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EXPERIMENTAL DETERMINATION OF COMPLEX HEAT TRANSFER COEFFICIENT PATTERNS USING STATISTICAL INFERENCE

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ABSTRACT

Development of thermal management and physics-based process simulation of composites has been well-established in recent years. However, the heat-transfer coefficients (HTCs) at the air-part and air-tool interfaces during autoclave curing, remain a challenge and a major source of uncertainties. Calculation of HTC using physics-based simulations has often been developed based on simplified 1D models or costly 3D simulation tools such as Computational Fluid Dynamics. However, these methods fail to capture the effect of uncertainties in estimating these HTC values on the corresponding thermal histories of curing parts. The applicability of statistical inference-based models to calculate HTC distributions and associated uncertainties have been previously explored using synthetic datasets generated from finite element simulations. In this study, the resulting validated model has been used on available experimental datasets to determine the most probable HTC distributions with an estimate of associated uncertainties. The HTC estimates obtained for two tools with different substructures were compared to understand the effect of the interaction of tooling substructure and airflow on the effective HTCs.

1 INTRODUCTION

Fiber-reinforced composite polymers have become integral in various industries, spanning aerospace to recreational technology. The manufacturing of thermoset polymer matrix composites often employs autoclave-based curing processes, wherein meticulously laid-up prepreg materials undergo thermal transformation. This transformation, crucial for developing the mechanical properties of the composite, is conducted under precisely controlled temperature and pressure conditions. Among the pivotal factors influencing this transformation, heat transfer coefficients (HTCs) take center stage, emerging as critical parameters that demand precise determination for confident and reliable process design workflows. Physics-based process simulation models have been shown to be valuable in quickly and efficiently reducing the uncertainties in design practices without the need for repetitive experimental runs thus leading to reduced material, labor, and time costs [1][2][3][4]. Particularly as the size and intricacy of components escalate, the need for robust process modeling frameworks becomes more pronounced. In such process simulation frameworks, the HTCs assume a paramount role as essential boundary condition inputs to model the heat transfer phenomenon at the fluid-solid interface. Thus, an accurate knowledge of HTCs is indispensable, as it not only facilitates enhanced process simulations but also enhances the design and optimization of cure cycles, which ensures the production of composite parts with the desired mechanical properties. The significance of confidently ascertaining HTCs is therefore underscored, forming the cornerstone for the development of advanced thermal management strategies in composite manufacturing. However, the measurement of HTCs has been associated with several complexities. In a composites manufacturing setup, different deterministic methods have been used historically to calculate HTCs ranging from lumped mass calculations, which are simplified 1D analyses, to using computationally expensive Computational Fluid Dynamics (CFD) for simulating the airflows and associated HTC fields in a 3D model [5][6][7]. However, these are insufficient to capture the uncertainties associated with the estimation of HTCs and their corresponding impact on thermal predictions. Hence, a statistical inference model based on Bayesian inference has been employed in this work to estimate the HTCs along with associated uncertainties in these parameters which can be used to understand the consequent effect on thermal history predictions in process simulation models.

2 METHODS

2.1 Experiments

2.1.1 Tooling

The tools used in this work were made from structural steel and had different substructures as shown in Figure 1. For both the tools, the top skin had dimensions of 30cm x 45cm and the substructure had a height of 30cm. The thickness of the top skin was 12.7mm and the substructure had a thickness of 9.5mm. The closed substructure tool weighed 35.2kg whereas the open substructure tool weighed 30.4kg.

