Multi-Criteria Thermal Optimization by Evolutionary Algorithms of Resin Cure, Processing Stresses and Cycle Time in Liquid Composite Molding

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SUMMARY: *Liquid Composite Molding* (LCM) regroups a number of increasingly used composite manufacturing processes. A proper selection of process parameters is crucial to yield successful molding results and obtain an appropriately cured part with minimum defects. In the case of thermosetting resins, the polymerization shrinkage increases the complexity of the thermo-mechanical problem. Numerical analysis of the internal stresses developed during resin cure and subsequent part cooling does not only help to understand the process, but it is also necessary to make thermal optimization reliable. The scope of this work concerns the optimization of resin cure, cycle time and residual stresses during LCM composite processing. A multi-criteria optimization algorithm called *LeCoq* (Logical Evolutionary Curing Optimization and Quenching) based on evolutionary algorithms was developed to optimize a multi-dimensional objective function that incorporates the following conflicting goals: minimization of residual stresses, maximization of the final degree of cure and reduction of cycle time. An optimized temperature profile obtained with this approach minimizes cycle time and processing stresses while avoiding thermal degradation of the matrix and composite delamination. Process optimization with two different objective functions is conducted for a thick composite part. Two optimized temperature cycles are obtained and the results are compared and discussed.

KEYWORDS: Liquid Composite Molding, thermal analysis, residual stress, optimization.

INTRODUCTION

In LCM fabrication, a number of process parameters such as mold temperature and inlet pressure have a great impact on part performance. Adequate process parameters are critical to ensure successful molding conditions and reduce cycle time, heating sources, mold deformation, etc. Minimization of the mold filling and curing time diminish energy consumption during the molding cycle. Finally, and maybe this is the most important point to consider in the case of thick composites, an optimum choice of process parameters results in minimum number of defects, such as micro-cracks, delamination, warpage, spring-in, etc. The work on LCM curing optimization reported in the literature can be divided as follows: (1) reduction of cycle time; (2) reduction of cure gradients; (3) reduction of thermal gradients; and (4) reduction of cooling stresses.

This investigation aims at developing a comprehensive thermal optimization methodology that considers simultaneously each of the above mentioned effects. The optimization algorithm must be based on the physics of the curing process in order to provide meaningful results. The study focuses on the minimization of the internal stresses that appear during *cure* and *cooling* of the thermosetting matrix as a result of temperature and cure gradients. The objective function to be minimized is constructed from physical information on the cure and temperature gradients, cure and cooling stresses, cycle time and maximum allowed exothermic temperature. An evolutionary strategy based on Genetic Algorithms (GA) is implemented for the minimization of the objective function. Optimization studies are carried out for a thick glass/polyester laminate to demonstrate the advantages of the proposed methodology.

PROCESSING STRESS ANALYSIS

In the present work, the composite cure is analyzed through the thickness of the part by a one-dimensional Crank-Nicolson finite difference formulation to solve the energy equation [1]. An adaptative time step control based on Fourier's number and on the reaction rate was implemented to avoid computational inconsistencies. In this approach, different thermal boundary conditions can be set at the mold surface or at the positions of the heating/cooling system inside the mold wall. To properly simulate the heat exchanges across the mold cavity, thermal and kinetic properties of the composite (and mold) must be appropriately characterized. The thermo-chemical and viscoelastic models for a glass/polyester composite are taken from [2]. It was experimentally found that long after the gel point the resin elastic modulus is still very low, for a polymerization degree less than 40%. This degree of polymerization, called *After Gel Point* (AGP) [2], was then taken as base line to analyze the evolution of mechanical properties. Properties and durability of composite parts are strongly affected by processing stresses. Excessive stress levels may lead to important defects during cure or after processing, when the part is cooled to room temperature. A comprehensive curing optimization algorithm should account for the internal stresses that appear during composite processing and aim at reducing these stresses. Processing stresses can be calculated by the Classical Laminate Theory (CLT) in a one-dimensional analysis. In this investigation, the one-dimensional energy equation was coupled to the CLT equations to evaluate the internal stresses developed during part processing [3].

Evolutionary algorithms

During the last years, Evolutionary Algorithms (EA) have received increasing attention in numerous research and industrial applications. Generally, EA outperform conventional optimization algorithms for problems which are discontinuous, non-differential, include multi-modal noise and are not well defined [4]. In the applications to LCM optimization, EA are often coupled to numerical process simulation. In order to evaluate the objective function (or *fitness* function) for a given set of process parameters (called *design variables*), numerical simulation of the process must be carried out for these design variables. In the case of curing optimization, the energy and kinetic equations must be computed for a set of thermal boundary conditions selected by the optimization algorithm. This means that optimization may become infeasible if the numerical evaluation of the fitness function requires large computational efforts.

