Creating Training Data for Surrogate Models Using FE Draping Simulation

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OBJECTIVE

Finite Element (FE) simulations play an increasingly important role in the development and optimization of manufacturing processes. They enable a reduction of trial-and-error experiments in the development phase, saving costs and time. However, especially for fiber reinforced composites, FE simulations can take a considerable amount of computation time [1]. A promising approach to address this issue is to approximate the process behavior, using computationally inexpensive, artificial-intelligence-based surrogate models. They can predict the outcome for a given input accurately, if the model was trained with sufficient training data. However, a common issue for this approach is the lack of training data.

Therefore, this study focuses on the efficient generation of training data for a surrogate model, using FE analysis. Towards this goal, we developed an automated routine for data generation (including pre-processing, solving and post-processing of a parametrized FE model using Python scripts). To evaluate the suitability of the FE results as training data, we trained a U-Net based surrogate model (see [2]). The resulting surrogate model predictions were compared with the respective simulation results. Additionally, we determined the minimum amount of training data necessary for the surrogate model to predict results correctly, by conducting a parametric study with varying training set sizes.

METHODS

The FE draping process model was created using the commercial software package Abaqus/CAE. For the draping process, a fabric blank cut is draped onto a rib tool (see Fig. 1a). The blank cut is held and manipulated using six springs which are attached to it with clamps (see Fig. 1b). The draping is a one-step process in which the springs lower onto the tool and uniform pressure is applied on the blank cut top surface, mimicking diaphragm forming.

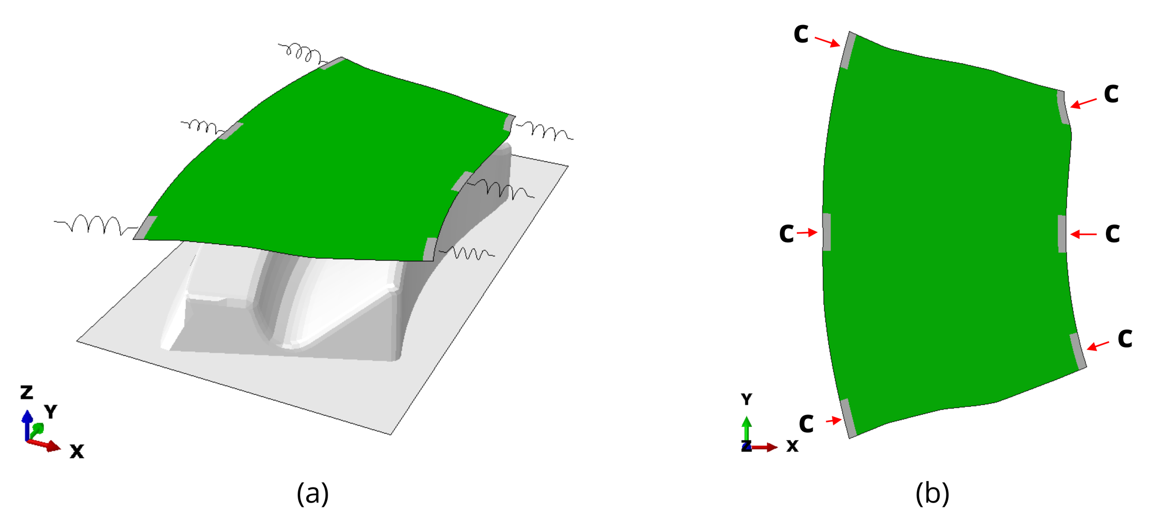

Fig. 1: (a) Isometric view of the draping simulation model, (b) blank cut with clamping areas (denoted with **C**)

The FE model was parametrized using a Python script, to enable a parameter study. Two different training data sets were created: *pressure magnitudes* and *patch size.* For the *pressure magnitudes* data set, the blank cut was divided into three patches A1, A2, A3, onto which different combinations of pressures (varying from 0.01 to 0.11 N/mm^2 in steps of 0.02 N/mm^2) were applied (see Fig. 2 top). For the *patch size* data set, pressures were kept constant (F1 = F3 = 0.05 N/mm^2, F2 = 0.01 N/mm^2), while the patch sizes were varied by moving the division lines along the y-direction (see Fig. 2 bottom).

