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# TITLE: Evaluation of different Machine Learning techniques for modelling of Resin Transfer Moulding process

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## ABSTRACT:

In Resin Transfer Moulding (RTM) processes, a dry fibrous reinforcement is placed in a rigid mould and impregnated with liquid viscous resin. Quality of the resin injection, i.e. absence of large dry spots or large number of smaller air entrapments, is directly linked to the mechanical performance of the final product. Often, suitable design of the RTM process can be achieved by performing a small number of predictive numerical simulations. However, in cases where material or process variability are more prominent, the process design may require a significant number of simulations.

A typical numerical simulation of the RTM process would rely on a solver that employs either a Control Volume Finite Element Method (LIMS, PAM-RTM and other specialised solvers [1]) or Volume of Fluid method (OpenFOAM, Ansys Fluent and other general-purpose solvers). Running these simulations would typically take between 10 s and 30 s for simple 2D problems, and several hours for complex 3D problems with heterogeneous permeabilities, which makes the numerical design of the process prohibitively expensive and time-consuming.

Machine Learning (ML) techniques have been recently used to construct surrogate models, for which the simulation time is below 1 s. Such surrogate models enable multiple evaluations not only for fast design of the RTM process, but also for real-time defect detection and process control. However, the existing range of ML-based surrogate models makes it difficult to select the most appropriate model for a particular application.

Various ML-based surrogate models have been tested on different mould geometries and different process conditions, making it difficult to compare them between each other. Multilayer Perceptron (MLP) models have been used since 2004 [2] and have been shown to perform well in predicting resin flow in rectangular 2D domains, but the output from such models is often limited to discrete values e.g. final fill time or pressure at pre-defined locations of pressure sensors at discrete time steps [3]. In contrast, Convolutional Neural Network (CNN) models predict continuous (or near continuous) flow front and pressure distributions, which gives more flexibility in how the data can be used [4].

This work compares two ML-based surrogate models, MLP and CNN, in their ability to predict resin flow in a rectangular geometry with heterogenous permeability and race-tracking channels. The approaches will be compared in terms of their accuracy on a validation set, inference time, and amount of training data required to produce the model. In addition, both surrogate models will be also used for detecting variability and race-tracking in real experiments. The laboratory experiments used in this study consist of a square RTM mould with transparent top and 21 pressure sensors. Experiments with different fibre preforms and deliberately introduced race-tracking were conducted (Figure 1).

As mentioned above, the CNN-based model is capable of predicting flow front position at any given time. A comparison between experiment and the model is shown in Figure 2. It can be seen that the model captures most of the flow front features. Figure 3 shows the comparison between the local permeability predicted using MLP-based and CNN-based models. Both models predict the presence of local inclusion and subsequent change in the permeability.

Further quantitative analysis will be conducted to evaluate the models' performance and their robustness. The models will be evaluated in the context of process analysis and process control. Strengths and limitations of different approaches will be discussed.

## References

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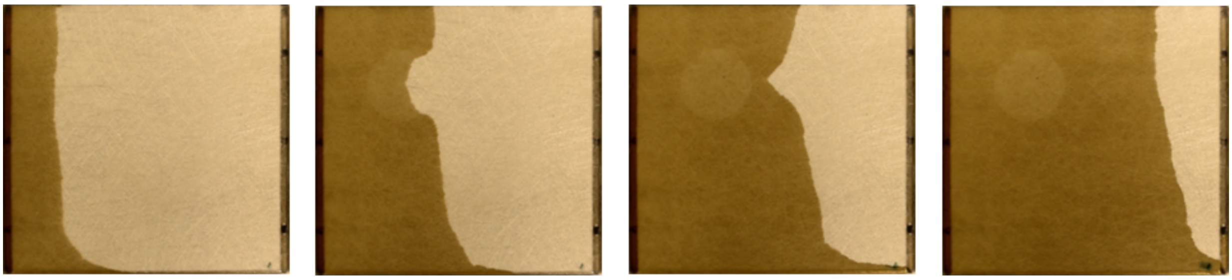

Figure 1. Example of flow front progression in an experiment with a race-tracking and a local inclusion [3]

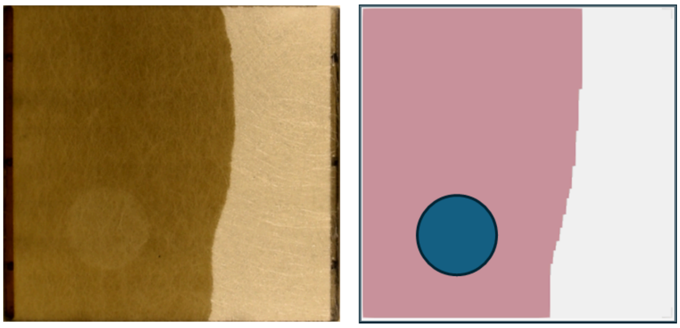

Figure 2. Snapshot of the flow front progression in a laboratory experiment (left); flow front position predicted using a surrogate model (right).

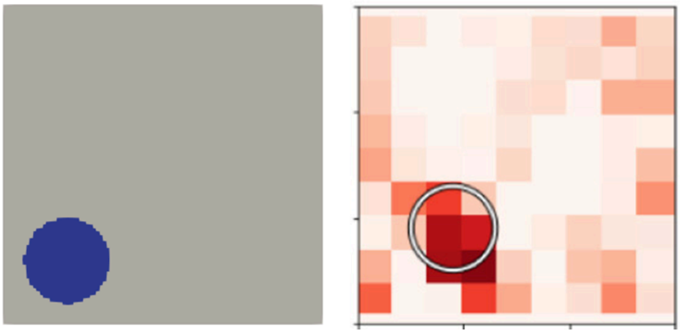

Figure 3. Local permeability as predicted by CNN-based (left) and MLP-based (right) models [3].