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MACHINE LEARNING FOR REDUCED-ORDER MODELING OF COMPOSITES PROCESSING

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ABSTRACT

Machine learning concepts have made their way into industry practice and can offer quick and accurate solutions for various design and in-service applications including process simulation of composites. High-fidelity finite element simulation tools are currently used for thermo-chemical analysis of parts during processing. This research investigates reduced-order modeling of complex composite parts using machine learning methods to speed-up the simulation. At first, process simulations of representative 2-D stringer geometries were conducted using finite element analysis to extract leading and lagging responses. Equivalency of exothermic responses of 2-D simulations to 1-D finite element analysis was established using an in-house developed machine learning framework at the University of Washington (CompML). It is demonstrated that for a given 2-D geometry, a trained NN can identify an equivalent 1-D thermal stack to yield similar exothermic responses. The results and methods developed in this study can significantly reduce the computational cost of finite element simulation by successfully establishing reduced-order models of complex geometries.

Keywords: Machine Learning, Reduced-Order Modeling, Simulation, Finite-Element
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1. INTRODUCTION

Aerospace composite components are fabricated following process specifications (i.e. specs) to mitigate process-induced defects and meet certification requirements. However, we continue to face an emerging fast-paced market where every facet of the production system is challenged to reach new levels of optimization. Design criteria is certainly an area that is often looked to for tolerance relief, but each new consideration for a particular design change often comes at a high cost for validation.

For thermal requirements, thermal profiling is typically performed on representative test coupons by embedding several thermocouples (TCs) in a part to monitor its temperature history, identify leading and lagging locations, and develop thermal cycles that satisfy specs in production parts [1–4]. Nowadays, mature finite-element (FE) process simulation tools are routinely used by engineers to simulate the thermo-chemical behavior of the material during processing, and develop robust cure cycles without the need to conduct comprehensive experiments [5–8]. However, as the fidelity of FE tools increase, the simulation cost also increases (time to calibrate, setup and perform). Design optimization by iterating through such high-fidelity and time-consuming FE simulations has shown to be quite challenging.

As computer science and materials science converge in the industrial environment, innovative applications of Machine Learning (ML) are finding their ways to improve existing simulation approaches [9–12]. One major emerging application is reduced-order modeling via ML to speed-up simulation tools (e.g. [13,14]). Reduced-order modeling can be achieved by decreasing complexities in the constitutive model and/or geometry. ML is utilized to establish correlations between low fidelity and high-fidelity simulation results. For this, typically random simulations are conducted by varying input parameters. Simulation results are then used as training data for ML models.

To speed-up analysis, here we aim to use ML and develop reduced-order modeling for process simulation of composites. This was achieved in this study by correlating 2-D thermo-chemical analysis of composite parts to equivalent 1-D cases. For FE analysis, COMPRO software package [15] in ABAQUS was used to generate training data for ML. Parameterized simulations were conducted through the use of python-based programming script and automating pre- and post-analysis processing tasks in ABAQUS. To develop ML models based on FE simulation results, CompML [16] software package developed at the University of Washington was used. A Neural Network (NN) was trained with input parameters of 2-D FE simulations, to make classification predictions for 1-D FE equivalency. The trained model can take geometric and cure-cycle parameters of a 2-D simulation and, in real-time, predict if the response of the leading location is dominated by heat transfer through the thickness direction. This indicates a 1-D response for the leading location, eliminating the need to conduct full 2-D analysis. In addition, for cases where the response of the leading location is not a simple 1-D response, a trained NN in CompML was used to find equivalent 1-D cases with similar thermal histories to leading locations of 2-D geometries. While the implemented material model includes both in-plane and through thickness orthotropic material properties, the 1-D analysis only considers the through-thickness heat transfer behavior. Based on this, an equivalent 1-D thermal stack configuration can be identified to yield a similar thermal response to a given 2-D configuration. The successful reduced-order modeling will save time in product design analysis and enable design optimization by fast exploration of the entire design spectrum.

