Manufacturing Technology and Research (An International Journal)| Volume 13 | Issue 1-2 | Dec(2020) ISSN: 0973-0281

A comprehensive review on process optimization of composite moulding processes

Anita Zade[a], Raghu Raja Pandiyan Kuppusamy[a1]

[a]*Department of Chemical engineering, National Institute of Technology Warangal,*
Telangana, 506004, India

Abstract

A review on numerical optimization of parameters involved in mould filling, and curing that affects a class of composite moulding processes, namely Liquid Composite Moulding (LCM) processes are presented. The critical issues and prevention techniques of the entire process cycle are discussed to manufacture a void-free and cost-effective composite part. The key parameters discussed under mould filling stage are preform parameters such as permeability and porosity, gate and vent location, injection pressure, and mould geometry. Whereas, the key parameters discussed under curing stage are degree of cure, mould temperature and viscosity of resin. The number of single objective and multi-objective optimization techniques have been developed to optimize the objectives like the degree of cure, temperature overshoot, process time, gate and vent location and mould fill time. The Nelder mead simplex method, simulated annealing, GA, NSGA-II, and MOOGA are the most used traditional techniques for optimizing the process as well as mould parameters. The scope of meta-heuristic or hybrid optimization techniques for constrained single and multi-objective optimization problem in the LCM process has addressed.

Keywords: Composite processing; cure kinetics; mould filling; numerical optimization; stochastic techniques.

1. Introduction

The designing of composite process parameters has become crucial factor in different industries with increase in applications of composite materials in vital sectors. There have been various composite part manufacturing techniques from traditional methods like hand-layup which is cost and labour intensive to the use of automated techniques such as autoclave, injection moulding, extrusion and liquid composite moulding (LCM) process etc. [1–3]. Although, each technique has different manufacturing procedure, the major objectives and design parameters will be same to manufacture the cost effective void free composite part. In this article we will mainly focusing on the LCM process parameters, as this method is effective in manufacturing properly finished composite parts with complex geometries [4-8].

LCM is a closed moulding process, hence after closing the mould, it is difficult to know whether fibre preform has impregnated with resin or there are unsaturated regions where the air has entrapped [9]. Therefore it is important to identify and optimize the parameters during the process as depicted in figure 1.

This paper addresses following research questions for making the cost effective and void free composite part using LCM process.

Research questions

a. Which factors need to consider to manufacture a void free cost effective composite part?
b. Why there is need to develop meta-heuristic techniques over traditional numerical techniques?
c. What advancements needed in meta-heuristic techniques for optimizing LCM process parameters for constrained single and multi-objective optimization problem?

[*] Corresponding author. Tel.: +91-8002486897
E-mail address: raghuraj@nitw.ac.in

Following objectives formed to address these questions.

Objectives:

a. To analyze the effect of mould, raw material, and process parameters on mould fill time and cure time
b. To develop proper optimization technique for addressing the full-fledged complex and non-linear optimization problem
c. Development of effective hybrid MOO algorithm to optimize the objectives related to mould fill time with minimum void content and cure time with given temperature range

