Optimisation of Mould Filling Parameters of the Compression Resin Transfer Moulding Process

Sherry Hsu, Matthias Ehrgott and Piaras Kelly
Department of Engineering Science
The University of Auckland
New Zealand
m.ehrgott@auckland.ac.nz

Abstract

The Compression Resin Transfer Moulding Process (CRTM) is a popular type of Liquid Composite Moulding Process (LCM) commonly used for manufacturing composite materials. In this paper we consider the optimisation of the manufacturing processing time and the machine tooling force for the CRTM process. Since this process requires large forces during compression, force evaluation and prediction provides great advantages for the industry as it enables structural analysis of the moulds. Not only it does lead to cost effective tooling design, it also allows for proper selection of cost effective moulds and supporting equipment. The tooling force, moreover, is in conflict with manufacturing time, which is another objective of particular interest in the industry.

In recent years, the advancement of CRTM simulation software allows accurate prediction of the processing objectives thus making it unnecessary to run through the expensive experiments physically. In this process, we use such a simulation software called SimLCM and combine it with a popular NSGA-II evolutionary multi-objective optimisation (EMO) algorithm to optimise maximum tooling force and processing time with respect to three manufacturing parameters. The EMO algorithm uses SimLCM as a black box to evaluate the objective function values for a population of solutions. We report results on a simple rectangular plate model (for calibration) and an industrial example.

Key words: Composite materials, compression resin transfer moulding, finite elements, multi-objective optimisation, genetic algorithm.

1 Introduction

1.1 The Compression Resin Transfer Moulding Process for Composite Materials Manufacturing

Composite materials are commonplace in everyday life: Concrete, milk bottles, sporting equipment, car bodies and spacecraft are just a few examples where composite materials are used. Composite materials are made by combining two or more materials which have different properties, but where the resultant material has more desirable properties than either of the individual constituents. The two types of material that make up composites are called *matrix* and *reinforcement*. In this paper we consider the manufacturing of polymer composites by a liquid composite moulding process. For more information on composite materials the reader is referred to Polymer Science Learning Center, The University of Southern Mississippi (2005)

Although many materials can be used as reinforcement, glass fibres are by far the most common. While glass is usually brittle, it is strong and flexible when spun into fibres. For some composite parts that must be able to sustain extremely high stress such as aircraft parts, stronger but more expensive reinforcements such as Kevlar and carbon fibres are used. A reinforcement material that has undergone initial shaping but has not been processed into the final part is called a preform.

The matrix holds fibre reinforcements together and adds toughness to the fibres as it can absorb energy by deforming under stress and two common types of polymer resins are used as the matrix, namely *thermosets* and *thermoplastics*. Thermoset resins are liquid at room temperature. They solidify after the chemical/thermal activation known as curing. The process cannot be reversed so that the material will not return to a liquid state even under high temperature. Thermoplastics are hard at room temperature and need to be melted above their crystallisation temperature in order for them to flow. Thermoplastics are highly viscous fluids once melted. They are cooled to solidify after the composite parts are made. The process is thus reversible.

The Liquid Composite Moulding Process (LCM) is a type of manufacturing process that is able to mass produce composite parts. Initially, the fibrous reinforcement is manufactured into a perform and placed inside a mould. The mould is then closed and compacted to allow resin to be injected. After the injection process finishes, the resin is allowed to cure and the part is demoulded once sufficient rigidity is reached Kelly and Bickerton (2009). We consider two of the variants of LCM, namely Compression Resin Transfer Moulding (CRTM) and its special case Resin Transfer Moulding (RTM).

The CRTM process proceeds in the following stages.

- Stage 1: Preform Manufacture and Lay-up. First, the reinforcement is manufactured into perform and laid inside the mould.

- Stage 2: Initial Dry Compaction. The mould is closed to some desired height. At the end of dry compaction, the mould usually remains partially open. This will allow resin to flow through the mould with relative ease due to the low fibre volume fraction.

- Stage 3: Resin Injection. The resin is injected into the mould with constant pressure or constant flux. The injection process will stop once the required volume has been reached.