2. PROCESS SIMULATION USING FE

The part design that was chosen for this experiment was a composite co-cured blade stringer on a wing panel undergoing a two-hold cure cycle to represent a typical part and process that would likely be seen in a future production environment. A schematic of the stringer cross-section and the two-hold cure cycle are shown in Figure 1. The schematic shows boundary conditions where heat transfer occurs on the top surfaces of the composite stringer and bottom of the tool, and no heat transfer at the edges. HexPly 8552 woven carbon prepreg (AGP193-PW fabric) which consists of HEXCEL 8552 toughened epoxy resin system and AS4 carbon fibers [17], on an Invar tool was selected for this study. 2-D FE simulations were performed using COMPRO software [15] in ABAQUS. The results were used as training data for machine learning.

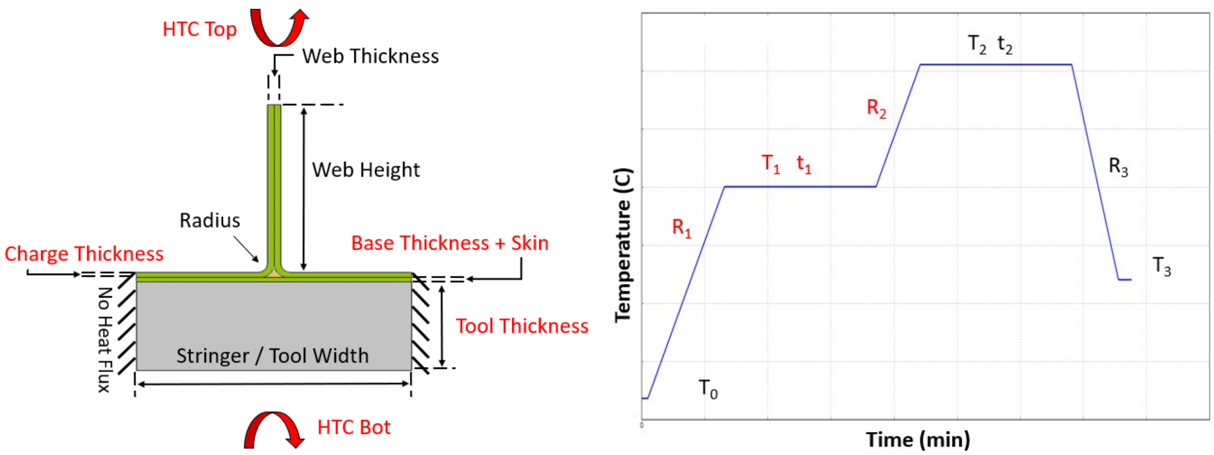

Figure 1 Schematics of the co-cured stringer and the two-hold cure cycle

2.1 Model Parameters

From the parameters shown in Figure 1, eight input parameters were varied for FE simulations: four parameters for the thermal stack and four parameters for the two-hold curing temperature profile as listed under Table 1. The range of variables and constants were selected based on typical values for large composite wings with consideration for design flexibility. Using the range of parameters in , more than 5000 random cases were selected (i.e. random distribution of parameters) to conduct 2-D process simulations.

Table 1 Simulation parameters

Stringer and Tool Configuration	
HTC Top *(HTC_T)*	$10 – 100 \left(\frac{W}{m^2 K}\right)$
HTC Bottom *(HTC_B)*	$10 – 60 \left(\frac{W}{m^2 K}\right)$
Tool Thickness *(Tt)*	$5.08 – 17.78 \left(mm\right)$
Part/Web Thickness *(Pt/Wt)*	$9.90 – 53.34 \left(mm\right)$
Part Radius	$6.35 \left(mm\right)$
Web Height *(Wh)*	$76.20 \left(mm\right)$
Part/Tool Width	$177.80 \left(mm\right)$
Two-Hold Cure Cycle	
(Heating) Ramp 1 *(R1)*	$1 – 8 \left(\frac{^oC}{min}\right)$
Hold Temperature 1 *(T1)*	$110 - 172 \left(^oC\right)$
Hold Time 1 *(t1)*	$0 - 120 \left(min\right)$
(Heating) Ramp 2 *(R2)*	$0.5 – 8.0 \left(\frac{^oC}{min}\right)$
Initial Temperature *(T0)*	$20 \left(^oC\right)$
Hold Temperature 2 *(T1)*	$180 \left(^oC\right)$
Hold Time 2 *(t1)*	$120 \left(min\right)$
(Cooling) Ramp 3 *(R3)*	$-3.5 \left(\frac{^oC}{min}\right)$
Final Temperature *(T3)*	$20 \left(^oC\right)$

