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MACHINE-LEARNING BASED CURING CYCLE OPTIMIZATION IN WIND BLADE MANUFACTURING

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ABSTRACT

The vacuum-assisted resin infusion mold (VARIM) process is widely used in wind blade manufacturing for its cost-effectiveness and reliability. However, the current method faces challenges such as long curing times and defects due to nonuniform heating across the blade structure. To address this, a multi-zone heated bed setup tailored to blade thickness has been considered. However, determining an optimal temperature for each zone poses a computational challenge, which can be tackled with a novel machine-learning approach. Using a digital twin based on a high-fidelity multiphysics solver, a time-distributed LSTM model was trained to understand complex resin curing dynamics. This eliminates the need for costly lab experiments, as the model learns heating patterns and curing behavior efficiently. Once trained, the ML model acts as a digital twin by predicting the degree of cure for a given temperature setpoint with 96.73% accuracy. This model, when used as a surrogate for a Nelder-mead optimization workflow, improves the curing time by roughly 12.5% and presents a more uniform curing rate throughout the part.

Keywords: Composite manufacturing, Machine learning (ML), Physics-informed surrogate model, long short-term memory (LSTM)

1. INTRODUCTION

Vacuum Assisted Resin Infusion Mold (VARIM) process is widely used for wind turbine blades manufacturing. In this process, the composite layups are placed on a heating table as the resin flows in and cures due to the heat from the table. Presently, the heating table has a single temperature setpoint that is set to the whole table and by extension, to the whole composite. The wind turbine blade is a complex composite containing parts of varying thickness and structural composition. This implies that the blade components heat and cure at uneven rates when heated at a fixed temperature. The curing differential can potentially lead to mechanical defects such as distortion, delamination, etc. Extensive results have been reported on the effect of thermal boundary conditions on the material properties of the resulting composite. Factors such as mold temperature [1], thermal stresses during curing, and chemical shrinkage [2], thermal oxidation [3], the difference in thermal expansion between fiber and resin [4] affects the material properties of the final product.

To address these challenges, it has been proposed that the heating devices be divided into separate zones and assigned individual set points based on the thickness and structural composition of the sandwich structure. However, determining the precise temperature of each zone requires numerous time-consuming experimental trials. High-fidelity simulations have proven themselves as a promising approach for predicting curing degrees [5,6] like practical experiments. Yet, the need to iterate through multiple permutations of temperature zone temperatures poses a practical limitation.

In recent years, Machine Learning (ML) models, particularly Long-Short Term Memory (LSTM) models, have garnered attention for their ability to capture complex underlying principles across various domains such as machine health [7], virus mobility and infection prediction [8], brain tumor [9], deformations in composites during curing [10], and proposed as digital twins [11,12], for smart manufacturing [13], active manufacturing control for composites [14], temperature, residual stress, and distortion modeling for composites [15]. LSTM ML stands for Long-Short Term Memory Machine Learning models, which is a special class of machine learning model that specializes in understanding time-series data. Compared to standard ML models, LSTM models store the underlying differences between individual elements of a time series data and hence it can understand the changes in temperature and curing of the resin as it evolves.

Building on these developments, this study proposes leveraging LSTM-based ML models as surrogate models to optimize temperature setpoints in wind turbine blade manufacturing. Using the quick predicting capability of ML while understanding the complex curing parameters, aiming to enhance efficiency, reduce costs, and improve the overall quality of wind turbine blades. This paper explores the feasibility and potential benefits of integrating LSTM-based ML models into the manufacturing process, paving the way for smarter and more efficient production practices in composite manufacturing processes.