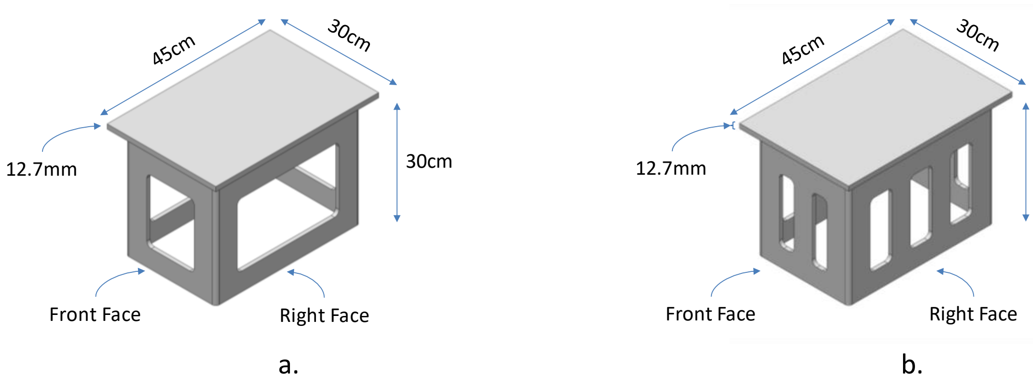


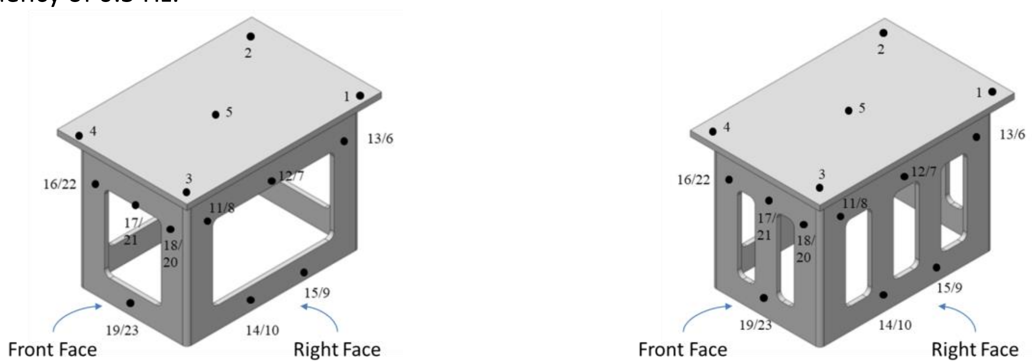
Figure 1. Schematic of the (a) open and (b) closed substructure steel tools used in this work

Table 1. Material Properties of Steel Tools

Property	Value
Density (ρ)	7859 kg/m^3
Specific Heat Capacity (C_p)	465 J/kg/K
Thermal Conductivity (k)	52 W/m/K
Thermal Diffusivity (α)	1.4x10^{-5} m^2/s

2.1.2 Measurement

To measure the thermal performance of the tools, 28 thermocouples (TCs) were placed at different locations on the surface of each of the tools. The locations of TCs numbered 1 till 23 are as shown in Figure 2. TCs 24 till 28 were inside of the substructure. The locations of all the TCs are as mentioned in Table 2. Another TC was taped to the side face of the top skin with its tip 2 inches away from the tool to measure the air temperature. All the TCs were connected to a National Instruments' data acquisition (DAQ) module, which was set up to read and write values at a frequency of 0.5 Hz.



a. b.

Figure 2. Thermocouple locations on the open mould (a) and closed mould (b) tools. At any location x/y denotes TC_x is located on the visible face and TC_y is located on the opposite face not visible on the images

Table 2. Thermocouple locations on the tool

TC#	Location	TC#	Location	TC#	Location	TC#	Location
1	Top Skin	8	Left Face	15	Right Face	22	Back Face
2	Top Skin	9	Left Face	16	Front Face	23	Back Face
3	Top Skin	10	Left Face	17	Front Face	24	Underneath TC5
4	Top Skin	11	Right Face	18	Front Face	25	Inner surface where TC12 is
5	Top Skin	12	Right Face	19	Front Face	26	Inner surface where TC7 is
6	Left Face	13	Right Face	20	Back Face	27	Inner surface where TC17 is
7	Left Face	14	Right Face	21	Back Face	28	Inner surface where TC21 is

2.1.3 Equipment

There were two main equipment used in this experiment – a Thermotron oven and an in-house constructed wind tunnel. The wind tunnel was constructed using wooden frames, heavy duty tarp and a large drum fan. The wind tunnel consisted of three sections – A) a settling chamber of length 0.9m for the airflow to become uniform, B) the test section of length 1m where the tool was placed during the experiment, and C) the exhaust chamber of length 1.8m from where the air leaves the wind tunnel as shown in Figure 3a. The tool was placed on a platform to load it into the wind tunnel as shown in Figure 3b. The mount was constructed such that it could be rotated and tilted as well as raised or lowered to capture different airflow scenarios.

a. b.

Figure 3. (a) Image of the wind tunnel (b) Open tool mounted on platform

2.1.4 Process

The oven was switched on and its set point was set at 130°C. Once the oven reached the required temperature, the tool was placed in the oven until all the functioning thermocouples were in the range of 128-130°C. Next, the tool was removed from the oven and quickly placed in the wind tunnel with the fan running. The tool was then allowed to cool down to ambient temperature and the temperatures were recorded at all the TC locations. The process was repeated for both the open and closed mould tools for different airflow conditions by varying the rotation from 0° to 45° to 90° and the tilt from 0° to 15°. Thus, a total of 6 different orientations for each tool was possible. In this work, the notation RθTϕ has been used to denote the airflow condition when the tool was at a rotation θ degrees and tilt ϕ degrees. The 0° rotation corresponds to the front face of the tool being the windward side while the 90° rotation corresponds to the right face of the tool as the windward side.

