

TITLE: Development of High Dimension Gaussian Surrogate Models of Resin Infusion Process

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ABSTRACT:

Interest in the use of Resin Infusion based manufacturing methods in the Aerospace, Automotive, Wind, and other industries has been expanding, and is expected to keep growing for the foreseeable future. Sustainability pushes to reduce weight and economic pressures to reduce maintenance requirements requires the use of more and more high-quality composite materials. These are also being incorporated into larger parts and in quantities higher than previously possible. Conventional Prepreg based methods have historically been used for their ability to produce consistent high-quality parts. However, high material and storage costs, as well as bottlenecked production rates due to the requirement for expensive and slow autoclave consolidation cycles, are limiting this expansion [1].

Resin Infusion methods are seen as a potential solution, offering lower material costs, out-of-autoclave processing, and can allow for more complex geometries. Unfortunately, as many organisations such as the NCC, GKN, and Airbus have found out in testing programs like ASCENT and the Wing of Tomorrow, Resin Infusion methods are unpredictable, especially at larger part sizes and production rates. Fabric shearing during deposition, misplaced preform gaps, variation in resin viscosity, atmospheric temperature and pressure changes, and inaccurate inlet openings can all perturb resin flow, resulting in dry spots and resin rich areas requiring inspection and potentially part rejection [2]. These issues can theoretically be mitigated through Robust Process Design and Optimisation. However, accounting for all these variabilities is impractical and would require an exhaustive physical testing campaign. Digital simulation as an alternative, while attractive, suffers similar problems. Accurate Resin Infusion Simulations are computationally expensive, and running the number of iterations required for a full robust optimisation for full scale parts would require an almost impossible computational resource [3].

To circumvent this problem, Surrogate simulation models have proven of significant interest as once trained these would have a query time orders of magnitude lower than conventional simulations. The main issue holding back the use of these surrogates is the necessary size of training simulation training data required to ensure accuracy, with many conventional methods such as Convolutional Neural Networks requiring impractically large numbers of training samples potentially numbering into the thousands [4]. As a result, solving this training problem is key to improve the reliability of complex, high-rate manufacturing through resin infusion.

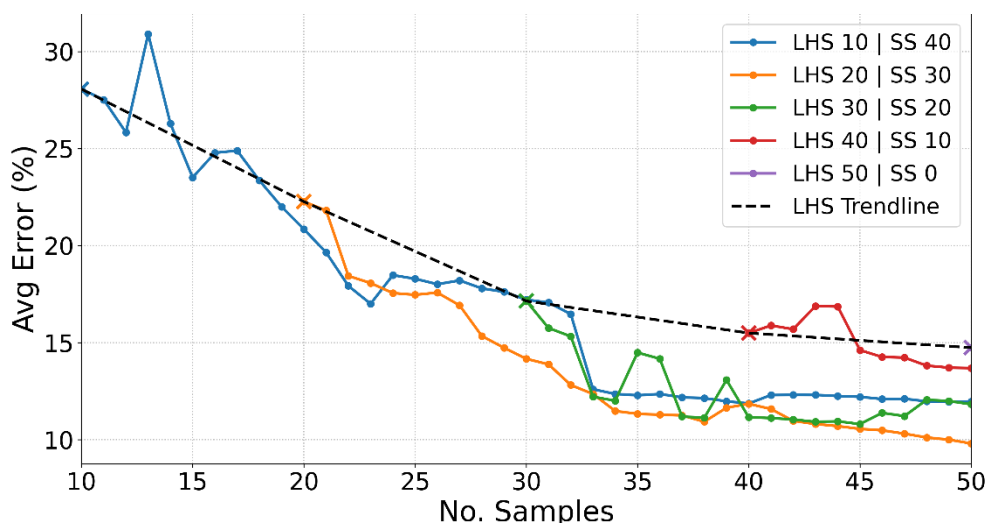


Figure 1: Avg Error for different numbers of total samples for a 3D Gaussian Model for Resin Infusion with varying Latin Hypercube initial training seed before Smart Sampling to total number

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This work develops Gaussian Machine Learning models which offer potential opportunities to improve this. Gaussian models behave differently to conventional Machine Learning algorithms and output both a mean predicted value, and an uncertainty metric. Using these models, previous work at the Bristol Composites Institute investigating forming simulations has shown that the implementation of advanced techniques such as Dimension Reduction and Sequential Design in combination with Gaussian Modelling techniques has shown that an accurate surrogate model can be made with very few simulation samples with which optimisations can then be conducted [5,6,7,8].

This work has built upon this to adapt these techniques to the field of resin infusion simulation. Elements such as Smart Sampling have shown to be powerful tools for improving accuracy and reducing the required number of samples, with an example of this shown in Figure 1. Alongside this, a key development has been the incorporation of local input dimensions such as shearing-induced-permeability changes, inlet-inlet pressure variation, and local racetracks. These variables are introduced in a generic fashion, allowing much greater flexibility than previously prescribed settings. This has required developing new methods of calculating input variables and the introduction of Time stepping which unlocks new opportunities for the use of these surrogates for more advanced active control algorithms. The models are then expanded into 3D coordinate space and resin flow to allow for thick and varying-thickness problems to be run. An early, very low training data example output of this 3D space, 8D input time stepping model is shown below in Figure 2. Several different solver iterations are shown for different applications with their capability, accuracy, runtime, and required sample sizes compared.

3D Scatter Plot with Color Dimension Pressures for time 48.529508

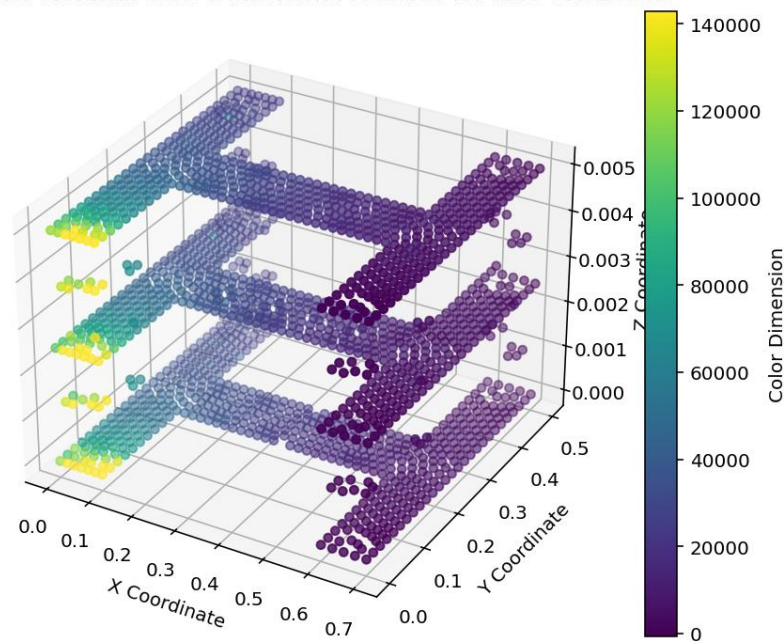


Figure 2: A Early Output of Low Sample Data Pressure Prediction for 3D space with a 8D Input Time Stepping Model

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