

Integrated Product and Process Design (IPPD) for Resin Transfer Molded (RTM) Parts

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Abstract

Composite materials have gained increasing attention in the past several years due to their superior mechanical properties and improved strength-to-weight ratio over traditional materials. Resin transfer molding (RTM) is an attractive composite processing method due to its potential for providing consistently superior parts at a lower cost than other manufacturing techniques. The RTM process involves a large number of variables that are strongly related to the system performance, for example mold filling time, and RTM product quality. The need for understanding the impact of RTM product and process design variables on part quality and process performance is crucial. This paper describe an integrated product and process design (IPPD) approach for RTM product/process design in which genetic algorithms (GA), in conjunction with the cascade correlation neural network architecture (CCA-NN), are utilized. The approach is illustrated through an example.

1 Introduction

The technical knowledge behind advanced composite materials and composite materials processing alone will not lead to the successful development of a competitive RTM product exhibiting high quality at a lower cost. A National Research Council (NRC) publication indicated that the manufacturing of advanced engineered materials is a research priority and recommends that "an early focus on integration of materials and processing requirements must be part of any manufacturing scheme [1991]". Optimum design of RTM product and process design variables will result in high quality parts and enhance the efficiency and robustness of the RTM process [7]. This, in turn, will lead to

longer part life, predictable and reliable performance, lower life cycle costs and improved product yield.

The objective of this research is to incorporate an integrated product and process design optimization approach in the resin transfer molding process in order to determine the crucial product and process design parameters and their settings. By using such an approach, the effect of specific design parameter settings on part quality and process performance can be predicted without actual manufacture of the part. Through this integrated design approach, the resin transfer molding process will be optimized and the quality of the molded parts will be maintained. The thrust of the research is the integration of modeling and simulation technologies that make integrated product and process design a viable concept.

In the integrated product and process design optimization stage, the following variables are investigated: mold preheat temperature, mold outlet pressure, driving pressure - outlet pressure minus inlet pressure, and fiber content. Through a series of experiments, the effects of these variables on the void content and interlaminar shear strength are determined in order to optimize the RTM process. In addition, the effects of the above mentioned variables on mold filling time are investigated. Through training of the cascade correlation algorithm, the effect of mold temperature, outlet pressure, driving pressure and fiber content on void content, interlaminar shear strength and mold filling time are predicted and the genetic algorithm, based on neural network data, optimizes the resin transfer molding process. Therefore, the GA-CCA system successfully carries out integrated product and process design optimization.

2 Literature Review

Much of the RTM research has focused on the modeling of the process, evolving from one-dimensional mold filling models to three-dimensional models that encompass the mold filling, heat transfer and cure stages. Although these models have assisted in the understanding of the RTM process, there is only a limited amount of information that can be obtained from such simulations. Experimental work in recent years has focused on permeability issues, but again, these findings do not yield conclusive answers on some of the current processing problems in resin transfer molding. Therefore, increasing attention is being placed on studying the interaction of design and processing parameters, as well as their effect on the overall performance of the system.

Han, *et al.* [5] studied the effect of gate design on fiber mat deformation. Experimental results indicated that the effect of fiber mat deformation is limited to a small region near the injection gate. It was concluded that modifying the gate design will reduce the maximum pressure, thereby reducing the fiber mat deformation. The influence that process parameter exhibit on void formation in resin transfer molding has been studied by Lundstrom and Gebart [9]. A significant conclusion from the study was that the void content was strongly

reduced by an applied vacuum and, furthermore, can be almost completely eliminated.

An algorithm for the optimization of the resin fraction at the completion of a fiber reinforced composites manufacturing process was developed for two-step press processing [2]. Optimal parameters were defined to be the initial pressure value and the time moment when the pressure changes to a second value. In another study, Rudd et al. [10] addressed process modeling and design issues for resin transfer molding. Process models and results were presented for reinforcement drape, compaction and in-plane permeability and the implications for mold design were discussed. Hayward and Harris [6] discussed the effect of variations in process variables on the quality of RTM moldings. Significant improvements were found in the mechanical properties and porosity levels of moldings made with vacuum assistance.

Although the processing of RTM parts is better understood and more accurately characterized, there remains a great need for work in the area of design optimization in the RTM process, beginning with identifying the relationship among the significant variables and their combined effect on the resulting composite part. It is necessary that an integrated product and process design approach be taken if the achievements of a robust design, and the desired part properties and performance are to be realized.