2.2 Finite Element Model Setup

Using symmetry conditions, the FE model for the co-cured stringer was set up for the half of the geometry shown in Figure 1, to speed-up simulations. The same boundary conditions seen in Figure 1 applies, with no heat flux on the symmetry line. The half part mesh is shown in Figure 2 with the light-colored mesh as the composite blade stringer on a wing skin panel, and the red elements representing the Invar tool. Red dots on the mesh surface indicate locations of virtual thermocouples (TCs) to extract part and tool temperature histories. Eight-node linear heat transfer brick (DC3D8) and six-node linear heat transfer wedge (DC3D6) elements were used for the model.

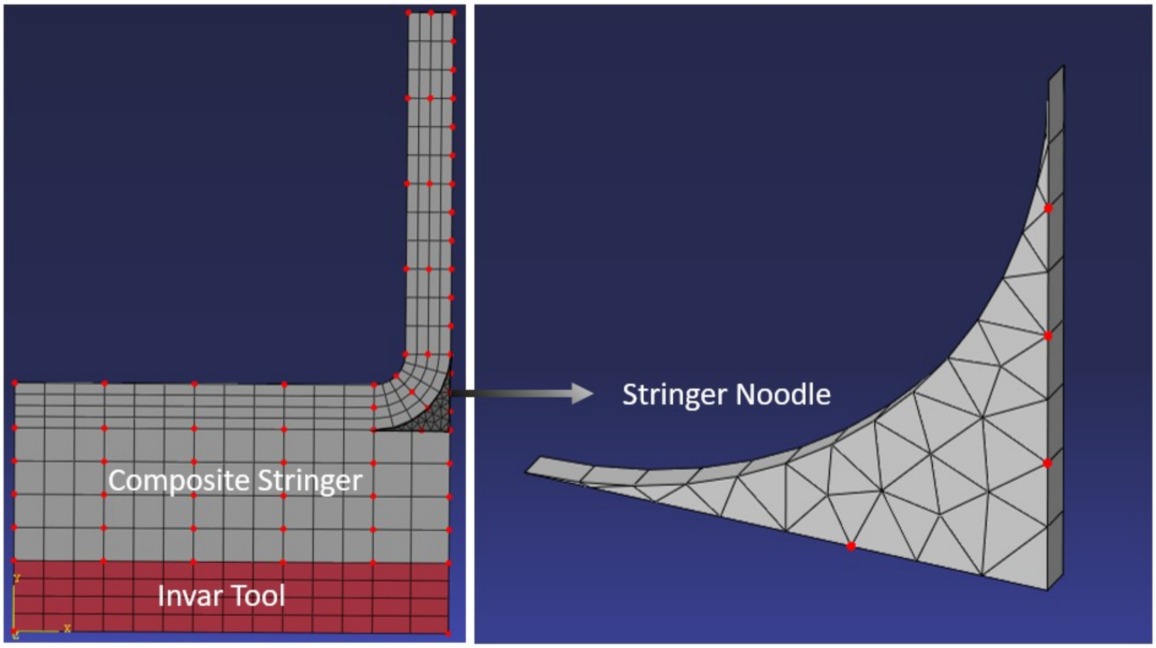

Figure 2 Finite element mesh of the co-cured blade stringer

A total of 275 elements were used to construct the above model and simulated to capture the thermal responses at the indicated prescribed nodes for each randomly generated input. Element size best practices were utilized to sufficiently capture the overall temperature distribution. The meshing pattern used for the 2-D assembly takes four DC3D8 (An 8-node linear heat transfer brick) elements through each part and tool thickness, six elements for the radius, fourteen elements across the width, and twelve elements across the web height. The noodle region of the stringer was independently meshed with eight DC3D6 (A six-node linear heat transfer wedge) elements along the edges and fifteen elements for the radius. This resulted in aspect ratios less than ten for the final model shown in Table 2.