2. METHODS

To address the challenges of experimentation and the computational cost of high-fidelity solvers, a Machine Learning model is used as a surrogate for the evaluation of the curing degree during the VARIM process. The dataset for the ML model was generated in a multiphysics solver called PAM-RTM. PAM Composites is a commercially available solver that can simulate the composite manufacturing process using Finite Element Modelling to create an approximate solution. The solver uses Darcy's equation for resin flow, the autocatalytic model for the kinetic curing, and thermal properties to model the heat flow. The modeled equations are popularly considered in the literature to be a reliable approximation of the experimental setup. The use of Finite element techniques creates an approximate solution to the problem statement and as the mesh is refined, the accuracy improves. However, computational models consider the general assumptions of continuum mechanics such as material homogeneity, isotropic material, absence of defects, etc. The following problem statement was considered:

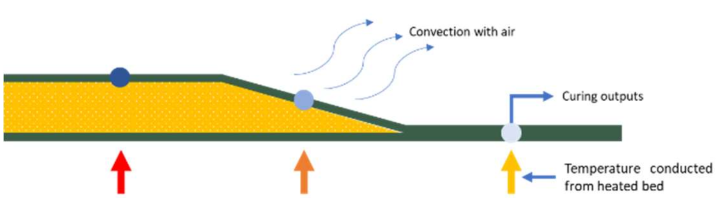


FIGURE 1: PROBLEM STATEMENT FOR DATASET GENERATION.

The team has access to a lab-scale composite manufacturing setup used to fabricate glass fiber sandwich composites which is used for understanding and characterizing the process parameters. The composite layup considered consists of 3 plies (~2mm) of glass fiber reinforced composites infused with Airstone 760E Epoxy Resin sandwiching a 0.5-inch H60 foam core. The foam core is given a tapered section in the center hence creating three distinct zones for multizone heating. The model is acted upon by a temperature boundary condition on the bottom surface that is in direct contact with the heating bed along with a convection boundary condition on all the top surfaces exposed to air. A convection coefficient of 25 W/m^2-K while the temperature setpoint of the heating bed is varied parametrically.

The experimental procedure usually involves the use of vacuum bags, peel plies, and flow media to ensure a uniform flow of resin as well as a clean removal of the sample from the heating bed. These parts are, however, in the order of 0.1-0.2 mm thickness and hence do not produce a significant effect in the thermal conduction or curing of the sample. Hence, the effects of the vacuum bag and peel plies are ignored for the sake of simplicity. The temperature value on the bottom surface is parameterized and permutations of temperature values range from 60ºC to 80ºC. The values were chosen since these are the common range for lab-scale composite experiments and are the effective range of the setup to which the team has access. The convection reference temperature is set to 25ºC as the ambient temperature and a coefficient of 15 W/m-K. The resin is modeled as an autocatalytic kinetic-cure model and the thermal characteristics were acquired using a Light Flash Apparatus (LFA) 467 HyperFlash. The Light Flash Apparatus uses a laser to heat a given specimen and analyzes the heat in the specimen to calibrate the thermal properties of the material such as thermal conductivity, emissivity, specific heat, etc.

To swiftly generate curing curves in response to given temperature profiles, a digital twin employing an LSTM-NN architecture was created. A summary of the model's architecture is shown in Figure 2.

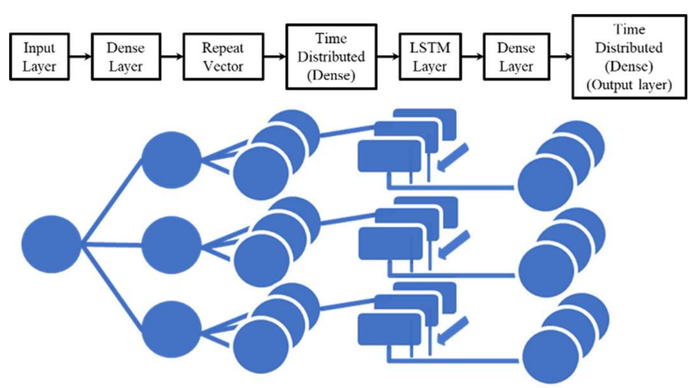


FIGURE 2: LSTM-BASED ML MODEL ARCHITECTURE.

