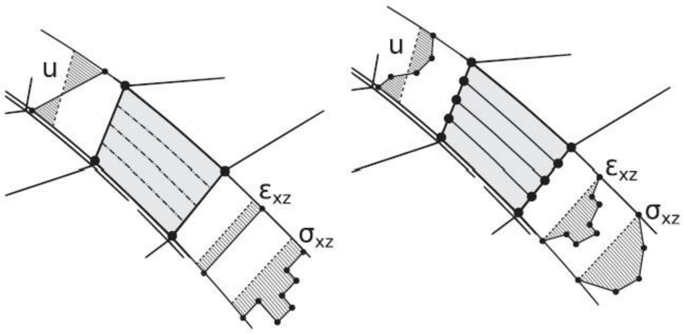

Figure 2: Examples of multi-fidelity structural theories: Equivalent Single Layer (left) and Layer-Wise (right)

Funding

This work was partly supported by the Italian Ministry of Foreign Affairs and International Cooperation (grant number US23GR12).

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