Table 2 Mesh Properties

	Hex Elements (DC3D8)	Wedge Elements (DC3D6)
Quantity	232	43
Average Aspect Ratio	7.06	1.84
Highest Aspect Ratio	9.51	5.90

3. RESULTS

3.1 Comparison of 2D and 1D simulations

A preliminary detailed analysis of the temperature along the center of the web was performed for a 2-D case with a web height of 254 mm, and parameters similar to the values in Section 2.1. All of the nodal temperature histories along the center of the web were extracted and compared with the nodal temperature history at the middle of the web (127 mm from the top). This comparison showed that a large portion of the web (about 176mm) has a thermal response similar to the middle of the web with less than 1% difference. This indicates that away from the top of the web and noodle region, and close to the center of the web, the heat transfer through the thickness of the web becomes the dominant heat transfer mechanism. Consequently, the thermal response for a large portion of the web can be estimated with a simple 1-D analysis at the middle of the web. Based on this preliminary analysis, a constant web height of 76.20mm was selected for parametric study, where it is expected that the location about 19mm from the top of the web will behave similar to a 1-D condition.

3.2 2-D Simulation Results

More than 5000 2-D FE simulations were conducted by randomly varying input parameters as listed under and by automating simulations using python in ABAQUS. Each simulation run time was approximately four minutes on a typical computer workstation. From each simulation, temperature histories in 68 nodes were recorded surveying the entire assembly. Results were analyzed to determine the maximum exotherm temperature and its corresponding location in each simulation. Cases with exotherm values more than 70 ℃ were deemed as unrealistic scenarios and removed from further analysis. This reduced the total number of cases from 5000 to about 4000. An example of temperature distribution in a stringer during processing and the temperature histories of several nodes are shown in Figure 3.

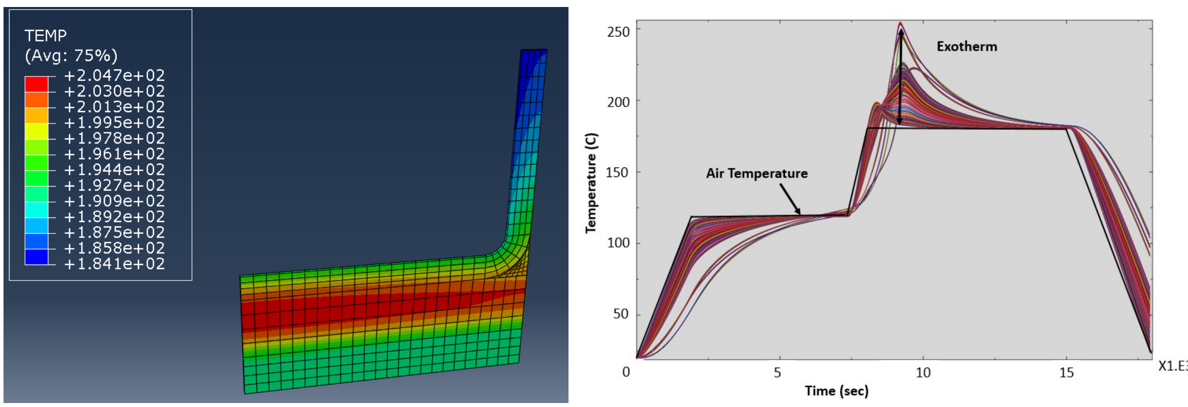

Figure 3 2-D Simulation results for a representative case and temperature histories of selected nodes.

Based on further analysis, the remaining cases were categorized into three different groups. In 870 cases, the thermal response of the leading location was within two degrees of a representative node at the flange edge to behave in a 1-D manner (i.e., dominant through-thickness heat transfer). Similarly, in 320 cases, the thermal response of the leading location was similar to the response of a node at the center of the web to behave in a 1-D manner. The remaining cases behaved as 2-D cases with non-negligible heat transfers in X and Y directions in the leading location. The classification summary is outlined in Table 3.