- Stage 4: Final Wet Compaction. In the wet compaction stage, the mould is closed down fully until the final desired part thickness is reached. The wet compaction stage is usually carried out with constant velocity or constant force. The resin inside the cavity will be forced through the remaining dry region of the preform, fully saturating the part.

- Stage 5: Curing and Removal. The part is cured and demoulded once sufficient rigidity has been attained.

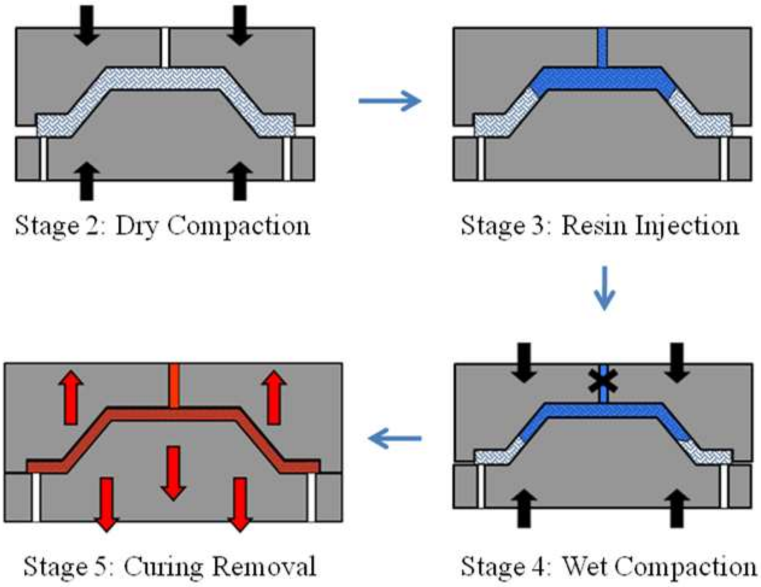


Figure 1: LCM process: Stages 3 to 5.

Stages 2 to 4 are the main focus of the optimisation of the CRTM process. Figure 1 shows the CRTM process from Stage 2 to Stage 4.

The Resin Transfer Moulding (RTM) process is a special case of the CRTM process. However, in Stage 2 of the RTM process, the mould is always closed to the final part thickness. This results in a high fibre volume fraction inside the cavity before resin injection starts and thus a typical RTM process requires more processing time than a CRTM process.

1.2 Simulation Software

To simulate the CRTM and RTM processes we use a generic LCM process simulation software called SimLCM developed at the University of Auckland Kelly and Bickerton (2009). SimLCM uses the finite element methods to solve the differential equations of the mixed elastic compaction model that describe the fluid flow through the mould, the stresses taken by the preform reinforcements and the permeability of the material. During simulation, the finite element meshes of the composite part are input into SimLCM. SimLCM simulates the moulding process according to the specified manufacturing parameters as well as the given part material and geometry. As a result of the simulation, quantities of interest such as the process time and maximal tooling force can be observed.

2 Optimising the CRTM Process

2.1 The Optimisation Problem

Optimisation of the moulding process may consist of a variety of processing objectives and parameters. Common objectives are minimising processing time, tooling force, void content and injection pressure. Processing parameters include the injection pressure, compression velocity, gate location and materials etc.

In this paper we consider the objectives processing time T (because shorter process time obviously allows higher production rates) and the maximal tooling force

F_{max} required to close the mould during the process (because this determines the required capabilities of the manufacturing equipment and therefore its cost). It is desirable to keep both T and F_{max} at a minimum. Unfortunately, these goals contradict each other, because shorter process times can be achieved by increasing the tooling force.

T and F_{max} are largely determined by three important manufacturing parameters, namely the injection pressure P_{inj}, the wet compaction velocity V_{wet} and the mould height H before the wet compaction stage. Although the dry compaction velocity also has an influence it was found that it can be neglected. For any given values of P_{inj}, V_{wet} and H, SimLCM can be run to obtain the values of T and F_{max}. The values of the three parameters need to be restricted to reasonable ranges. In this paper we use typical values that occur in practice, i.e. P_{inj} between 100 and 450 kPa, V_{wet} between 0.000008333 and 0.000416667 m/s and H any value between the final part thickness and the initial preform thickness.