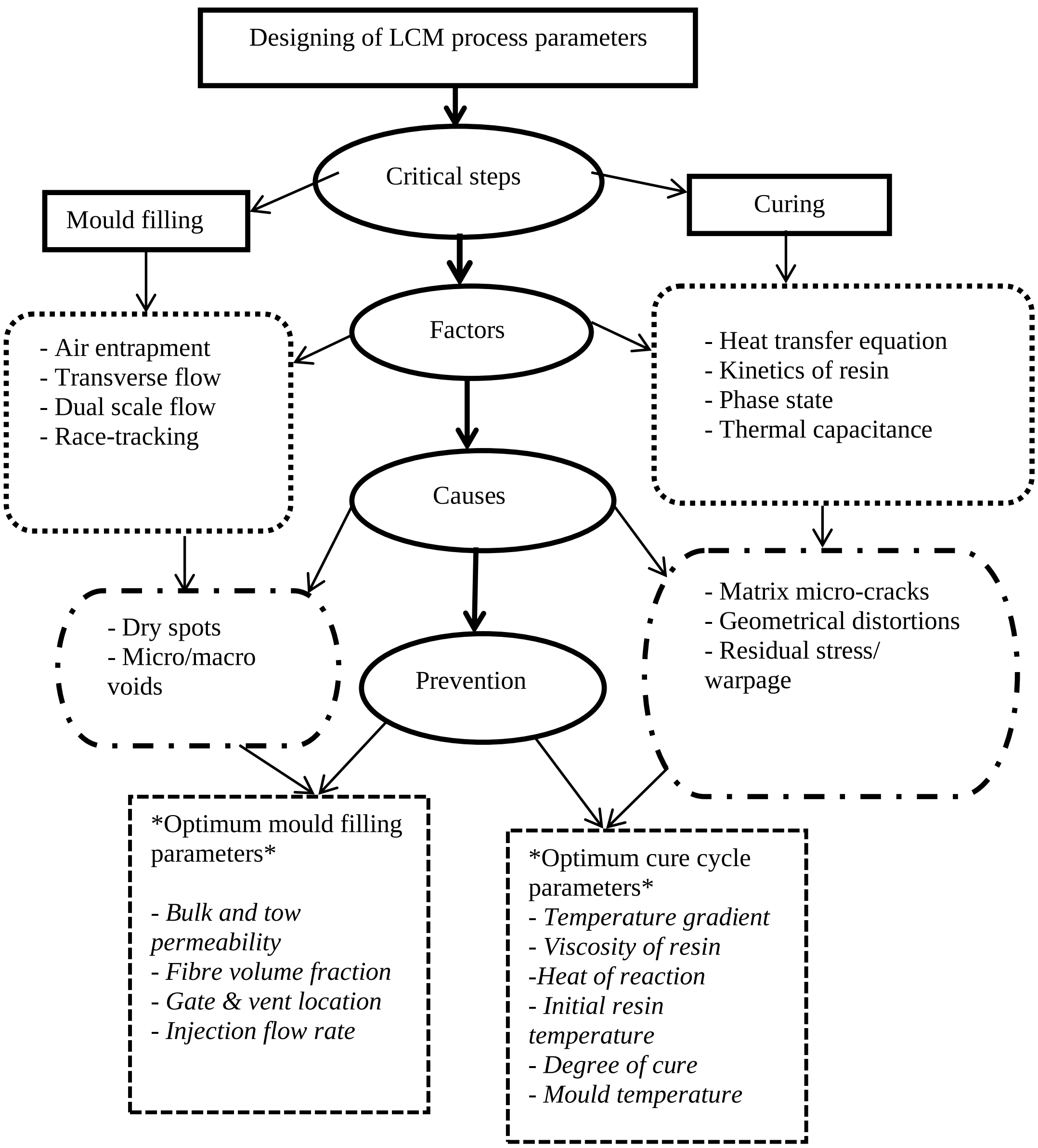
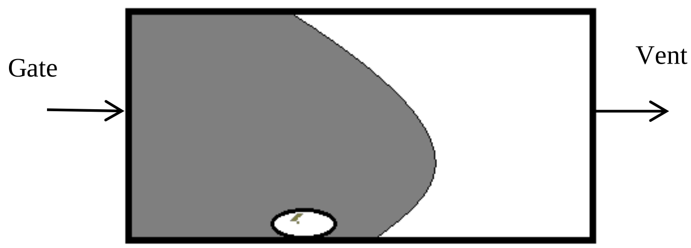
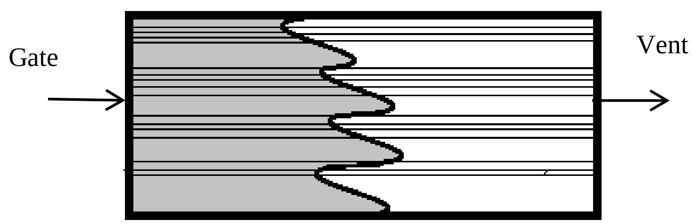