The model was trained for ~6,000 epochs with 'Reduce LR On Plateau' and 'Early Stopping' as callbacks. Once trained, the model shows a mean average error of 3.26% and a maximum error of 16.6%. An example of the ML model predictions compared to the Multiphysics solver is shown below.

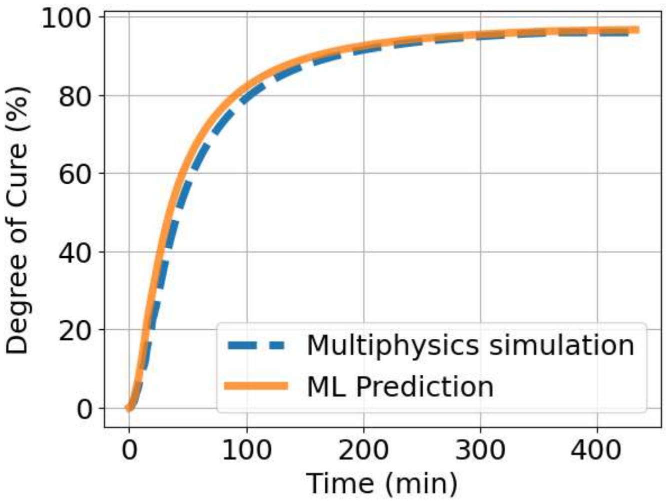


FIGURE 3: EXAMPLE PREDICTIONS OF THE ML MODEL VS MULTIPHYSICS SIMULATIONS.

To evaluate the appropriate temperature setpoint for each zone, it is intended to minimize the curing rate difference between the zones as well as the overall curing time. Hence, an optimization algorithm is required. Generally, efficient optimization algorithms require the computation of the gradients of the objective function. The curing phenomenon is, however, a complex phenomenon that requires a multiphysics solver, and the implementation of a machine learning model turns the objective function into a black box function. Therefore, a derivative-free method called the Nelder-Mead algorithm is used which uses the concept of simplex to approximate the local optimum of a problem for non-linear optimization problems heuristically.

An objective function that quantifies the combined effects of curing rate difference and curing time is defined. This function serves as the metric for evaluating the performance of different temperature configurations. Initially, temperature setpoints for each zone (A, B, and C) were randomly assigned within feasible ranges. The objective function is evaluated using the LTSM-based surrogate model. The algorithm iteratively adjusts the temperature setpoints based on the objective function evaluations. At each iteration, the algorithm updates the temperature configurations to minimize the objective function.

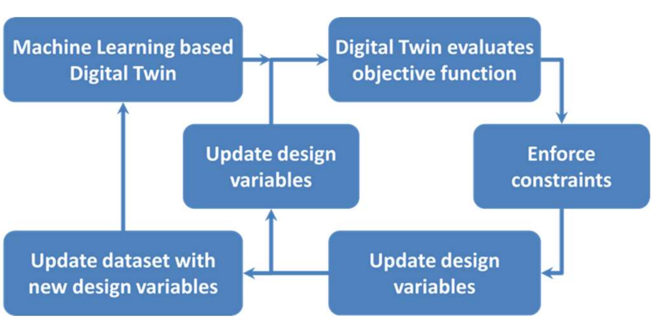
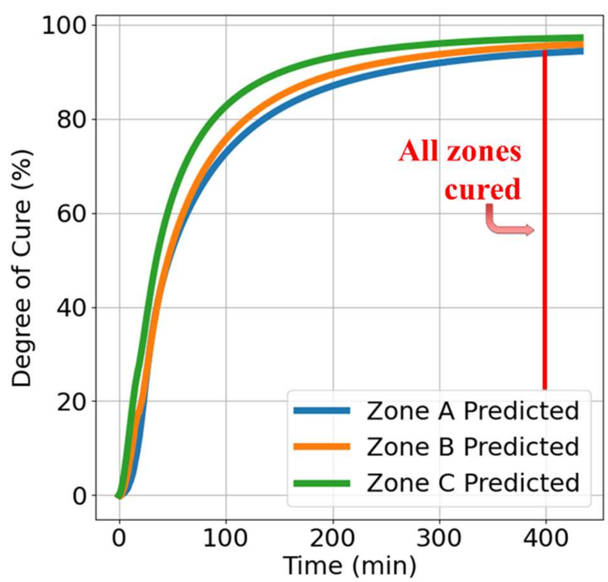


FIGURE 4: OVERVIEW OF THE WORKFLOW.