Table 3 Classification summary

Classification Type	2-D Simulation Quantity
Unrealistic Exotherm	1258
1-D Web	320
1-D Flange	870
2-D	2715
Total	5163

4. MACHINE LEARNING

A ML model was developed to determine if performing a conventional 2-D finite element analysis is required for a particular assembly, or 1-D simulations can be performed instead. CompML software was used to train classification Neural Networks for cases under Table 2. A feed-forward architecture was used consisting of three types of layers: an input layer with eight nodes similar to inputs of the FE model, five hidden layers with 32 nodes each, and an output layer with 3 nodes for classification. Figure 4 shows a simplified schematic of the NN architecture used for training. Hyper parameters for training are supplied in Table 4. The trained neural network was able to predict the classification to an accuracy of 81 percent. To increase confidence in the trained NN, the model prediction could be accepted if the accuracy is 90 percent or higher. If the accuracy of predictions is less than 90 percent, then a 2-D finite element analysis would have to be conducted. Potential limitations that inhibit increasing the accuracy of the trained model could be due to the under representation of the class distribution within the data. The model seeks to establish correlations between the eight input parameters and the classification label assigned. It is expected that with an increase in training data that includes more cases for the 1-D flange and 1-D web, a more accurate classification NN can be trained.

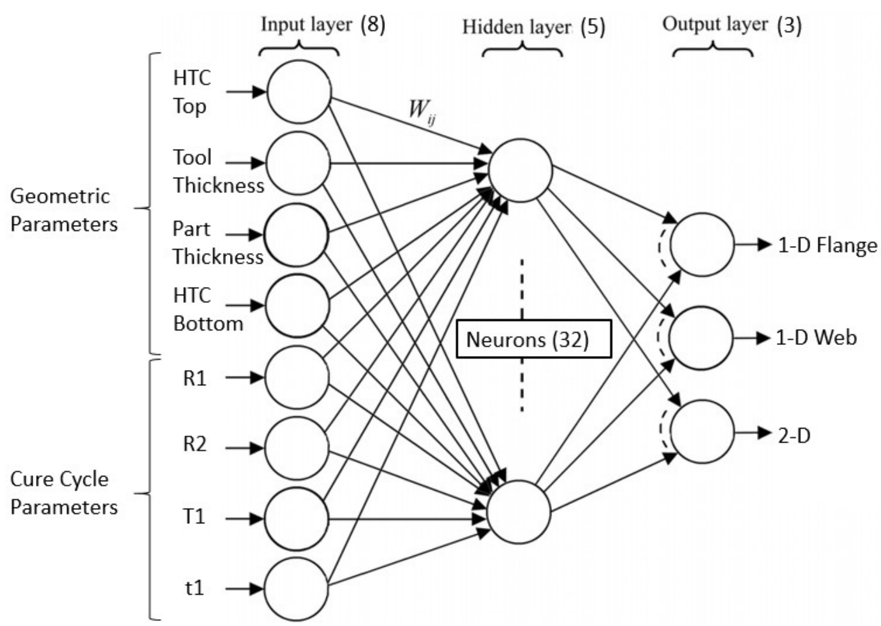

Figure 4 Artificial Neural Network (ANN) Schematic

Table 4 Neural Network Hyper Parameters

Parameter	Selection
Hidden Layers	5
Neurons/Nodes	32
Activation	tanh
Learning Rate	0.001
Regularization Weight	0.0002
Epoch	200
Batch Size	64

4.1 Inverse Thermal Stack

Further steps were taken to investigate the 2-D cases and determine an equivalent 1-D scenario for the leading location of each 2-D simulation. A CompML module (LSTM Inverse) was used to find equivalent 1-D cases by evaluating thermal responses over a range of parameters for part thickness, tool thickness, and top and bottom heat transfer coefficients. The program uses a trained recurrent NN with a long short-term memory (LSTM) architecture to predict thermal history as a function of thermal stack and air temperature profile [16]. The speed of the trained LSTM model is such that it can cover a wide range of potential 1-D cases quickly. For each 2-D case, maximum errors between temperature history of the leading location of a 2-D scenario and potential 1-D cases were determined using CompML. By minimizing the error below 2 ℃ across the entire temperature history, an equivalent 1-D case was determined. For example, consider the 2-D scenario in Figure 5 and Figure 6. For this case, using the thermal stack of the 2-D case to conduct 1-D simulation (identified as original 1-D case in Figure 6), a large mean error of 20.8 ℃ between thermal histories of 2-D and 1-D cases is observed. Figure 6 also indicates a very large exotherm deviation. The LSTM module in CompML was used to find the best-fit 1-D thermal response over a range of input parameters. The best-fit solution with a mean error of 0.8 ℃ is presented in Figure 5 and Figure 6 (identified as equivalent 1-D). The thermal history at the center of the part in 1-D case, is very similar to the thermal history of the leading location in 2-D case as shown in Figure 6. While the HTC at the top of 1-D case is similar to the 2-D case, the rest of the parameters including part and tool thicknesses vary. This validates the existence of an equivalent 1-D thermal stack for reduced-order modeling of the 2-D case.