Fig. 1. Flow diagram depicting designing of LCM process parameters

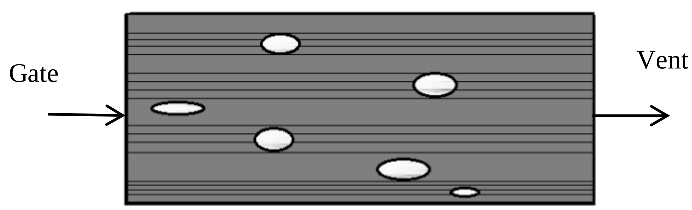
In the LCM process, mould filling and curing are the critical steps [10-12]. The factors which affect during the mould filling stage are air entrapment, transverse flow, race tracking effect and dual scale flow [13]. Air entrapment arises due to non-uniform impregnation of fibre preform with resin. Usually, composite structures are very thin hence flow along the thickness direction has been considered negligible. However, when the in-plane permeability component of fibre preform along the thickness direction will change significantly then the transverse flow has to take into account [14]. When air channels will be present between the mould wall and fibre preform the race-tracking occurs. This effect arises mainly along mould wall edges, joints, inserts and around ribs for complex structures. When there is a difference between the fluid flow within the fibre tows and in between the tows the dual scale flow arise [15, 16]. Due to these defects voids and dry spots forms in the composite part as shown in figure 2 [17]. Therefore, proper selection of bulk and tow permeability, gate and vent location, porosity and injection pressure/flow rate need to take into account [18-23].



a. Macro-void formation



b. Dual-scale flow



c. Micro-void formation

Fig. 2 (a, b, c). Flow issues in LCM Process

Curing is an exothermic process where heat transfer occurs between mould and saturated preform. With an increase in temperature of saturated preform liquid resin will convert to gel and then gel to solid this phase transition called as gelation and solidification respectively [24-27]. The factors which affect the curing process are temperature overshoot, glass transition temperature during phase change, and resin viscosity [28, 29]. This may develop the temperature and cure gradients along thick sectioned parts which results to matrix micro-cracks, residual stresses and geometrical distortions [30-35].

Numerous numerical techniques used by researchers to optimize the mould filling and curing parameters of LCM process [36, 37]. We found few review articles, book chapters and thesis chapters related to numerical optimization of composite process parameters [38]. They are particularly specified to some application based on use of traditional numerical techniques. To the best of our knowledge we did not found review article in last ten years addressing use of meta-heuristic or hybrid optimization techniques for constrained single and multi-objective optimization problem in the LCM process.

This article describes the comprehensive review on identification of problem statement, formulation of optimization problem and use of suitable optimization technique based on the type of optimization problem in the composite processing. Depending on the accomplishment of target objectives, design parameters need to set. Then, we will present the different types of optimization techniques used for optimizing the different parameters of LCM processes. After that, to optimize the different conflicting objectives simultaneously the studies on multi-objective optimization (MOO) in composite processing has been reviewed. Here, the combination of different mould parameters, cure parameters and both mould and cure parameters optimized simultaneously.

2. Numerical optimization for composite processing

2.1. General formulation of optimization problem

Generally, the optimization problem formulated as,

$$\begin{aligned} &\max_X/\min f_k(X) && k = 1, 2, \ldots, N \\ &\text{Subject to,} && \\ &\quad h_l(X) = 0 && l = 1, 2, \ldots, L \\ &\quad g_m(X) \le 0 && m = 1,2,\ldots M \\ &\quad lb \le X \le ub && X = (x_1, x_2, \ldots x_d)^T \end{aligned} \tag{1}$$

here, $f_k(X)$ is the scalar objective function which has to maximize or minimize, $h_l(X)$ represents the J number of equality constraints also called active constraints, $g_m(X)$ represents the M number of inequality constraints and X is the vector of d-dimensional design variables.