In an abstract form we therefore want to solve the following bi-objective otpimisation problem:

$$
\begin{array}{rl}
\text{minimise} & (T, F_{max} = f(P_{inj}, V_{wet}, H) \\
\text{subject to} & 100 \leq P_{inj} \leq 450, \\
& 8.333 \times 10^{-6} \leq V_{wet} \leq 4.167 \times 10^{-4}, \\
& H_I \leq H \leq H_f.
\end{array}
$$

Note that in the special case of the RTM process the preform is compressed to the final part thickness in the dry compaction phase. This means that $V_{wet} = 0$ and $H = H_f$ and hence the optimisation has only one variable, namely P_{inj}.

There is not much literature on the optimisation of LCM manufacturing processes. Lin *et al.* (2000) investigate two cases of RTM process optimisation. In the first one they determine the optimal gate location to minimise the filling time and in the second one they vary the permeability of layers to minimise resin waste in addition to filling time. A genetic algorithm (GA) and the quasi-Newton method were tested. Lin *et al.* (2000) show that the GA has a poor rate of convergence compared with the quasi-Newton method. Kim *et al.* (2000) also investigate minimising RTM filling time by finding optimal gate locations. Numerical simulation and optimisation are conducted on a complex geometry, an automobile bumper core. It is shown that the filling time can be reduced by about 100 seconds using a GA. Na (2008) formulates the CRTM process optimisation problem using the same variables and (a weighted sum combination of the) objectives as in this paper. The study reveals that the optimisation problem is non-convex and a global optimisation heuristic is created from the problem pattern analysis. Kam (2009) in a preliminary study uses a GA to solve the CRTM process optimisation problem (1). While the algorithm is not fine-tuned for the problem, he demonstrates that the GA is able to find a set of efficient solutions.

2.2 Multi-objective Optimisation with Genetic Algorithms

2.3 Multi-objective Optimisation

As we have seen in Section 1.1, the optimisation of the CRTM process can be formulated as a bi-objective optimisation problem. In this section, we give a brief introduction to multi-objective optimisation and genetic algorithms for their solution, as well as the framework we use to solve the CRTM optimisation problem (1).

A mutli-objective optimisation problem can be written as

$$\begin{aligned} \text{minimise } f(x) &= (f_1(x), \ldots, f_p(x)) \\ \text{subject to } x &\in X, \end{aligned}$$

where X is some feasible set. We say a solution $x^* \in X$ is efficient if there is no other $x \in X$ such that $f(x) \leq f(x^*)$ and $f(x) \neq f(x*)$. Hence the goal of multi-objective optimisation is to find efficient solutions. The objective function vectors $y^* = f(x^*)$ of efficient solutions are called non-dominated points. $Y = f(X)$ is the feasible set in objective space and $Y_N = \{y^* = f(x^*) : x^* \text{ is an efficient solution}\}$ is the set of all non-dominated points. Since multiple efficient solutions can map to the same non-dominated point, the goal of multi-objective optimisation is usually more precisely defined as finding Y_N, and for each $y \in Y_N$ some solution x with $y = f(x)$.. Multi-objective optimisation algorithms therefore focus on the objective space, i.e. finding Y_N. For further details on multi-objective optimisation see Ehrgott (2005).

In the case that X is a continuous set and f is a continuous function, Y_N is usually infinite and in all but the most basic cases (X is a polyhedron and f is linear) it is not possible to obtain an exact description of Y_N. This problem is aggravated if f is not convex. Hence approximation methods or heuristics have to be used to solve multi-objective optimisation problems. Such algorithms aim to find a finite set of solutions $X' \subset X$ such that the finite set $Y' \subset Y$ has two properties:

1. Each element of Y' is close to Y_N.

2. The set Y' covers the entirety of Y_N.

While approximation algorithms such as Ehrgott (2005) do have some guarantee on their performance with respect to these principles, heuristics do not.