3 Methodology

3.1 Resin Transfer Molding Process

In the resin transfer molding process, fiber preforms or mats are placed into the mold. The mold is closed and evacuated after which time the resin mixing and injection system is connected to the mold. The system is preheated and when the resin viscosity is sufficiently lowered, the inlet gate to the mold is opened and the resin is forced into the fiber preforms or mats under pressure. Often, the temperature of the resin and mold are different, leading to a nonisothermal process. At this point, heat transfer occurs from the mold walls and fiber preform to the fluid. Once the mold is filled, pressure is maintained and heat continuously supplied to cure the resin matrix. As a final stage, the mold is removed and the finished part retrieved.

3.2 Cascade Correlation Algorithm

Cascade correlation is a supervised learning architecture, which means that a set of outputs is provided for each set of inputs during learning. There are two primary features of the cascade correlation algorithm. One is the cascade architecture, where hidden units are added to the network one at a time, as necessary. Once these hidden units are created, they do not change. The second feature is the nature of the learning algorithm that adds hidden units, which maximizes the magnitude of the correlation between the hidden unit's output and the residual error signal at the output layer [3].

CCA performs gradient descent in the space of network topology as well as weights. Initially, the network structure contains no hidden nodes. Each input is connected to each output, with an adjustable weight corresponding to each connection. A bias input is also present, permanently set to +1. The network attempts to establish a relationship between the input-output patterns. Once a hidden unit is added to the network, its input weights are frozen. Repeating the same learning procedure, but now with an additional unit, the network again attempts to learn. If the error is too large after training reaches an asymptote, meaning no significant additional learning occurs, a second additional hidden unit is added to the network using the procedure described above, its input weights are frozen and learning continues. Hidden units are added until the error drops to a desired level.

3.3 Genetic Algorithms

Genetic algorithms have drawn much attention in solving a wide range of optimization problems with their ease of understanding and implementation [4]. GAs are search procedures based on the mechanics of natural genetics and natural selection. In addition, GAs are different from traditional search methods in the following ways: 1) they work with a coding of the design variables as opposed to the variables themselves -- continuity of parameter space is not a requirement; 2) they search from a population of points, not a single point -- parallel processing of points reduces the chance of trapping into a local optima; 3) they use probabilistic transition rules, not deterministic transition rules -- leads to high quality solutions; 4) they require only the objective function values -- minimal requirements broaden GA's application.

There are three basic components necessary for the successful implementation of a genetic algorithm. Initially, there must be a code or scheme that allows for a bit string representation of possible solutions to the problem. Next, a suitable function must be devised that allows for a ranking or fitness assessment of any solution. The final, and perhaps most important components, are the transformation functions that mimic the biological evolution process when applied to a population of chromosomal representations of solutions to the problem. Once a population of solutions is generated, the genetic search can proceed to produce new solutions with a higher level of fitness than members of the current population. The search steps are repeated for successive generations of the population, until no further improvement in the fitness is attainable. The member in this generation with the highest level of fitness is the optimal solution.

3.4 Mathematical Model for Design Optimization

3.4.1 Notations

This section defines the notations used in the product and process design optimization model:

v_c = void content, % by volume	v_r = void content, % by volume
P_d = driving pressure, psi	P_{d_u} = upper limit on P_d , psi
P_{d_l} = lower limit on P_d , psi	P_o = outlet pressure, psi
P_{o_u} = upper limit on P_o , psi	P_{o_l} = lower limit on P_o , psi
F = fiber content, % by volume	T = mold temperature, °F
T_l = lower limit on T , °F	T_u = upper limit on T , °F
S_H = shear strength of part, N/m ²	S_{H_r} = min. allowable S_H , N/m ²
t = mold filling time, min	

3.4.2 Constraints

In the RTM design optimization problem, three categories of constraints are imposed: process constraints, quality constraints and part characteristic constraints.

Process constraints

- Driving pressure

$$P_{d_l} \leq P \leq P_{d_u} \quad (1)$$

An upper limit on the driving pressure is necessary since, if the pressure is too high, displacement of the aligned fibers will occur; this phenomenon is known as "fiber wash" and has a detrimental impact on the strength of the finished part. A lower limit must be satisfied or the resin may not completely fill the part before curing initiates.

- Outlet pressure

$$P_{o_l} \leq P \leq P_{o_u} \quad (2)$$

An upper limit on the outlet pressure is important. If the outlet pressure is higher than the inlet pressure, as derived from the driving pressure, the resin will flow backwards in to the mold, introducing air into the part. However, if the outlet pressure is too low, it will increase the driving pressure to a point where excessive fiber wash or air entrapment may occur.