For the sake of understanding and correlation we have discussed the mathematical formulation of one example based on composite process parameter optimization. Jahromi et al. [39] used a dynamic artificial neural network (ANN) for achieving the uniform temperature and degree of cure for thick fibre reinforced composite parts, which is directly dependent on the temperature profile of mould wall. The objective function was formulated to minimize the temperature gradients between two selected points i.e. central and corner, to indicate the overall cure process subject to constraints on the degree of cure. Mathematically,

$$\begin{aligned} &\min \sum_{i=1}^{n} \left(T_{i(center)} - T_{i(corner)}\right)^2 \\ &\text{Subject to,} \quad \alpha_{corner} \ge \alpha_{crit} \\ &\qquad \text{where} \quad \alpha_{crit} = 0.8 \\ &\qquad 298\,K \le T_i \le 430\,K \qquad i = 1, 2, \ldots 5. \end{aligned} \tag{2}$$

2.2. Classification of optimization techniques

After the formulation of the optimization problem, the task is to solve it using an appropriate optimization technique. There are different types of optimization techniques based on the nature of optimization problem they can be classified as [40]:

I. Deterministic techniques: These techniques are very effective for achieving good convergence. For highly non-linear and complex problems they may stick in the local optima.

II. Stochastic algorithms: These techniques are very effective for achieving the global optimal solution [41-43].

III. Hybrid algorithms: These types of algorithms used for achieving better convergence as well as the global optimal solution. Usually, Deterministic techniques and stochastic techniques are combined by taking into account the convergence property of the deterministic algorithm and exploration property of the stochastic algorithm as shown in figure 3. In composite processing, different optimization problems have been addressed in the literature using this method. For example, a hybrid GA-gradient based algorithm used to optimize the gate location, on the flow channels.

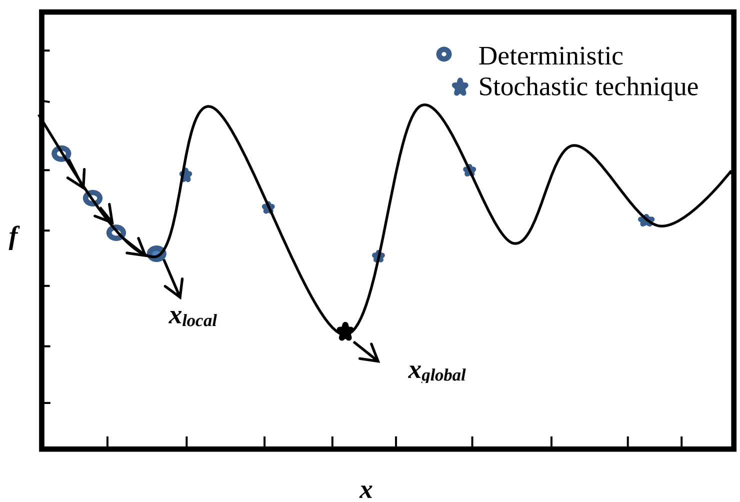


Fig. 3. Convergence flow of optimal solution for stochastic and deterministic techniques

3. Numerical studies on optimization

3.1. Numerical studies on single objective optimization

The number of research articles found on the single objective optimization of gate and vent location using numerous deterministic and stochastic techniques. Particle swarm optimization (PSO) and genetic algorithm (GA) found to be the most used stochastic algorithms with the aim of reducing computational time and increasing accuracy [44]. The mostly formulated objective was minimizing mould fill time with reduced void content [45-54]. To optimize the curing stage the majorly formulated objective was cure process time with respect to variables on temperature and cure gradients, a constraint on degree of cure. Table 1 reviews the categorization of single-objective optimization studies of composite processing in terms of objectives, parameters and numerical techniques.