In many practical applications an additional problem arises, namely that the objective function f is not known analytically, but only through simulation or other black box evaluation that may require long computation times. This is of course the case in our problem (1), where for given P_{inj}, V_{wet} and H a run of SimLCM is needed to obtain T and F_{max}. In this case, mathematical optimisation methods that require information about f are not applicable and heuristics are used. The most popular heuristics for multi-objective optimisation are evolutionary algorithms, also called evolutionary algorithms.

2.4 Evolutionary Multi-objective Optimisation

An evolutionary algorithms (EAs) mimics the principles of biological evolution. It works with a population of solutions of size N and, in each iteration, evaluates the "fitness" of the individuals in the population, modifies the individuals ("parents") to create "offspring" through mutation and recombination operators, and decides which of the parent and child individuals survive into the next generation according to the principle of survival of the fittest. A typical EA proceeds as shown in 1.

In this paper we use the very popular NSGA-II (Non-dominated Sorting Genetic Algorithm) described in Deb *et al.* (2002). The algorithm is defined by the specific choices in each of the steps of Algorithm 1. Fitness assignment is done as follows. Given a population of parents and offspring, the individuals that are not dominated by any other individual are assigned rank 1 (the fittest). These individuals are then removed and the procedure is repeated to find individuals of rank 2 etc. For selection of individuals for the next generation the so-called crowding distance is used in

Algorithm 1 Pseudocode for a typical EA.

```
(Randomly) generate initial population
repeat
    Assign fitness values
    Select parent individuals
    Variate parent individuals to produce offspring individuals
    Select N fittest individuals as the population for the next generation
until termination criteria met
```

addition. This is the average distance of an individual to its nearest neighbour over all objectives. Individuals are compared according to rank and crowding distance, where individuals with lower rank are preferred (fitter), and in case of ties the larger crowding distance is preferred, as individuals with larger crowding distance are in "less crowded" areas of the non-dominated set. Individuals are added to the population for the next generation until the population size N is reached. This procedure is aimed at preserving the fittest individuals while at the same time ensuring diversity of the population.

Parent selection follows a roulette-wheel selection process. Then three different variation operators are used. Since we cannot describe them in detail here, we refer to the literature. We use two recombination operators, namely uniform crossover (Zitzler *et al.*, 2000), simulated binary crossover (SBX) (Deb and Agrawal, 1994), and one mutation operator, the polynomial mutation operator proposed by Deb and Goyal (1996).

Finally, we need to mention the termination criteria. We imposed a maximum number of generations. The algorithm will stop as soon as this maximum m is reached. In order to be able to control convergence, we also implemented two common measures to compare populations of solutions. The hypervolume indicator (Zitzler and Thiele, 1999) measures the dominated region of the objective space that is bounded by a reference point which is at least weakly dominated by the non-dominated front. In our problem, the larger the bounded hypervolume, the better the non-dominated front. The algorithm is terminated if the percentage increase of the hypervolume indicator falls below some threshold. We found the highest F_{max} value by using SimLCM with the highest P_{inj}, V_{wet} and lowest H value and the highest T value by suing SimLCM with opposite settings. The second measure is the binary epsilon indicator of Zitzler *et al.* (2003). Given two sets of individuals A and B, where A dominates B, it calculates the smallest value ϵ by which each element of B can be multiplied so that every point in B is weakly dominated by some element of A. We use it to compare the non-dominated elements of subsequent generations and terminate as soon as it is close enough to 1. During initial test we noticed that Using the epsilon indicator and hypervolume measures as convergence criteria may cause problems during the first few generations, when the set of non-dominated individuals (those with rank 1) does not change between two generations. We avoid this by imposing a minimum number of generations.