- Mold temperature

$$T_l \leq T \leq T_u \quad (3)$$

A second constraint sets the lower and upper limits for the mold temperature. There is an optimal range for the temperature at which the resin has sufficient flow during the mold filling stage, yet premature resin cure is inhibited.

Quality constraints

- Void percentage

$$v_c \leq v_r \quad (4)$$

The above constraints ensure that the quality of the part is adequate in regard to the size and frequency of voids. Voiding affects the strength of the part due to areas of insufficient resin impregnation in the fiber matrix. In the long term, the life of the part is reduced since void regions are more susceptible to fatigue failure.

Part characteristic constraints

- Part strength

$$S_H \geq S_{H_r} \quad (5)$$

3.4.3 General Model

The task is to optimize the three objective functions, mold filling time (t), void content (v_c) and part strength (S_H), subject to the constraints of driving pressure, outlet pressure and mold temperature. The design optimization problem is formulated mathematically as follows:

$$\text{Min } t, v_c; \text{ Max } S_H$$

Subject to:

$$P_{d_l} \leq P \leq P_{d_u}; P_{o_l} \leq P \leq P_{o_u}; T_l \leq T \leq T_u; v_c \leq v_r; S_H \geq S_{H_r}$$

The solution of the above equations will provide an optimal product and process design that results in efficient and robust manufacturing, and that produces parts of consistently high quality. Thus, an integrated product and process design approach is used for enhancing the resin transfer molding process.

3.4.4 Solution Procedure

The cascade correlation algorithm is integrated into the genetic algorithm, as shown pictorially in Figure 1. Beginning with a set of experiments, the quality and performance measures are obtained by one of two methods: the actual resin transfer molding process or a simulation model of the process. When using the simulation model, however, it is imperative that it is validated by the actual process to ensure that the simulation provides accurate results. The simulation model is limited in its output; e.g., it does not predict void content or mechanical properties. Therefore, it will be necessary to use experimentation to obtain information not possible through simulation of the molding process.

Once the results are obtained, the next step is optimization using the GA-CCA system. Design variables [x_1, x_2, x_3, x_4] are used to generate the initial population members. The cascade correlation algorithm provides the objective function values for each population member based on experience provided by previous training of the network. Using this fitness information, the genetic algorithm will select the members that will continue into the next generation. Once again, the new members are evaluated by their fitness; the process repeats for the maximum number of generations or until a suitable solution is found.

3.5 Experimental Procedure

In the resin transfer molding experimental procedure, the following variables were investigated: mold preheat temperature, mold outlet pressure, driving pressure (inlet pressure minus outlet pressure) and fiber content. Through a series of experiments, the effects of these variables on the void content and strength were determined in order to optimize the RTM process. In addition, the effects of the above mentioned variables on mold filling time were investigated.

Due to its efficiency, the experimental design procedure utilized in this study was a central composite design; in such a design, the maximum number of levels for each factor are investigated with a limited number of experiments. The total number of experiments conducted was nineteen. Table 1 describes the settings for each factor in the complete set of experiments.