Table 1. Objective function categorization for Single Objective Optimization of Composite Processing

Objective	Parameters	Numerical Techniques	Reference	Year
Least square error between experimental & predicted data from simulation	In-plane 3D permeability components	FEM, golden section search method	[55]	2011
Flow front progression time	Characterization of 3D permeability	FEM, golden-section search method	[56]	2017
Buckling load, Fundamental frequency, Structural weight	Geometry, Temperature	Meta-heuristic technique	[57]	2018
Stress distribution, Critical buckling load, Fundamental frequency	Material distribution pattern,	GA, PSO, ANN, ANFIS	[58]	2019
Gate location	Permeability, Fill time, Mould fill fraction	GA, Gradient-based algorithm	[59]	2007
Injection gates and vents	Permeability	Graph-based two-phase heuristic algorithm (GTPH)	[60]	2008
Fill time	Gate and vent location,	Depth-first search and	[61]	2015

	Distribution media, Race-tracking effect	Tree search algorithm		
Total cure cycle time	Central temperature, Duration of two steps	ANSYS, Simulated Annealing (SA), NM-simplex method	[62]	2014
Process cycle time	Mould temperature profile	GA	[63]	2005
Mould fill time	Gate locations	GA, exhaustive search, Centroidal Voronoi Diagram (CVD) method	[64]	2016
Mean square error between corner and centre part of temperature	Temperature	ANN, SQP	[39]	2012

3.2. Numerical studies on multi-objective optimization

Multi-objective optimization (MOO) problem contains more than one objective which is conflicting to each other. Hence, there will be more optimal solutions which are rep-resented in terms of Pareto fronts. The best optimal solutions are called non-dominated solutions. Different MOO techniques have been developed to find out the Pareto front between the quality and productivity of the composite part. Evolutionary algorithms like MOOGA, NSGA-II has been mainly used for optimizing the process and design parameters for composite parts. Different objectives addressed using numerous MOO techniques such as mould fill and cure process time, gate and vent location [66], temperature overshoot and degree of cure, etc. Few algorithms have been developed for thick and ultra-thick components for simple geometries to optimize the trade-off between temperature overshoot and cure process time [67]. Table 2 reviews the categorization of multi-objective optimization studies of composite processing in terms of objectives, parameters and numerical techniques.

Table 2. Objective function categorization for Multi-objective Optimization of Composite Processing

Objectives	Parameters	Numerical Techniques	Reference	Year
Crowding distance, Filling time	Gate and vent location	NSGA-II	[66]	2009
Warpage, Shrinkage rate, Short shot possibility	Process parameters: part cooling time, melt temperature, pressure holding time, & mould fill time; Geometric parameters: modified edge & Round gate	FAHP, TOPSIS	[68]	2018
Cure degree difference, Set up cost, Fill time, Variance of cure degree, Cure time	First temperature rise, Dwell time, Dwell temperature, Second temperature rise, Hold temperature	NSGA-II	[65]	2019
Setup cost, Fill time	Resin temperature, Temperature of mould	Hybrid FE/FD method	[69]	2019
Weld line, Fill time, Wasted resin, Dry spot	Gate and vent location	FEA, MOOGA	[70]	2016
Cure time, Temperature	First and second dwell	Surrogate model,	[67]	2018

overshoot	temperature, duration of 1st dwell, heating rate	Monte-Carlo simulator, MOOGA		
Standard deviation and Average of degree of cure	Mould temperature, Heat flux, Cure part temperature	Ant swarm strategy	[71]	2015
Tensile load, flexural strength	Duration and temperature of the 1st curing step, heating rate	MOOGA toolbox	[72]	2018
Residual stresses, Cure process time, Degree of cure	Temperature profile	MOOGA	[73]	2006
Cure process time, Temperature gradient, Degree of cure at the end of mould filling, Filling time	Cure profile, Thermal profile of mould filling, Initial resin temperature, Gate & vent location	MOOGA	[74]	2014
Cure process time, Temperature overshoot	Thermal profile, Thickness of composite part, Mould geometry	MOOGA	[75]	2016
Warpage, Volumetric shrinkage and Residual	Fibre content, fibre aspect ratio, Melt temperature,	NSGA-II	[76]	2018