By utilizing this workflow, the model can efficiently explore the temperature space, identify optimal temperature configurations, and achieve the desired balance between curing rate uniformity and time efficiency.

3. RESULTS AND DISCUSSION

The workflow presented iterates till the curing time is minimal and the difference between the curing rates from zones 1,2, and 3 are as similar to each other as possible. The results of the optimization were 70.35ºC, 69.61ºC, and 63.36ºC for the three respective zones. When these values were provided as inputs into the multiphysics solver, the curing rates were evaluated and plotted as shown in Figure 5 along with the predictions by the ML model for the same value. Figure 6 shows the curing rates of the three zones together.



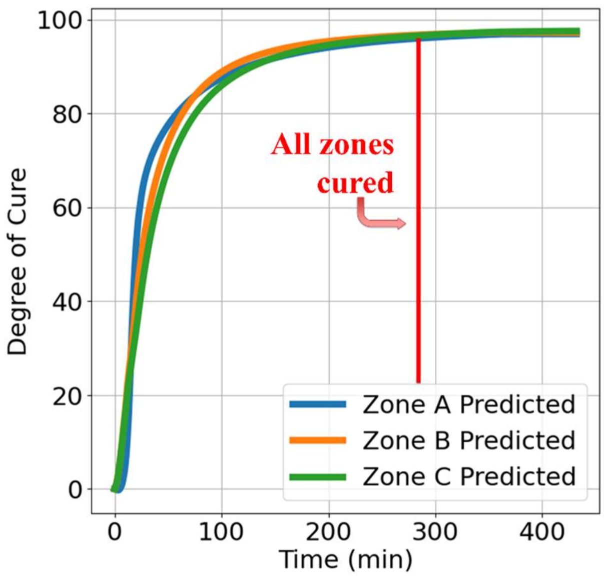


FIGURE 5: PREDICTED CURING RATES PLOTTED TOGETHER TO SHOW THE CURING CURVES OF THE THREE ZONES AT 60º C EACH (ABOVE) AND AT THE OPTIMIZED VALUES OF 70.35ºC, 69.61ºC, and 63.36ºC (BELOW) AND THE CURING TIME IMPROVING.

The results show good agreement of the ML model compared to the multiphysics solver and the curing rates of the three zones overlap greatly at all time instances proving that the curing rates over the part are uniform.

4. CONCLUSION

This study validates the effectiveness of LSTM-based models in understanding the intricate time series dynamics of resin curing. It also demonstrates the feasibility of employing ML models as surrogate models within optimization algorithms. Specifically, the model's success in optimizing curing cycle times for composites with varying thicknesses, such as wind turbine blades was shown. While the study is a proof of concept for a lab-scale sample, the algorithm can also scale up to large wind turbine blades. Machine learning models, once trained, can make predictions instantaneously. Using the ML model as a digital twin enables this method because multi-physics simulations' computational time and permutations of temperature setpoints increase drastically. Hence, the ML based optimization algorithm is scalable and reproducible.

These findings signify a significant step forward in enhancing efficiency and performance in composite manufacturing processes.

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REFERENCES

[1] Kedari, V. R., Farah, B. I., and Hsiao, K.-T., 2011, "Effects of Vacuum Pressure, Inlet Pressure, and Mold Temperature on the Void Content, Volume Fraction of Polyester/e-Glass Fiber Composites Manufactured with VARTM Process," J. Compos. Mater., **45**(26), pp. 2727–2742.