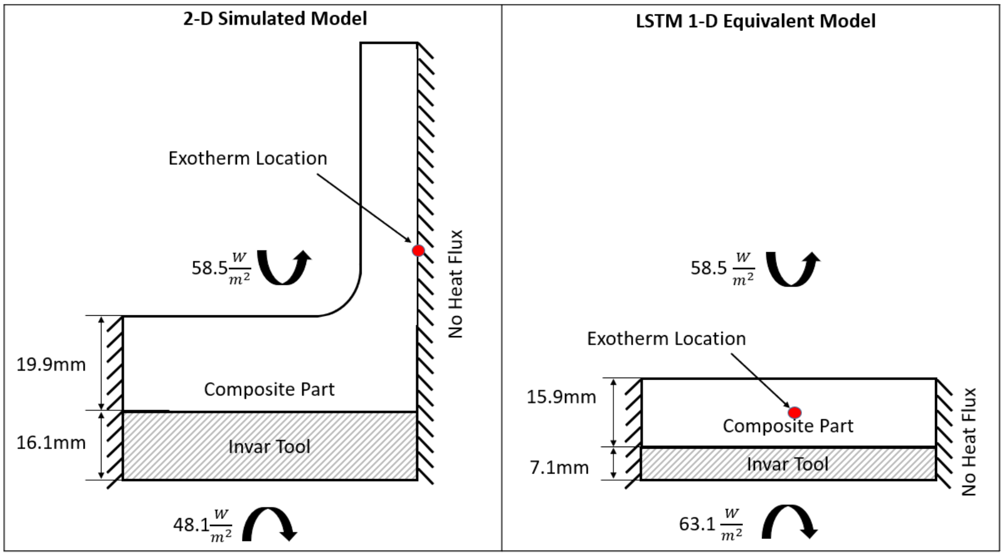

Figure 5 2-D Simulated Model and the best fit LSTM 1-D equivalent model

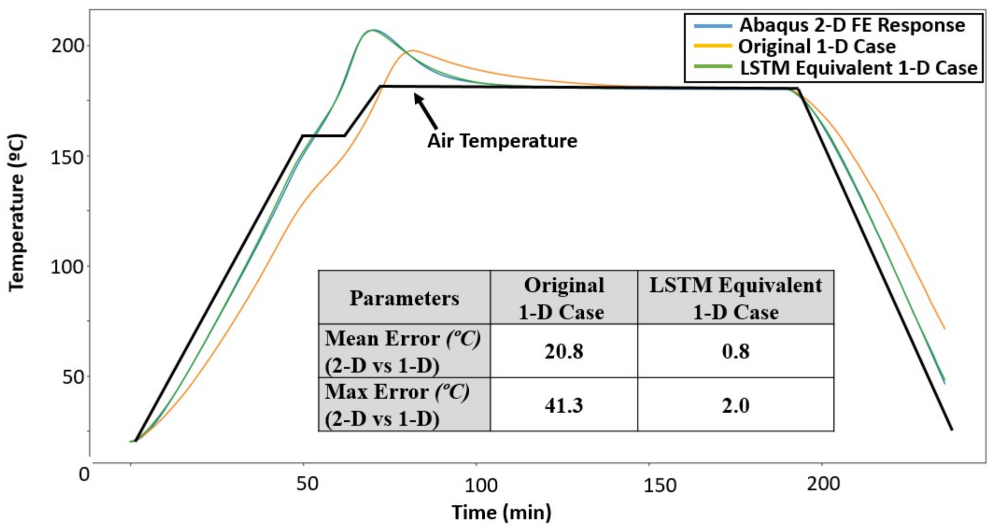

Figure 6 Error of 1-D case with original parameters and LSTM equivalent 1-D case

The remaining 2-D cases reported in Table 3 were analyzed using CompML to find equivalent 1-D cases. Out of 2715 2-D cases, CompML was able to identify equivalent 1-D cases for 728 cases with mean error less than 2 ℃. It was observed that for cases with part thickness larger than 30mm, no equivalent 1-D case could be determined. Figure 7 shows the distribution of error with respect to the part thickness of the assessed model. In addition, it was observed that in cases where composite part is heated with a fast-heating rate above 5ºC/min (R_1), it decreased the possibility of finding an equivalent 1-D solution. In summary, it can be concluded that for cases with thick parts or fast heating rates, an equivalent 1-D scenario most likely cannot be determined, and therefore conducting a 2-D simulation is required.

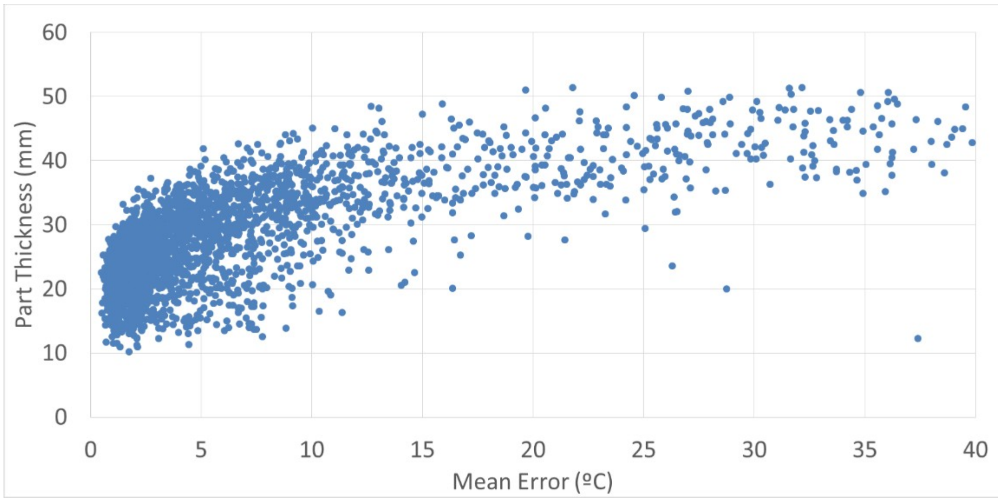

Figure 7 Mean error between all 2-D thermal histories and their best fit 1-D equivalent solutions

5. CONCLUSIONS

In this study, reduced order modeling of a composite co-cured stringer assembly on a wing panel was investigated. This was to identify equivalent 1-D cases for the 2-D geometry to speed-up process simulation. COMPRO software in ABAQUS was used to conduct 2-D thermo-chemical analysis of stringer geometry during processing. Results were used with a machine learning software, CompML, to identify equivalent 1-D cases. By