stress	Cooling time, Injection pressure			
Peak tensile residual stress, Roller speed	Degree of bonding, Peak residual stress, & Thermal degradation	NM-Simplex method	[77]	2007
Maximum difference in degree of cure, Total cure time and Maximum difference in temperature	Temperature, Degree of cure	MOOGA	[78]	2018
Weld line, Void content, fill time, wasted resin	Void fraction, Distance between gate	MOGA	[16]	2019

4. The mathematical formulation of optimization problems studied in the literature

4.1. The mathematical formulation of single objective optimization problems

1. An optimal heating control problem was formulated as [79],

$$J = \max_{\Omega}(|\nabla\alpha|_{t_0}) \tag{2}$$

Subject to, $\alpha_1 \leq \langle\alpha\rangle_{t_0} \leq \alpha_2$

$$\langle\alpha\rangle = \int_{\Omega}\alpha(r,T,t)d\omega;$$

$$\langle\nabla\alpha\rangle = \int_{\Omega}|\nabla\alpha(r,T,t)|d\omega$$

The boundaries α_1 and α_2 were used differently at each stage of the process, that is α_1=0.15, and α_2= 0.25 at liquefaction stage and α_1=0.97 and α_2=1 at the solidification stage or final stage of curing.

2. Two different optimization problems were addressed, to minimize the peak tensile residual stress and to maximize the roller velocity of tape placement of thermoplastic composites [77].

$$\min \sigma_r \tag{3}$$

Subject to, $D_b = 1$

$\alpha_d \leq \alpha_d^{all}$

$0.5\text{cm} \leq h_l \leq 9 \text{ cm}$

$20\ ^0\text{C} \leq T_0 \leq 135\ ^0\text{C}$

$1 \text{ mm/s} \leq v_r \leq 25 \text{ mm/s}$

$400\ ^0\text{C} \leq T_{hg} \leq 750\ ^0\text{C}$

$\max v_r$

Subject to, $D_b \geq D_{b,min}$

$\alpha_d \leq \alpha_d^{max}$

$0.5\text{cm} \leq h_l \leq 9 \text{ cm}$

$20\ ^0\text{C} \leq T_0 \leq 135\ ^0\text{C}$

$400\ ^0\text{C} \leq T_{hg} \leq 1000\ ^0\text{C}$

3. Ruiz & Trochu (2005) proposed the methodology based on GA implemented in C++ to minimize the thermal & cure gradients & the reduction of processing stresses. To increase the convergence rate of the search algorithm seven sub-objectives were constructed with sigmoid functions.

$$F_f(V_d) = \frac{A_f}{B_f + e^{-F_w C_f}} + D_f \tag{4}$$

$$F_w = w_{fc} J_{fc} + w_{T_{\max}} J_{T_{\max}} + w_{AGP} J_{AGP} + w_{cure} J_{cure} + w_{stress} J_{stress} + w_{cooling} J_{cooling} + w_{time} J_{time}$$

Subject to, $V_d \in Cs$

The vector of design parameters V_d defined as $V_d = [Q_1, dt_1, Q_2, dt_2, Q_3, dt_{31} ......, Q_7, dt_7]$ where the discrete set of Q_i defines the heating ramps and dt_i defines the dwell time. The pair sum of *(Q_i, dt_i)* describes the mould temperature profile.

The constraint vector $Cs = [T_{init}, T_{room}, Q^{+}_{\max}, Q^{-}_{\max}]$

Where $Q^{+}_{\max}$ defines the maximum permitted heating ramps, $Q^{-}_{\max}$ defines the maximum cooling ramps allowed by the mould, T_{init} is the initial room temperature and T_{room} the room temperature. $F_f(V_d)$ is the fitness function to be optimized and parameters w are the weighting coefficient for each subjective function. A_f, B_f, C_f, & D_f are the coefficients of the sigmoid function. The definitions of each sub-objective function described in the article [63].

