MULTI-OBJECTIVE OPTIMISATION OF COMPOSITES CURE USING GENETIC ALGORITHMS

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Abstract

The challenges related with processing of composite components are currently highlighted as the complexity of parts increases constantly. The determination of appropriate process parameters is key to achieving robust and efficient manufacturing. The present paper focuses on the optimal design of the cure profile in order to minimise the process duration and the likelihood of a temperature overshoot. This multi-objective optimisation problem is addressed using a genetic algorithm verified using benchmark problems and reproducibility tests. The design parameters of the optimisation problem were the temperature and duration of the dwells of the cure profile as well as the ramp rate applied during heating up between the dwells. The objectives of the multi-objective problem were the minimisation of cure duration and of maximum temperature during the cure. The results showed significant improvement compared to conventional profiles. Furthermore, the trade off curve between process duration and extend of exotherm follows a characteristic L shape which allows identification of a set of parameters that result in significant benefits in both objectives.

1 Introduction

Processing of composites is a current area of focus due to the increased use of these materials in complex components. The curing step of the manufacturing process involves a number of challenges related to product quality, cost and environmental impact. The overall aim of satisfying requirements for an efficient and robust process are currently addressed only partially by the use of standard cure profiles that are developed based on empirical information. An alternative approach is to use numerical optimisation which involves the search of the best cure profile in order to achieve a prescribed degree of cure in minimum time, while keeping temperature overshoots as low as possible.

The single objective version of the cure optimisation problem has been addressed using both gradient based and zero order techniques. Simple gradient techniques have been used to minimise cure process time [1]. Similarly, Sequential Quadratic Programming has been utilised indicating that the non-linear nature of cure makes the problem more difficult to address as the thickness of laminates increases [2-3]. A scheme based on the Levenberg Marquard algorithm has been demonstrated to be effective in minimising the cure time subject to cooling and heating rate constraints [4]. Simulated annealing combined with the Nelder-Mead method has been utilised successfully to address the cure problem [5], whilst Genetic Algorithms (GAs) have allowed significant reduction of process time [6].

Investigation of multi-objective optimisation of composite cure have been relatively limited. The problem of minimising processing time and thermal gradients has been addressed using GAs [7]. An evolutionary strategy has been applied to find the optimal cure cycle of a thick composite laminate to minimise process time and to maximise degree of cure [8]. An evolutionary algorithm has been used to solve the problem of finding the optimal cure profile maximising the degree of cure and minimising the maximum temperature inside the part using weighting factors to augment the objectives [9-11]. The drawback of this approach is

that the quality of the solution depends strongly on the selection of the objective function. Similarly the problem of minimising cure time and residual stress has been translated to a single objective optimisation using weighting of the objectives, which was solved by an evolutionary algorithm [12-13].

The present paper describes a multi-objective methodology for cure optimisation based on GAs. The objectives of process time and exothermic effects minimisation are addressed. The methodology is demonstrated on two generic geometries; a flat panel and an L-shaped component.

2 Multi-objective optimisation using a GA

A genetic algorithm for multi-objective optimisation was adapted in this study [6]. The algorithm accepts inputs such as the number of generations, the number of individuals in each generation, the reproduction and elite number, the size of the Pareto front, the number of the objectives, the number of the optimisation parameters and their ranges and the probabilities of cross over and mutation. The output of the algorithm is the value of the objectives for all individuals in each generation and the Pareto front for every generation.

Four benchmark multi-objective problems have been selected to verify the behaviour of the GA; a simple convex problem proposed by Schaffer [14], one convex and one non convex problem proposed by Zitzler [15] and one non convex problem proposed by Fonseca [16].

| Problem | Generation Number | Individual Population | Individual Reproduction | Chromosome Size | Elite | |
|-----------|----------------------|--------------------------|----------------------------|--------------------|-------|--|
| Schaffer | 50 | 100 | 70 | 10 | 4 | |
| Zitzler-1 | 400 | 100 | 70 | 10 | 4 | |
| Zitzler-2 | 400 | 100 | 70 | 10 | 4 | |
| Fonseca | 400 | 200 | 105 | 15 | 15 | |

Table 1. Input for benchmarks

Table 1 reports the parameters of the GA for the benchmark studies. In all the problems the Pareto size was fixed at 50 individuals, the crossover probability at 0.5 and mutation probability at 0.005. Figure 1 illustrates the results of the test. It can be noted that the GA approximates successfully and gradually the non-dominated set in all of the cases. In the Schaffer problem the solution converges after only 10 generations and the approximation is entirely satisfactory. For the two Zitzler problems the convergence occurs within 100 generations a very close approximation of the theoretical front. In the most complex of the benchmarks, the Fonseca problem, the GA requires 150 generations to converge, whilst the approximation is in close to the theoretical front with some small errors in certain errors. Reproducibility tests have shown that the results of the GA are not sensitive to the random seed, indicating the robustness of the methodology and the implementation.