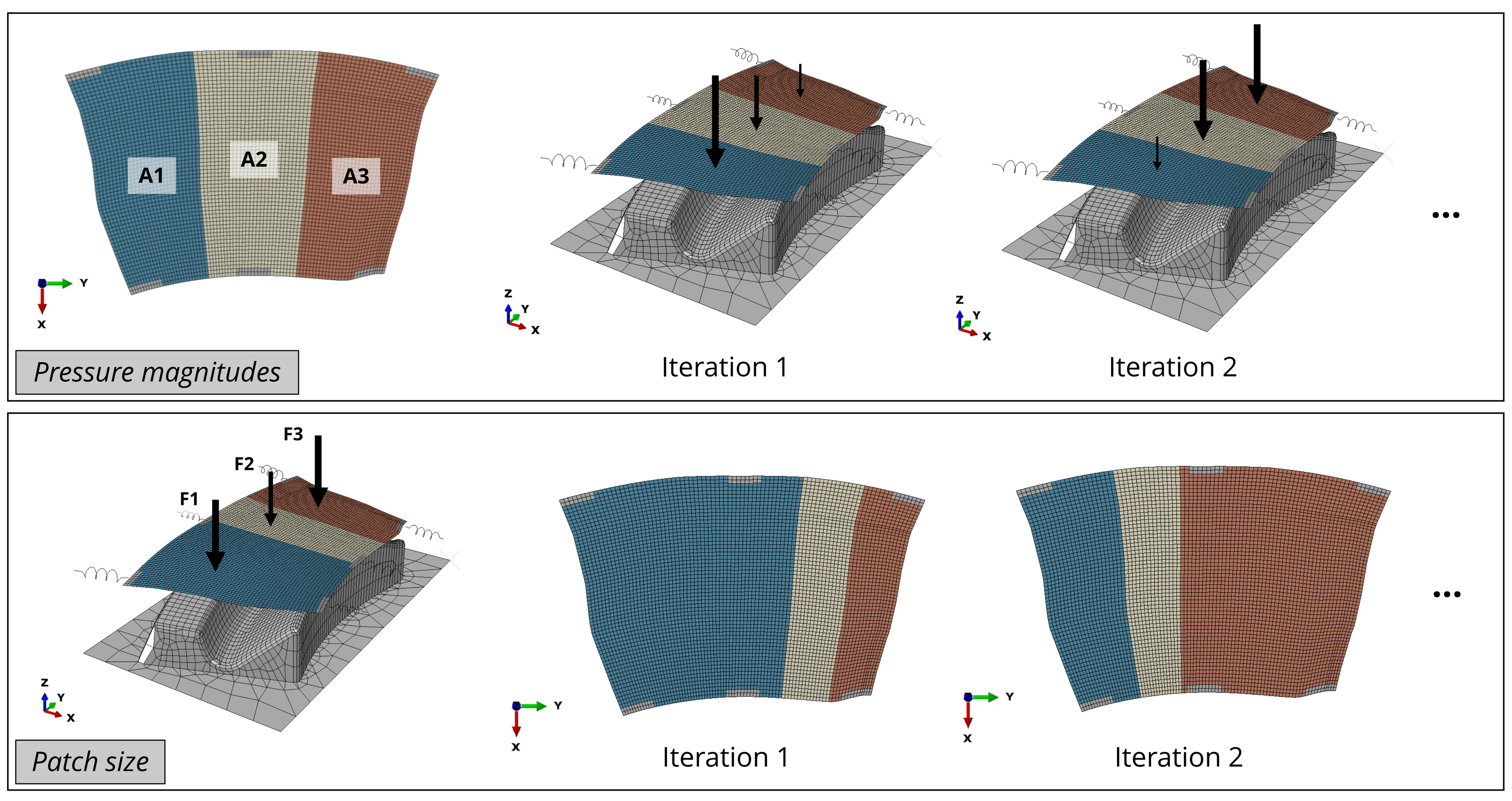

Fig. 2: Variations of the model parameters for creating the *pressure magnitudes* (top) and *patch size* (bottom) data set

For training, the stresses *S11* in local 1-direction and the *COPEN* parameter (indicating the distance between tool and lamina nodes) were evaluated. The pressure magnitudes and the output variables were encoded as single-channel color values on the blank cut top surface. The encoded images were fed into the U-Net.

The parametric study was conducted using the *pressure magnitudes* training data set. Therefor, the following training setup was used for 20 different seeds:

1. Perform a (seeded) random 80/20 train/validation split
2. Train a new model on a subset of training the set (2%, 4%, 8%, 16%, 32%, 64% and 100% of the training data respectively)
3. Evaluate the trained model on the complete validation set using the 2-norm between FE results and surrogate model prediction

This procedure enables an estimation of the amount of training data necessary to achieve a sufficient performance.

RESULTS & OUTLOOK

Suitability of training data. Using 4 CPUs of an Intel Core i7-8665U (1.90 GHz / 2.11 GHz) processor, one simulation run took about 3.2 minutes (simulation time: 2.9 min, export of output: 0.3 min). The *pressure magnitudes* data set (containing 216 simulations) was therefore created within about 11.5 hours and the *patch size* data set (containing 198 simulations) was created in about 10.5 hours. The resulting *COPEN* FE result and respective U-Net prediction for an exemplary patch division is shown in Fig. 3. Comparing the results qualitatively, only slight deviations can be observed. The shown result is representative for all results of the *patch size* and *pressure magnitude* data set. Thus, using 100% of the training data, the U-Net model was able to predict the *COPEN* values quite well for both data sets.