The implementation was carried out in the PISA (Platform and programming language independent Interface for Search Algorithms) framework of Bleuler *et al.* (2003). This framework allows to separate problem specific components of the implementation, such as the variation mechanisms from the problem independent ones such as selection mechanisms, which only require information about objective values. PISA divides the implementation of an optimisation method into the *Selector module* and the *Variator module*. The Selector module contains the selection mech-

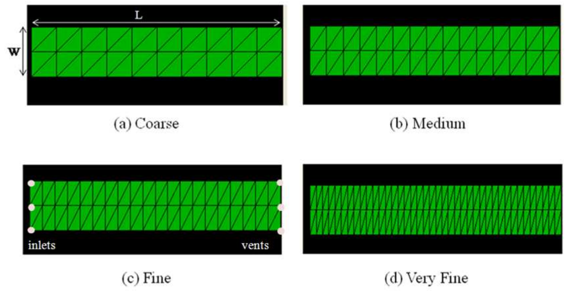


Figure 2: Four meshes for the flat rectangular plate model used in CRTM simulation.

anisms and algorithms while the Variator module contains the problem specific part: the representation of individuals, the generation of new individuals and the calculation of objective function values Zitzler *et al.* (2004). The two modules are compiled independently and communicate via a text-based interface.

3 Case Studies

In this section we report results of two case studies, first a simple rectangular plate and second an industrially manufactured object, namely a fireman's helmet.

3.1 Rectangular Plate

A convergence analysis was carried out observing the fluid force and comparing it with the analytical solution, which is known for a simple rectangular plate model. After running SimLCM with four different grades of mesh (coarse, medium, fine, and very fine, see Figure 2) and observing that the finer the mesh, the more accurate the simulation works, but the higher the computation time it was decide to work with the fine mesh.

We first report results for the RTM process. Recall that here $H = H_f$ and $V_{wet} = 0$, so there is only a single variable P_{inj}. We included V_{dry} to estimate its influence on T and F_{max}. The set-up of SimLCM used a fine mesh with 63 nodes and 80elements, three resin injection nodes (inlets) at one end and three vents on the opposite side (see Figure 2) and appropriate material parameters. The initial thickness of the glass fibres is $0.0063m$ and they will be compressed to the final thickness of $0.0035m$.

The range for P_{inj} is set between 100 kPa and 450 kPa and the range for V_{dry} is set between 0.5 mm/min and 25 mm/min and the GA parameters are a maximum of 60 iterations with population size 40. In each iteration, 20 individuals are selected as parents and 20 offspring will be generated. The tolerance for the hypervolume and epsilon indicator values are set to be 0.001 and 0.9, respectively.

The GA optimisation run terminates after 10 generations when the hypervolume indicator value is reduced to 0.00257 and the epsilon indicator value is 0.977. We compared the results of the GA with runs of SimLCM with different P_{inj} from 100 kPa to 450 kPa with 50 kPa step and fixed V_{dry}. The results are plotted on top of the population plot at the 10th generation of the GA in Figure 3).

This shows that $P_{inj}$is the key determining variable in the RTM process and that the same force is induced regardless of the compaction speed V_{dry}.

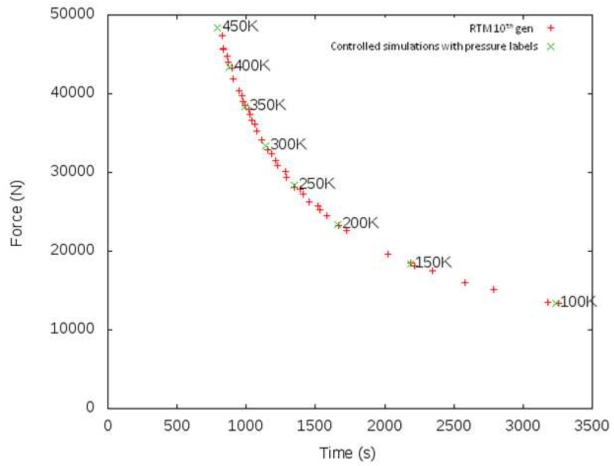


Figure 3: Plot of population at the 10th generation and the RTM simulations with 9 different pressure values.