The use of one-dimensional process modeling presents the advantage of being not too time consuming compared to two or three-dimensional finite element simulations. This allows performing a large number of evaluations (such as required by the EA optimization) in a relatively short computer time.

Problem identification

In this investigation, seven functions have been identified to describe the competing objectives of process efficiency versus part quality. The final fitness function to be minimized is a weighted combination of these partial objectives. The seven sub-objective functions proposed can be summarized as follows:

1) Maximum final extent of cure (J_{fc}).
2) Minimum processing time (J_{time}).
3) Minimum exothermic peak temperature ($J_{T_{\max}}$).
4) Minimum curing internal stresses (J_{stress}).
5) Minimum cooling stresses ($J_{cooling}$).
6) Constant trough-thickness degree of cure at AGP level (J_{AGP}).
7) Minimum through-thickness cure gradients after AGP level (J_{cure}).

Optimization procedures based on EA usually exhibit low convergence rates, requiring sometimes an exorbitant number of evaluations of the fitness function. It has been shown that the use of Gauss-Sigmoid fitness functions strongly increases the learning speed of EA [5]. In this work, the sub-objective functions were written in the form of unitary sigmoids (varying from 0 to 1) to increase the convergence rate of the optimization algorithm [3]. Considering that an improved LCM mold contains heating/cooling elements, a desired (i.e., optimized) temperature profile can be imposed during processing. In this investigation, the mold temperature profile is discretized in a series of heating and cooling ramps Q_i and dwell times dt_i (i.e., design variables to be optimized). The degree of success of a set of design variables (Vd) can then be quantified by a weighted combination of the sub-objective functions. The cure-cycle optimization in LCM can thus be stated as follows:

Minimize the sigmoid: $$F_f(Vd) = \frac{A_f}{B_f + e^{-F_\omega C_f}} + D_f \tag{1}$$

subject to: $$Vd \in Cs \tag{2}$$

with: $$Vd = [Q_1, dt_1, Q_2, dt_2, \ldots, Q_n, dt_n]; \qquad Cs = [Q^+_{\max}, Q^-_{\max}] \tag{3}$$

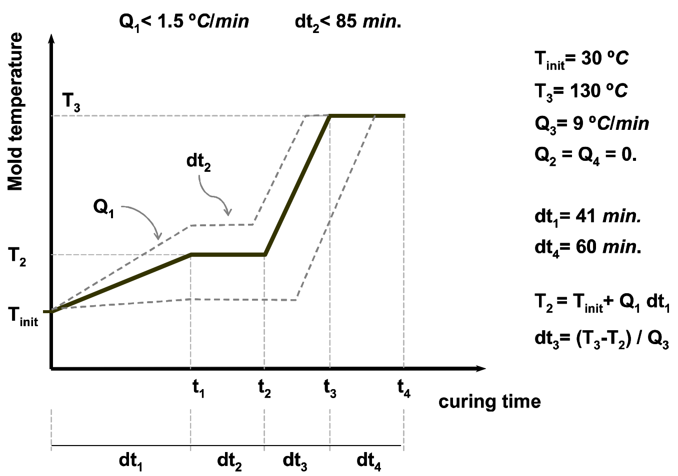
$$F_\omega = \omega_{fc} J_{fc} + \omega_{T_{\max}} J_{T_{\max}} + \omega_{AGP} J_{AGP} + \omega_{cure} J_{cure} + \omega_{stress} J_{stress} + \omega_{cooling} J_{cooling} + \omega_{time} J_{time}$$

where $F_f(Vd)$ is the fitness function to be optimized, and A_f, B_f, C_f and D_f are the coefficients of the sigmoid. Parameter Cs represents the constraints of the design vector Vd (i.e., the maximum mold heating/cooling ramps). Parameters ω are the weighting coefficients for each sub-objective function implemented to take into account a particular concern in the optimization procedure.

Note that the use of sigmoid sub-functions scaled between 0 and 1 simplifies the setting of the weighting coefficients. In fact, the default value of the weighting coefficients is 1, which indicates that the minimization of the fitness function considers proportionally the effects of each sub-objective function. Finally, an optimization algorithm called *LeCoq* (Logical Evolutionary Curing Optimization and Quenching) based on EA was developed to minimize the fitness function $F_f(Vd)$ [3].