[2] Wisnom, M. R., Gigliotti, M., Ersoy, N., Campbell, M., and Potter, K. D., 2006, "Mechanisms Generating Residual Stresses and Distortion during Manufacture of Polymer–Matrix Composite Structures," Compos. Part Appl. Sci. Manuf., **37**(4), pp. 522–529.

[3] Upadhyaya, P., Roy, S., Haque, M. H., and Lu, H., 2013, "A Novel Numerical–Experimental Approach for Predicting Delamination in High Temperature Polymer Matrix Composites," Compos. Struct., **104**, pp. 118–124.

[4] Fu, Y., and Yao, X., 2022, "A Review on Manufacturing Defects and Their Detection of Fiber Reinforced Resin Matrix Composites," Compos. Part C Open Access, **8**, p. 100276.

[5] Shojaei, A., Ghaffarian, S. R., and Karimian, S. M. H., 2003, "Modeling and Simulation Approaches in the Resin Transfer Molding Process: A Review," Polym. Compos., **24**(4), pp. 525–544.

[6] Ma, L., Athreya, S. R., Mehta, R., Barpanda, D., and Shafi, A., 2017, "Numerical Modeling and Experimental Validation of Nonisothermal Resin Infusion and Cure Processes in Large Composites," J. Reinf. Plast. Compos., **36**(10), pp. 780–794.

[7] Qiao, H., Wang, T., Wang, P., Qiao, S., and Zhang, L., 2018, "A Time-Distributed Spatiotemporal Feature Learning Method for Machine Health Monitoring with Multi-Sensor Time Series," Sensors, **18**(9), p. 2932.

[8] Muñoz-Organero, M., 2022, "Space-Distributed Traffic-Enhanced LSTM-Based Machine Learning Model for COVID-19 Incidence Forecasting," Comput. Intell. Neurosci., **2022**, pp. 1–12.

[9] Montaha, S., Azam, S., Rafid, A. K. M. R. H., Hasan, Md. Z., Karim, A., and Islam, A., 2022, "TimeDistributed-CNN-

LSTM: A Hybrid Approach Combining CNN and LSTM to Classify Brain Tumor on 3D MRI Scans Performing Ablation Study," IEEE Access, **10**, pp. 60039–60059.

[10] Feng, Y., Han, Z., Liu, M., Zheng, W., Liang, B., Xiong, Y., and Zhang, W., 2024, "Rapid Prediction for Deflection History of CFRP Beams during Curing Using LSTM Network and Its Application to Stacking Sequence Optimization with Genetic Algorithm," Compos. Part Appl. Sci. Manuf., **182**, p. 108195.

[11] Zhang, R., Liu, Y., Zheng, T., Eddin, S., Nolet, S., Liang, Y.-L., Rezazadeh, S., Wilson, J., Lu, H., and Qian, D., 2024, "A Fast Spatio-Temporal Temperature Predictor for Vacuum Assisted Resin Infusion Molding Process Based on Deep Machine Learning Modeling," J. Intell. Manuf., **35**(4), pp. 1737–1764.

[12] Tao, F., Qi, Q., Liu, A., and Kusiak, A., 2018, "Data-Driven Smart Manufacturing," J. Manuf. Syst., **48**, pp. 157–169.

[13] Kusiak, A., 2018, "Smart Manufacturing," Int. J. Prod. Res., **56**(1–2), pp. 508–517.

[14] Humfeld, K. D., Gu, D., Butler, G. A., Nelson, K., and Zobeiry, N., 2021, "A Machine Learning Framework for Real-Time Inverse Modeling and Multi-Objective Process Optimization of Composites for Active Manufacturing Control," Compos. Part B Eng., **223**, p. 109150.

[15] Xu, Y., Zhao, Z., Shrestha, K., Seneviratne, W., Liyanage, S., Palliyaguru, U., Karuppiah, A., Lua, J., Phan, N., and Yan, J., 2024, "A Coupled Data-Physics Computational Framework for Temperature, Residual Stress, and Distortion Modeling in Autoclave Process of Composite Materials," Compos. Part Appl. Sci. Manuf., **183**, p. 108218.