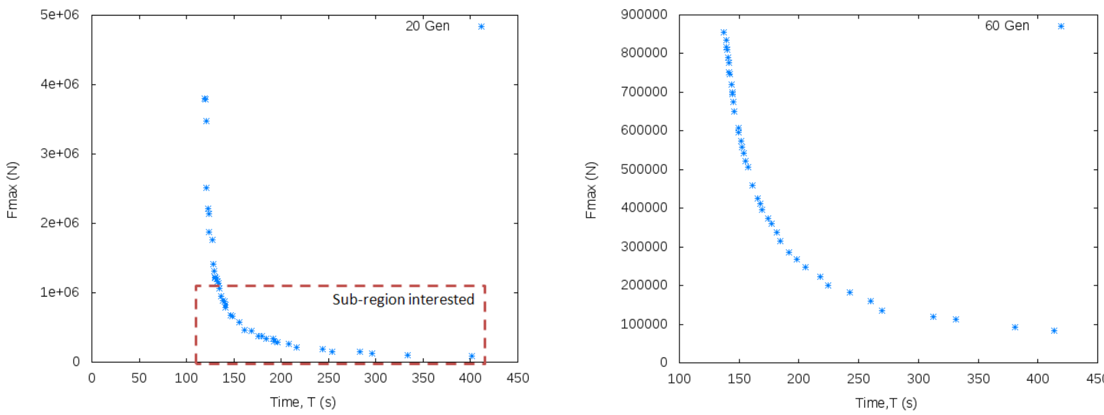


Figure 4: Populations of the 20th and 60th (final) generations of Tests 1 (left) and 2 (right).

Next, we report the results of the CRTM optimisation with the same rectangular plate and the same material parameters as before. Also, the GA parameters are the same as before. We perform two tests with different variable ranges. In both P_{inj} varies between 100 and 450 kPa. In the first, we have $0.5 \leq V_{wet} \leq 25mm/min$ and $0.05 \leq H \leq 2.85mm$ and in the second one $0.5 \leq V_{wet} \leq 5.4mm/min$ and $1 \leq H \leq 2.85mm$.

The first test terminates after the 20th generation with the hypervolume indicator and epsilon indicator values 0.001213 and 0.94. The population of the 20th generation is displayed on the left of Figure 4. Some of the individuals in this population have F_{max} values up to $4 \times 10^6 N$. In real life, it is unlikely that flat plate is manufactured with such a high force value. The sub-region with lower F_{max} and higher T values is of a higher interest. The individuals around that region are observed to have high P_{inj}, high H and low V values. Therefore we run the second test with the parameters specified before. The program terminates at the maximum number of 60 generations. The plot of the final generation from the second optimisation is displayed on the right of Figure 4.

We also compared the optimisation results with runs of SimLCM with the lowest

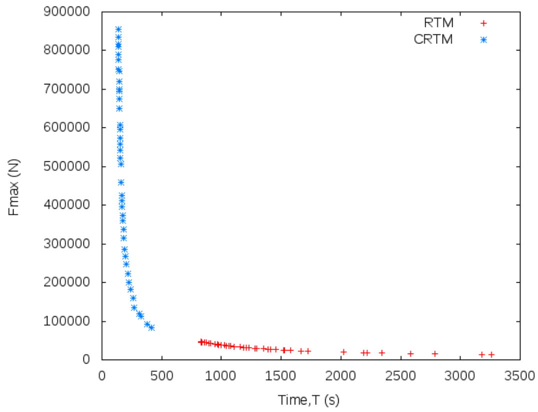


Figure 5: Plot of final CRTM and RTM populations.

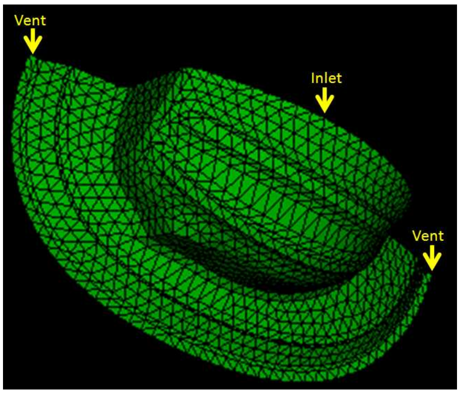


Figure 6: The medium mesh of a fireman's helmet.

P_{inj}, lowest V_{wet} and five different H values as well as with the highest P_{inj}, lowest V_{wet} and the same five values of H. In every case, the optimisation found solutions dominating all of the fixed variable simulations, clearly demonstrating the value of optimisation.