automating simulations in ABAQUS, more than 5000 2-D cases were simulated by randomly varying FE input parameters. Analyzing the results, it was shown that in more than 1000 cases, leading locations behaved similar to the middle of the web or end of the flange where the response is close to 1-D heat transfer. A classifier NN was trained to identify these cases based on FE input parameters with an accuracy of 81%. By increasing the size of the training data using additional 2-D simulations, accuracy of the trained NN model can be further improved. For the remaining 2-D cases, a trained LSTM model in CompML was used to find equivalent 1-D cases. While it was shown that 1-D equivalent cases can be identified for about 700 2-D cases, many 2-D cases did not have an equivalent 1-D solution. It was shown that in many of these 2-D cases, either the part is quite thick or the part is heated too quickly. For these cases, conducting 2-D simulations is required to obtain an accurate thermal response of the material. The results of this research show that for certain 2-D process simulations, an equivalent 1D simulation can be defined to speed-up the analysis in a reduced-order modeling. This enables analyzing a wide range of design parameters for optimization. A similar ML-based approach as presented in this study can potentially be used for reduced-order modeling of 3D FE simulations and establishing 2D and/or 1D simulation equivalency. Such an approach, however, requires conducing many 3D FE simulations in advance to train accurate ML models.

6. ACKNOWLEDGEMENT

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