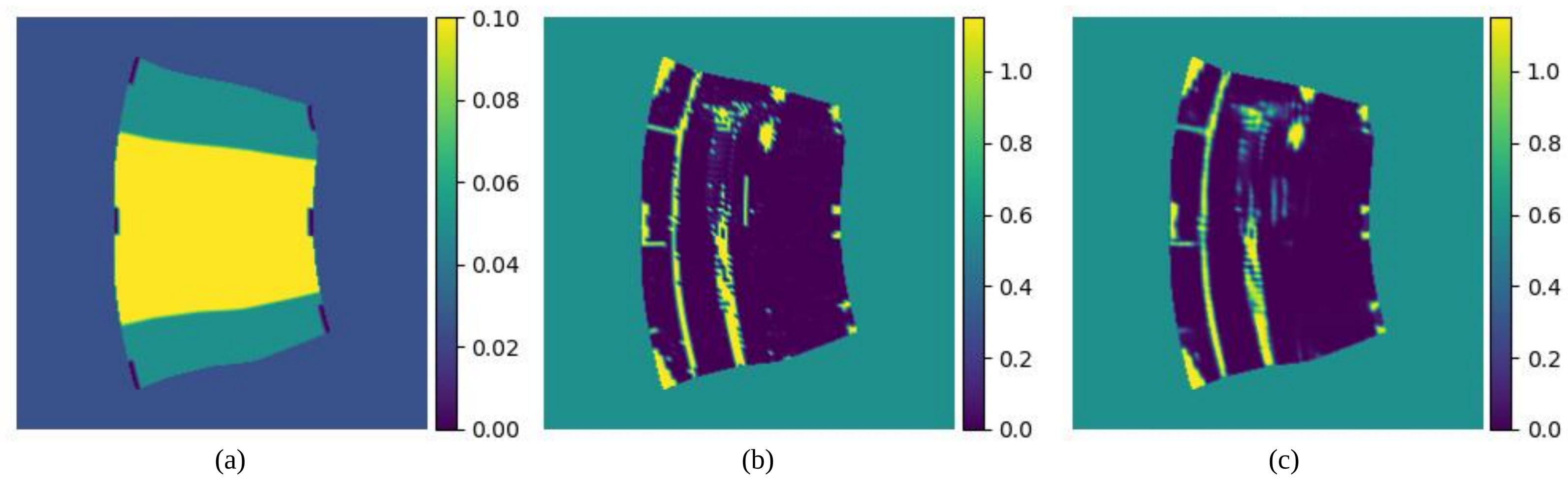

Fig. 3: (a) Exemplary patch division and respective *COPEN* values resulting from (b) FE simulation and (c) surrogate model

Parametric study. The *COPEN* values predicted by the surrogate model for an exemplary load case of the *pressure magnitude* data set are shown in Fig. 4 (for subsets containing 2% and 16% of the training data). The surrogate model trained on the 2% subset predicts no variation within the individual lamina areas, which severely deviates from the FE result (see Fig. 4d). A 16% subset, however, already leads to a quite accurate prediction (deviations only occur at the fringes of areas that are not in contact, as well as at two small areas (see Fig. 4d)).