Figure 1. Pareto front at different generations

4 Case studies

Two different geometries, a flat panel and an L shape geometry, fabricated by infusion using carbon fiber and epoxy resin RTM6 have been used. For each geometry a thickness of 3mm, 12mm and 24 has been considered. The FE solver Marc.Marc was used to solve the heat transfer problem. The lay up for the flat panel and for the L-shape was respectively:

$$\frac{[0/90/90/0]_{4s}}{[0/\pm 45/90/90/\pm 45/0]_{s}}$$

Table 3 summarises the general characteristics of each model.

| Model | Nodes Number | Elements Number | Element Thickness |
|--------------|-----------------|--------------------|----------------------|
| Flat 3mm | 36 | 8 | 8 |
| Flat 12mm | 36 | 8 | 8 |
| Flat 24mm | 36 | 8 | 8 |
| L shape 3mm | 630 | 248 | 4 |
| L shape 12mm | 954 | 416 | 8 |
| L shape 24mm | 2584 | 1008 | 16 |

Table 2. Finite element model characteristics

Boundary conditions of fixed temperature given by the cure profile were applied at nodes in contact with the mould and natural air convection on the surface in contact with the vacuum bag. Initial temperature conditions of 120 °C and initial degree of cure of 0.02 were applied to all nodes and elements respectively.

Object of the cure optimisation was to find the cure profile that could achieve the minimisation of both process time and temperature overshoot; the cure profile was parametrised in order to achieve this. Four parameters have been selected to define the cure profile: the temperatures of the first and second dwell, the first dwell duration and the ramp rate, Table 3 summarises the ranges of the parameters and Figure 2 illustrates the general

cure profile. All of the optimisations were run for 50 generations, 50 individuals, 40 individuals selected for reproduction, 4 elite individuals and 30 individuals in the Pareto front.



3 Material model

The cure kinetics behavior of the resin is described in [17-19]. The rate of the reaction is

$$\frac{d\alpha}{dt} = k_1 (1-\alpha)^{n_1} + k_2 \alpha^m (1-\alpha)^{n_2} \tag{1}$$

Where k_1 and k_2 are the reaction rate constants, α fractional conversion and *m* and *n* reaction orders. In addition to this k_1 and k_2 are defined as:

$$\frac{1}{k_i} = \frac{1}{k_{i,c}} + \frac{1}{k_d} \qquad i = 1,2$$
(2)

Where $k_{i,c}$ are Arrenius dependent reaction rate constants and k_d the diffusion rate constant defined as:

$$k_{d} = A_{d} \exp\left(-\frac{E_{d}}{RT_{c}}\right) \exp\left(-\frac{b}{f}\right)$$
(3)

$$k_{ic} = A_i \exp\left(\frac{-E_i}{RT}\right) \qquad i = 1,2 \tag{4}$$

where A_d and b are parameters, E_d the activation energy of the diffusion, T_c the cure temperature, f the equilibrium fractional free volume expressed by:

$$f = 0.00048(T_c - T_g) + 0.025$$
⁽⁵⁾

where T_g is the instantaneous glass transition temperature given by:

$$T_{g} = T_{g0} + \frac{(T_{g\infty} - T_{g0})\lambda\alpha}{1 - (1 - \lambda)\alpha}$$
(6)

4

Here T_{g0} is the glass transition of the monomer, $T_{g\infty}$ the one of the full network, and λ a model parameter. The thermal properties are based on experimental data presented in [6]. The specific heat capacity of the fibre is:

$$c_{pf} = 0.0023T + 0.765 \tag{7}$$

The specific heat capacity of the resin is:

$$c_{pr} = 0.0025 + 1.8T + \frac{0.25}{1 + \exp(c(T - T_g - \sigma))}$$
(8)

In order to find the specific heat of the composite the rule of mixture has been applied:

$$c_{p} = w_{f}c_{pf} + (1 - w_{f})c_{pr}$$
⁽⁹⁾

where w_f denotes the fibre weight fraction.