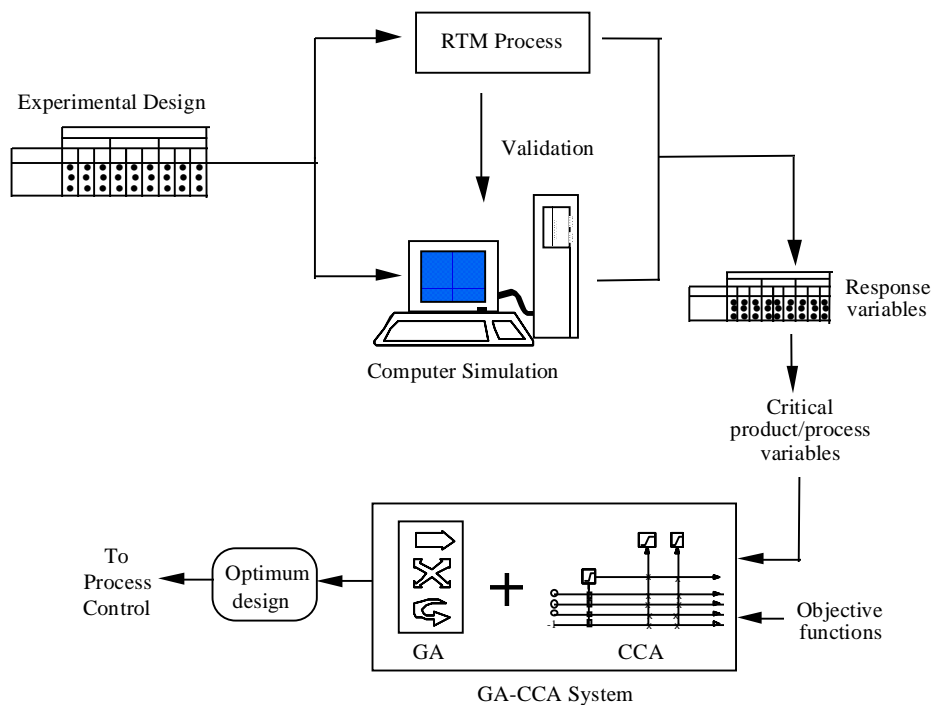


Figure 1: Integrated product and process design optimization scheme.

4 Experimental Setup

A rectangular mold of dimensions 13.97 x 15.27 x 0.98 cm was used in this study. The reinforcement was a unidirectional fiberglass material, Knytex D155, with the fibers aligned perpendicular to the direction of resin flow. The resin injection inlet was located at the center of one end of the mold and venting took place at the opposite end of the mold at the outlet. Since the fiberglass layers did not completely cover the area of the mold, a sealant was used to hold the layers intact and to prevent an "edge effect" from occurring. The resin system,

Tactix 123 (Dow) with Jeffamine D400 (Texaco) curing agent, was selected due to its common use and wide range of applications in commercial products.

In this study, nineteen sets of experiments were conducted. The performance of these processes varies. The average void contents range from 0% to 7.6%; strengths range from 699 lbs to 979 lbs; fill times range from 40 seconds to 1930 seconds.

5 Design Optimization

Before the design optimization stage, training of the neural network takes place. Using the four input variables (cure temperature, outlet pressure, driving pressure and fiber volume), the cascade correlation algorithm is trained to predict the values of the output variables (void content, strength and mold filling time). Experiment 10 had an unusually high mold filling time and experiment 14 was a short shot, i.e., the mold did not completely fill with resin; therefore, these are not included as mold filling time data.

After training the cascade correlation algorithm, the genetic algorithm is utilized for determining optimal design for the resin transfer molding process. The optimal variable settings of cure temperature, outlet pressure, driving pressure and fiber volume are shown in Tables 1-3 for minimizing void content, maximizing composite strength and minimizing mold filling time, respectively. Ten runs were performed for each objective function. It should be noted that for void content, a quality rating is used to determine part quality. A 5 percent void content within the composite part was considered unacceptable, any plaque that contained 5 percent voiding or higher was assigned a value of "1", or unacceptable. Parts with 4 percent voiding or less were given a rating of "0".

Table 1. Optimal designs for minimizing void content

Run #	Cure temp, C	Outlet pressure, psi	Driving pressure, psi	Fiber volume, # layers
1	59.50	-11.05	18.75	23
2	67.10	-12.00	16.85	25
3	56.65	-11.05	21.60	22
4	52.85	-10.10	27.30	24
5	50.95	-11.05	29.20	21
6	50.00	-12.00	14.00	22
7	51.90	-12.00	25.40	23
8	51.90	-11.05	26.35	25
9	53.80	-10.10	14.00	25
10	60.45	-10.10	19.70	21



Table 2. Optimal designs for maximizing strength

Run #	Cure temp, C	Outlet pressure, psi	Driving pressure, psi	Fiber volume, # layers
1	123.93	-4.00	21.99	21
2	118.93	-5.00	17.00	25
3	90.96	-9.00	27.99	21
4	60.99	-11.00	21.97	21
5	105.94	-11.00	24.99	23
6	88.92	-5.00	16.00	22
7	97.95	-5.00	31.98	21
8	51.00	0.00	27.99	24
9	58.99	-3.00	23.99	23
10	124.93	-10.00	23.99	25

Table 3. Optimal designs for minimizing mold filling time

Run #	Cure temp, _C	Outlet pressure, psi	Driving pressure, psi	Fiber volume, # layers
1	126.00	-11.00	34.00	24
2	114.00	-8.00	32.00	22
3	125.00	-2.00	31.00	23
4	124.00	-2.00	34.00	21
5	100.00	-10.00	32.00	21
6	129.00	-11.00	28.00	23
7	129.00	-8.00	26.00	22
8	107.00	-9.00	33.00	25
9	123.00	-6.00	32.00	22
10	124.00	-3.00	28.00	25

Although the genetic algorithm provides varying solutions for optimizing each objective function - minimizing void content, maximizing strength and minimizing mold filling time - the objective function values are the same. In Table 1, the minimum void content found by the genetic algorithm is 0 percent voiding. An overall part strength of 824 lbs is provided for the solutions in Table 2. Finally, the mold filling time solutions in Table 3 correspond to a time of approximately 80 seconds.