2.2 Analysis

2.2.1 Bayesian Inference

Stochastic methods like Bayesian inference have been used in recent times to estimate parameters like HTCs in a variety of thermal management analyses [8][9][10]. Based on Bayes theorem as given by Equation 1,

$$p(\theta|T_E) = \frac{p(T_E|\theta)p(\theta)}{p(T_E)} \tag{1}$$

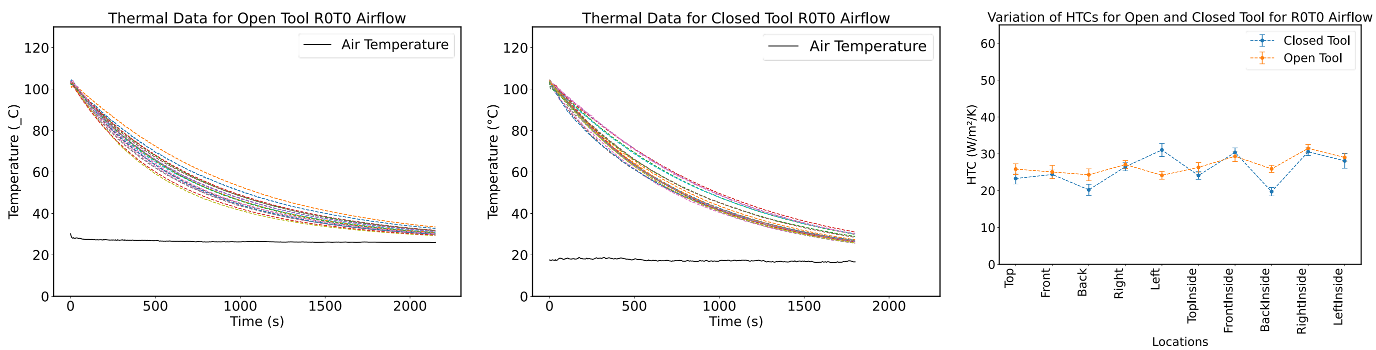
Where, θ represents the unknown parameters, in this case HTCs and local air temperatures, $p(\theta)$ denotes the prior probability density function for the parameters, T_E denotes the experimentally measured temperature, $p(T_E)$ is a proportionality constant such that $\int p(\theta|T_E)d\theta = 1$. $p(T_E|\theta)$ is hence the likelihood which describes how well the observed data can be explained for a given value of the parameters θ. Estimating the terms on the right-hand side of the equation, the posterior probability distribution of the parameters θ can be calculated as $p(\theta|T_E)$. Assuming the likelihood function to be a Gaussian distribution, and using Laplace approximation, the posterior probability distribution can be expressed as[10],

$$p(\theta|T_E) \approx \mathcal{N}(\theta; \theta_0, -H^{-1}|_{\theta=\theta_0}) \tag{2}$$

Where, θ_0 is the mode of the posterior probability density and H is the Hessian matrix. The covariance matrix of the parameters can be calculated by taking the negative of the inverse of the Hessian matrix as obtained in Equation 2.

3 RESULTS

The HTCs estimated at different faces of the tools for the R0T0 airflow condition along with the associated uncertainties has been shown in Figure 4. For the closed tool, the HTCs varied between 20 W/m^2K to 31 W/m^2K with a maximum uncertainty of 2 W/m^2K. For the open tool, the HTCs varied between 24 W/m^2K to 31 W/m^2K with a maximum uncertainty of 1.8 W/m^2K.



a. b. c.

Figure 4. (a)Thermal data for open tool (b) Thermal data for closed tool (c) Estimation of HTCs along with associated uncertainty for open and closed tool, for R0T0 airflow

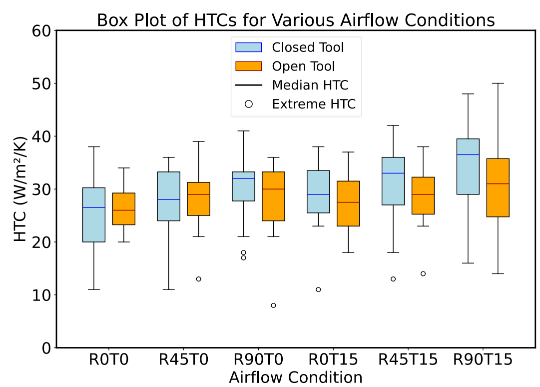


Figure 5. Box plot showing HTCs for both the tools for different airflow conditions

The distribution of HTCs for both the open and closed tool obtained for different airflow orientations are shown in Figure 5. Comparing across airflow conditions, the closed tool shows higher median HTCs for the 15° tilt cases compared to the 0° tilt cases. The open tool, however, does not show much variation for the two tilt cases. For a certain tilt, changing the rotation from 0° to 45° to 90°, shows an increase in the median HTCs for the closed tool whereas the open tool did not show significant variation for the same comparison. Across all airflow conditions, the HTCs were observed to vary between 9 W/m^2K to 50 W/m^2K. The median values for the HTCs ranged between 26 W/m^2K to 36 W/m^2K for the closed tool and 26 W/m^2K to 31 W/m^2K for the open tool.

4 CONCLUSION

Bayesian inference based stochastic methods are very useful in estimating the HTCs as well as the associated uncertainties from experimental data generated in a controlled airflow environment, as demonstrated in this work. The HTCs inferred for a range of airflow conditions for both an open and closed substructure tool were observed to be in the typical range of HTCs expected in force convection conditions. Thus, using this method for estimating HTCs in an autoclave-based curing process can be very useful in understanding the uncertainties associated with manufacturing processes, which in turn can be used to improve current process simulation models.

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