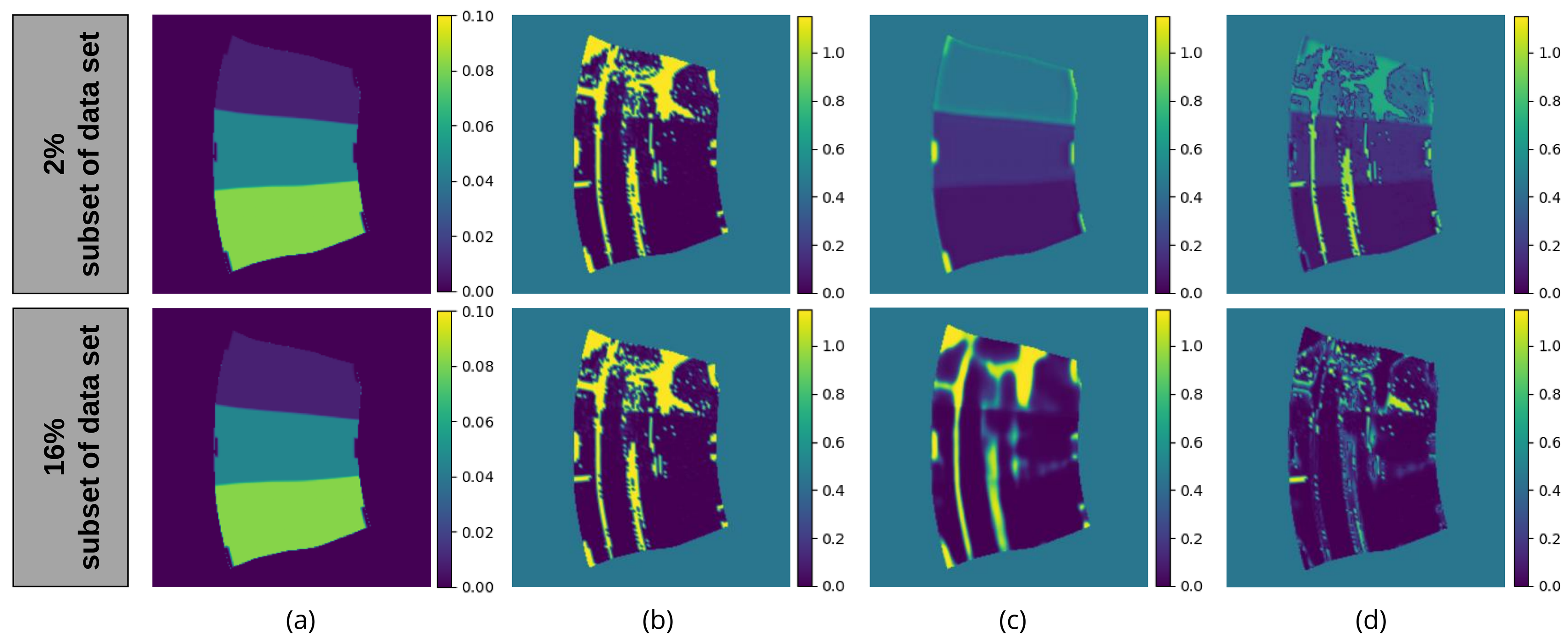

Fig. 4: (a) Exemplary patch division, the respective *COPEN* values resulting from the (b) FE simulation and (c) surrogate model prediction and (d) difference between FE und surrogate model result for 2% and 16% of the training data

Minimum required training data. Fig. 5 shows the average (over all seeds) difference of the *COPEN* and *S11* images for different training set sizes of the *pressure magnitude* data set. With increasing training set size, the average difference between FE and U-Net result is decreasing for both output variables. Due to less variability within the *S11* values, the trend is more distinct for the *COPEN* values, and *S11* values can already be predicted quite accurately with 2% of training data. A minimum of 16% of training data (i.e., 35 out of 216 simulations) is necessary for an accurate prediction of the *COPEN* values.

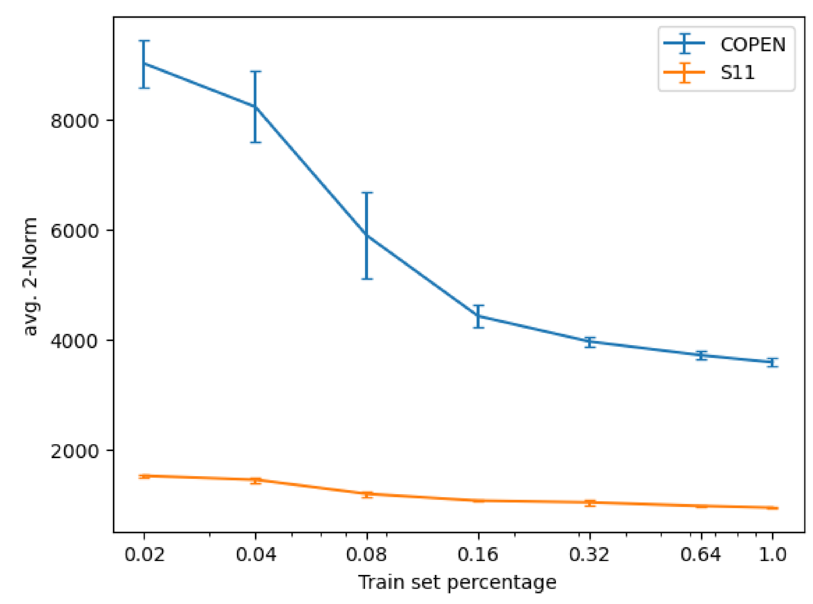

Fig. 5: Average 2-norm values of the *COPEN* (blue) and *S11* images (orange) for different training set sizes of *pressure magnitudes*

The evaluation of the *COPEN* data showed that the generated FE training data is well suited for simple U-Net surrogate models. Further investigations will focus on more advanced machine learning models to expand the capabilities of the model.

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