Table 4. Optimal designs for multiple objective functions

Run #	Cure temp, C	Outlet press, psi	Driving press, psi	Fiber vol., # layers	Void content	Strength, lbs	Fill time, sec
1	52	-8	32	23	0.228	738.867	269.05
2	53	-12	33	22	0.243	728.348	152.38
3	50	-5	28	22	0.275	751.628	307.14
4	61	-8	29	21	0.343	750.453	114.29
5	65	-12	33	23	0.249	743.037	152.38
6	51	-3	28	24	0.212	765.100	533.33
7	62	-12	32	25	0.160	753.579	411.90
8	69	-9	34	21	0.384	737.137	221.43
9	62	-12	30	23	0.230	752.447	261.90
10	58	-4	32	24	0.241	753.485	309.52

After determining the individual solutions for minimizing void content, maximizing strength and minimizing mold filling time, the genetic algorithm is utilized for optimizing the resin transfer molding process with multiple objective functions. The results are shown in Table 4. As expected, there are tradeoffs when deciding the settings for cure temperature, outlet pressure, driving pressure and fiber volume.

6 Conclusions

Although the RTM process has become better understood in recent years, there is still a great deal of knowledge to be attained in this field of material processing. One area in particular that needs attention is that of integrated product/process design. In many instances, the product and process design variables are selected arbitrarily and modified as needed during prototype development, which results in wasted time and resources. For this reason, it is important to develop a systematic procedure for design optimization. In addition, to ensure the quality of the product during the production stage, an accurate method of process control is necessary. The genetic algorithm-cascade correlation algorithm procedure developed in this research was employed for systematic product/process design. In addition, a robust design was determined so that part quality is maintained in the presence of fluctuations in the process variables.

References

1. The Competitive Edge: Research Priorities for U.S. Manufacturing, National Research Council, National Academy of Sciences, 1991, pp. 78-97.
2. Dementyev, V., Kostritskiy, S., Petuhov, M. and Torkunov, A., "On the Optimization of the Fiber Reinforced Composites Manufacturing Process with Two Pressure Steps," 3rd International Conference on Computer Aided Design Composite Material Technology CADCOMP '92, published



- by Computational Mechanics Publishing, Southampton, England, 1992, pp. 37-47.
3. Fahlman, S. and Lebiere, C., "The Cascade-Correlation Learning Architecture," in D.S. Touretzky *et al.* (eds.), *Advances in Neural Information Processing Systems*, Morgan Kaufmann, Los Altos, CA, Vol. 2, 1990, pp. 524-532.
 4. Goldberg, D.E., *Genetic Algorithm in Search, Optimization, and Machine Learning*, Addison Wesley, Reading, MA, 1989.
 5. Han, K., Trevino, L., Lee, J. and Liou, M., "Fiber Mat Deformation in Liquid Composite Molding. I: Experimental Analysis," *Polymer Composites*, Vol. 14, No. 2, April 1993, pp. 144-150.
 6. Hayward, J. and Harris, B., "Effect of Process Variables on the Quality of RTM Mouldings," *SAMPE Journal*, Vol. 26, No. 3, May/June 1990, pp. 39-46.
 7. Kendall, K.N. and Rudd, C.D., "Flow and Cure Phenomena in Liquid Composite Molding," *Polymer Composites*, Vol. 15, No. 5, October 1994, pp. 334-348.
 8. Lin, S.-S., "Integrated Mechanical Tolerancing for Design and Manufacturing," Ph.D. Dissertation, Florida State University, August 1994.
 9. Lundstrom, T.S. and Gebart, B.R., "Influence from Process Parameters on Void Formation in Resin Transfer Molding," *Polymer Composites*, Vol. 15, No. 1, February 1994, pp. 25-33.
 10. Rudd, C.D., Rice, E.V., Bulmer, L.J., and Long, A.C. "Process Modeling and Design for Resin Transfer Molding," *Plastics, Rubber and Composites Processing and Applications*, Vol. 20, No. 2, 1993, pp. 67-76.