RESULTS AND DISCUSSION

A simple curing cycle is now studied for a 20 *mm* thick glass/polyester composite [3]. The selected two heating ramps curing cycle (see fig. 1) has two variables: the first heating ramp Q_1 and the first dwell time dt_2, while the other parameters are fixed. By changing Q_1 and dt_2, a two-dimensional search space can be defined. The goal of this optimization is to minimize curing stresses and processing time. Because the curing temperature (T_3) is fixed, function J_{fc} can be neglected. Note that function $J_{cooling}$ is also be neglected in this example. Two different optimization strategies are tested for this thick part. In the first case, it is assumed that residual stresses can be minimized directly by minimization of the cure gradients. This means that only J_{AGP} and J_{cure} sub-objective functions need to be used to reduce curing stresses. To account for processing time and matrix degradation, the sub-objective functions J_{time} and J_{Tmax} are included in the fitness function. The weighting coefficients of such optimization become:



$$\omega_{AGP} = 1 \qquad \omega_{cure} = 1$$
$$\omega_{time} = 0.75 \qquad \omega_{T_{\max}} = 0.75 \tag{4}$$
$$\omega_{stress} = 0 \qquad \omega_{cooling} = 0 \quad \omega_{fc} = 0$$

$$0 < Q_1 < 1.5\ °C/min \tag{5}$$
$$0 < dt_2 < 85\ min$$

Fig. 1 Curing cycle used for the optimization of the 20 *mm* thick composite.

The two design variables were progressively increased, which resulted in the functional space drawn in the contour plot of fig. 2.a. A ditch of near optimum values vertically divides the fitness representation into two zones. At low values of Q_1 (zone 1), excessive processing times dominate the fitness function (i.e., J_{time}=1). Increasing Q_1 (zone 2), the processing time decreases, but an *outside-to-inside* cure appears resulting in high cure restrictions, although the contour plot is lighter than in zone 1. Between these two regions, the minimum (dark vertical ditch) can be found at the limit where the *inside-to-outside* cure changes to an *outside-to-inside* cure.

This temperature profile was then optimized using the *LeCoq* code, which found the optimum value shown in fig. 2.a. The second case consists of a full optimization, in which curing stresses are added to the previous optimization (i.e., in this case J_{stress}=1). Fig. 2 shows contour plots of the fitness function. Note that in this case, curing stresses are high and transform zone 2 of the previous case into a dark region, thus reducing the near optimum space into a thin knife-shaped region. Moreover, in this full optimization, the optimum value changes considerably from the previous solution (i.e., the solution without stress analysis).

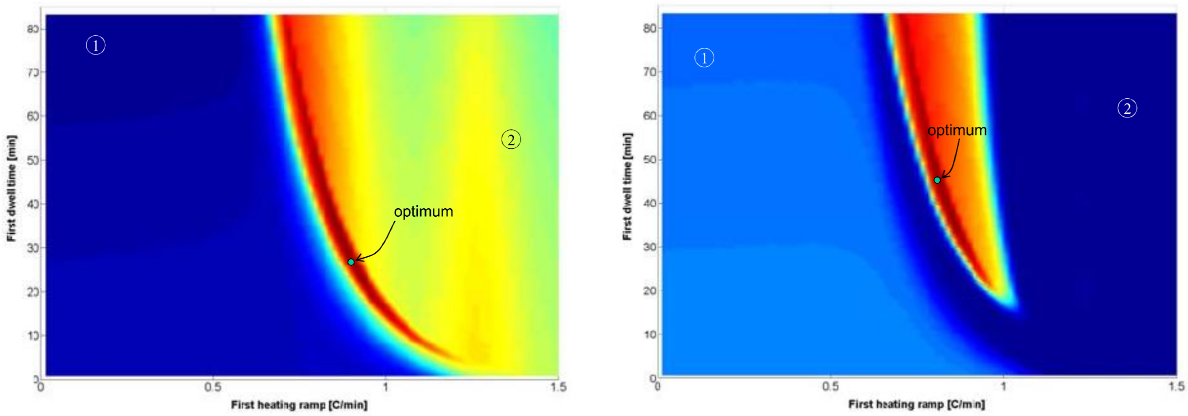


Fig. 2. Contour plots of the fitness function for the two heating ramps curing cycle: (left) without considering internal stresses; (right) considering internal stresses (full optimization).

CONCLUSION

In this investigation, a methodology is proposed for the optimization of the curing cycle in LCM manufacturing. Seven optimization criteria are presented to account for the minimum cycle time, maximum extent of cure, minimum exothermic temperature, minimum cure gradients and minimum curing and cooling stresses. The temperature profile to be optimized is discretized in a series of heating/cooling ramps and dwell times. An evolutionary algorithm was implemented to minimize the fitness function. The proposed methodology, used to minimize the cycle time and residual stresses in a 20 *mm* thick composite, was found to be a useful tool to improve composite cure while reducing processing stresses (i.e., part defects) for a minimum cycle time.

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