Combination of Eqs. 7-8 results in the following expression for the specific heat capacity of the composite:

$$c_p = A + BT + \frac{C}{1 + \exp(c(T - T_g - \sigma))}$$
(10)

The thermal conductivity is:

$$K_i = A_i + B_i T + C_i T \alpha^2 + D_i T \alpha + E_i \alpha^2 + F_i \alpha$$
(11)

Table 4. summarises the parameters of the material models described in Eqs. 1-11.

| Cure Kinetics | m n_1 n_2 b λ | 1.16 1.80 1.32 0.467 0.435 | $egin{aligned} &A_1ig(s^{-1}ig)\ &A_2ig(s^{-1}ig)\ &E_1ig(Jmol^{-1}ig)\ &T_{s^0}ig(^\circ Cig) \end{aligned}$ | 17580 21525 70500 -11 | $egin{aligned} & E_2ig(Jmol^{-1}ig) \ & A_dig(s^{-1}ig) \ & E_dig(Jmol^{-1}ig) \ & E_dig(Jmol^{-1}ig) \ & T_{g^\infty}ig(^\circ Cig) \end{aligned}$ | 59050 6.48E+18 136800 206 |
|--|--|--|---|--------------------------------|---|------------------------------------|
| С _р (J/ ^o C/Kg) | $A \Big(J g^{^{-1}\circ} C^{^{-2}} \Big) \ c \Big({}^\circ C^{^{-1}} \Big)$ | 0.0024 1.1 | $Big(Jg^{-1}{}^\circ C^{-1}ig) \ \sigmaig({}^\circ Cig)$ | 1.064 16.5 | $C(Jg^{-1} \circ C^{-1})$ | -0.072 |
| K ₁ | $A_{l}(Wm^{-1} \circ C^{-1})$ $D_{l}(Wm^{-1} \circ C^{-2})$ | 2.93 -4.4E-4 | $B_l(Wm^{-1} \circ C^{-2})$ $E_l(Wm^{-1} \circ C^{-1})$ | 4.36E-3 -3.75E-2 | $C_l (Wm^{-1} \circ C^{-2})$ $F_l (Wm^{-1} \circ C^{-1})$ | 3.2E-4 8.8E-2 |
| K _t | $A_t \left(Wm^{-1} \circ C^{-1} \right) \\ D_t \left(Wm^{-1} \circ C^{-2} \right)$ | 0.398 2.2E-4 | $B_t \left(Wm^{-1} \circ C^{-2} \right)$ $E_t \left(Wm^{-1} \circ C^{-1} \right)$ | 4E-5 1.87E-2 | $C_{t}\left(Wm^{-1}\circ C^{-2}\right)$ $F_{t}\left(Wm^{-1}\circ C^{-1}\right)$ | -1.6E-4 4.4E-2 |

Table 4. Cure kinetics and thermal parameters for RTM6 and carbon fibres composite

5 Results and discussion

Figures 3 and 4 illustrate the optimisation results at the 50th generation for the three flat panel and the three L shape cases considered.

Standard curing results in low temperature overshoots (in the range of a few ^oC) and process duration in the range of 10,000 s. The L shape of the Pareto fronts shows clearly that there is an area of the optimisation landscape in which there are significant benefits in terms of process duration with small improvement in temperature overshoot and an area of significant benefits in temperature overshoot with small improvements in process duration. The conventional cure profile is in the area of low sensitivity of temperature overshoot on process parameters but at a significant distance from the point where benefits in terms of process duration can be obtained. A natural engineering choice would be to move towards the corner of the L shaped Pareto front, in order to combine significant benefits in both objectives. Following this approach there can be significant benefits in terms of process duration. The reduction in cure time has a strong dependence on thickness, with a benefit of about 2 h in the case of the thin laminates and a benefit of slightly over 1 hour for the very thick cases.



Figure 3 Flat panel optimisation results at different thickness



Figure 4 L-shape optimisation results at different thickness.

6 Conclusions

The optimisation procedure presented in this paper can be used for the design of an optimal cure profile to minimise process time and temperature overshoot in composite manufacturing. The two objectives show a clear trade off behavior with an L shaped Pareto fornt. This presents an opportunity for selecting process parameter combinations that allow significant benefits in both objectives. These benefits that can be in the order of 2 h for a high performance aerospace system are subject to establishing that the selected design points present a robust set of conditions.

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