Intelligent Composites Forming - Simulations For Faster, Higher Quality Manufacture

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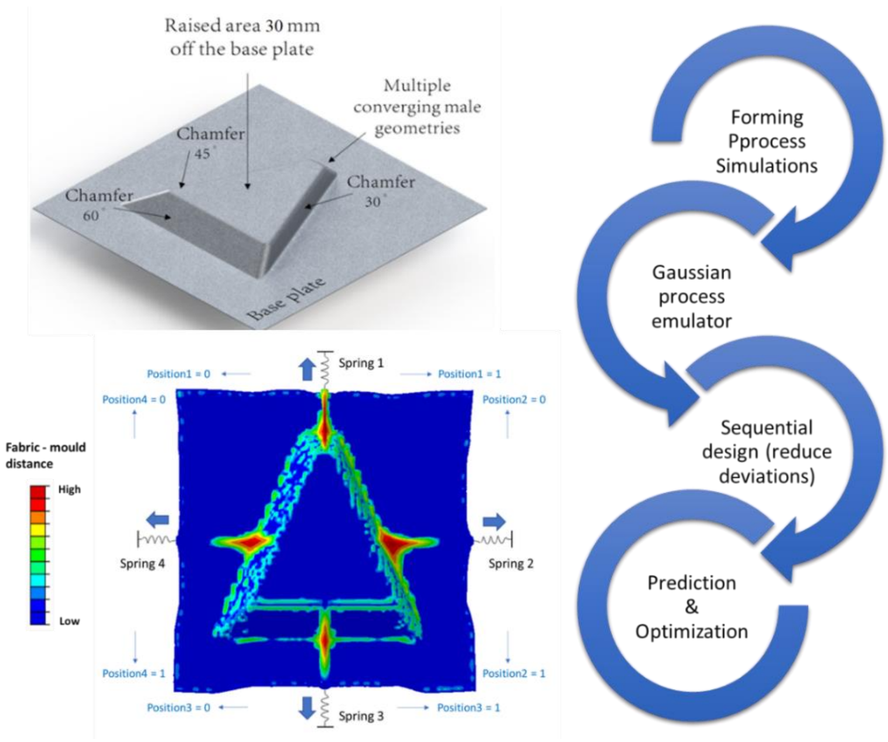
In the field of composites, infusion techniques are a cheaper manufacturing alternative to autoclave moulding of prepreg. However, the latter is often the favoured manufacturing route in the aerospace sector as it allows for the production of better quality parts (in this industry passenger safety is paramount). One of the challenges with infusion techniques is the high deformability of the dry fibrous precursor material, which makes it susceptibly to defects and part variability. In particular, prior to the infusion phase, the dry fibrous reinforcement, is formed to shape; the quality of the final part is sensitive to both variabilities in materials and the forming process itself. If the material and process (including their variabilities) are not understood or controlled, this can result in design tolerances not being met, reducing composites weight saving advantages through requiring "over design".

In the last two decades, FE-based methods have been developed to help optimise process conditions for the best part quality. However, these require large number of explicit iterations because of significant dynamic and non-linear behaviour, making them very time-consuming especially for complex models. The design space and the number of process parameters that can be optimised can be quite large (e.g. bagging material, boundary conditions etc) making the optimisation process computationally intensive. Therefore, an intelligent strategy must be used to design these simulation tests and conduct optimisation with the computational cost as low as possible.

In the present contribution, FE simulations of a forming process of an industrial inspired geometry are conducted based on forming simulation tools developed at the University of Bristol [1-2] to produce a small dataset required to build an emulator for process optimisation. The simulations consider four tensioning springs attached at the boundaries of the textile material to provide tensile force during forming process (see the figure), of which the positions and stiffnesses are variables. A Gaussian process emulator (surrogate model) is then built [3-5] to model and optimise these variabilities. Gaussian emulators excel in situations where only small datasets are available. They also have the added benefit of uncertainty quantification, thus no manipulations are required for inclusion of variability. This work will present the methodology for building such emulators for optimisation of composite manufacturing simulation, including the possibility to improve emulator performance through sequential design. The long term ambition of this work, is to build a fully autonomous forming rig with embedded sensors and active controls where the manufacturing conditions are adapted on the fly and defect formation mitigated based on rich, live experimental data feeding into real-time simulation and optimization of the process.



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