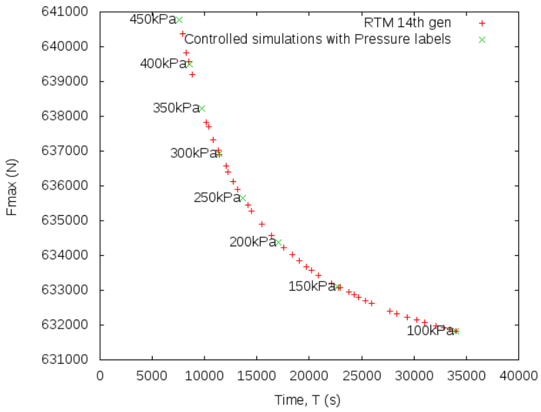
To conclude this section, we show the combined results for the RTM and CRTM processes. As expected, these confirm that RTM is a special case of CRTM, see Figure 5.

3.2 Fireman's Helmet

This study looks at a fireman's helmet manufactured by Pacific Helmets Ltd, of Wanganui, New Zealand. In this case we used a medium mesh to reduce computation time for SimLCM. This mesh has 988 nodes and 1862 elements. A run of SimLCM with $P_{inj} = 100\ kPa$, $V_{wet} = 10\ mm/min$ and $H = 1\ mm$ requires about 238 seconds on a computer with Intel® Xeon® 2.67 GHz processor to achieve an accuracy within 3 % of that of a fine mesh of 1707 elements requiring 1284 seconds.

The initial total preform thickness is 0.00714 m and the final part thickness at the end of moulding process is 0.002 m. The helmet has a length of 0.42 m, width of 0.32 m, and a depth of 0.17 m. The resin injection node is at the center top of the helmet and there are two vents at the sides (see Figure 6).

The variable ranges and GA parameters are the same as those used in Section 3.1. The termination criteria are met when the hypervolume indicator value reaches



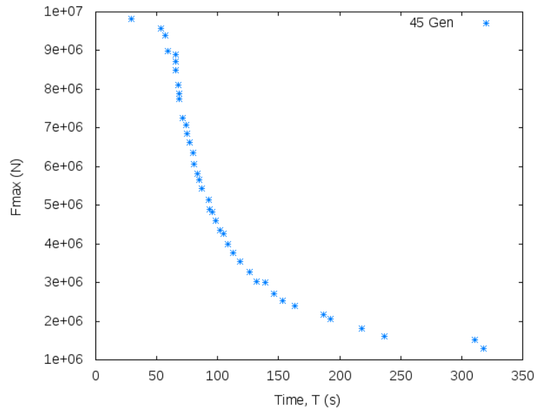


Figure 7: Populations of the 14th and 45th (final) generations of the RTM (left) and CRTM (right) optimisations.

0.0001 and when the epsilon indicator value reaches 0.95.

The procedure was as in Section 3.1. We optimised the RTM process first, comparing the results with runs of SimLCM with fixed P_{inj} to verify the optimisation. The optimisation process terminates after the 14th generation. The hypervolume indicator value and the epsilon indicator values are 0.998856 and 0.000008, respectively. The final population is shown on the left of Figure 7.

Second, we optimised the CRTM process using the same parameters as before once again. At termination of the optimisation, the hypervolume indicator value equals 0.000048 and the epsilon indicator value reaches 0.97. The plot of the 45th and final generation is given on the right of Figure 7.

4 Conclusion

In this paper we have described a framework for the optimisation of liquid composite manufacturing processes. We have focused on the RTM and CRTM processes and chosen the objectives of minimising the maximal tooling force F_{max} and the processing time T depending on the variables of injection pressure P_{inj}, wet compaction velocity V_{wet} and injection height H as variables. The optimisation was carried out using an evolutionary muti-objective algorithm using the finite element simulation software SimLCM for function evaluations. This was implemented within the PISA framework for ease of use and future modification. We have demonstrated that optimisation is valuable, producing better solutions than simulation with fixed variable values alone. Moreover, the illustration of a set of non-dominated solutions provides valuable information to manufacturers for setting up their processes and possibly for investment decisions. Further analysis of the solutions obtained provides valuable insights into the LCM processes and on how the objectives depend on the variables.

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