4.2. The mathematical formulation of multi-objective optimization problems

1. The MOO problem was defined to minimize the die temperature (T_1, T_2, T_3), and maximize the pull speed (u) subject to constraints on the degree of cure [80].

$$\min f_1(T) = \frac{c \times m \times [(T_1 - T_0) + (T_2 - T_0) + (T_3 - T_0)]}{\gamma \times t} \tag{5}$$

$$\max f_2(u) = u$$

Subject to,

$$\alpha_c \geq 0.9$$

$$\alpha_c - \alpha_w \leq 0.0035$$

$$373 \leq T_1 \leq 413$$

$$413 \leq T_2 \leq 458$$

$$413 \leq T_3 \leq 458$$

$$100 \leq u \leq 300$$

where c is the special heat of die, m is the mass of die, t is the heating time, T_0 is the environmental temperature, and γ is the thermal efficiency. T_1, T_2, T_3 & u are the design variables. This MOO problem was converted into SOO problem by using the weighted average method and constrained problem converted into unconstrained one using the penalty method.

$$\min F(X) = a \times F_1(T) + (1 - a) \times F_2(u) + P(\alpha)$$

where $F_1(T)$ and $F_2(u)$ are unitized forms of $f_1(T)$ and $f_2(u)$ respectively. a is weighting factor a [0,1], $P(\alpha)$ is the penalty function which was expressed as,

$$P(\alpha) = r_1 |\min\{0, \alpha_c - 0.9\}| + r_2 |\min\{0, 0.035 - \alpha_c + \alpha_w\}|$$

where r_1 and r_2 are penalty parameters.

2. The MOO problem was formulated using the Poisson regression analysis with backward elimination for tensile load and flexural strength. The design variables considered are heating rate (a ^{0}C/min), the temperature of the 1st curing step (T_1 ^{0}C), and duration of the

1^{st} curing step (h_1 hours). In the flexural strength regression model, only T_1 and h_1 are considered as independent variables because a was removed by backward elimination [72].

$$\max f(a, T_1, h_1) = \begin{cases} \max Tensile\ load = \min(1/tensile\ load) = \min(1/e^{Y_1'}) \\ \max Flexural\ strength = \min(1/flexural\ strength) = \min(1/e^{Y_2'}) \end{cases} \quad (6)$$

where,

$$Y_1' = -0.3 - 0.8 \times a + 0.524 \times T_1 - 0.83 \times h_1 + 0.784 \times a^2 - 0.002901 \times T_1^2 + 1.547 \times h_1^2 + 5.31 \times a \times h_1 - 0.1979 \times T_1 \times h_1 + 0.000003 \times T_1^3 - 0.285 \times h_1^3 - 0.3327 \times a \times h_1^2 + 0.00099 \times T_1^2 \times h_1 + 0.01975 \times T_1 \times h_1^2 + 0.0153 \times T_1^3 \times h_1 - 0.000064 \times T_1^2 \times h_1^2 - 0.000481 \times T_1 \times h_1^3 - 0.00573 \times a \times h_1^4$$

$$Y_2' = 4.6336 + 0.009461 \times T_1 + 0.1188 \times h_1 - 0.000792 \times T_1 \times h_1$$

3. The MOO problem has been formulated to find out the fibre content (C_f), fibre aspect ratio (A_f), melting temperature (T_{me}), injecting pressure (P_{in}), and cooling time (t_c) [76].

$$\min f(x) = \{\text{warpage, volumetric shrinkage, residual stress}\} \quad (7)$$

subjected to,
$$\text{warpage} < 0.15\ \text{mm}$$
$$\text{volumetric shrinkage} < 6\%$$
$$\text{residual stress} < 30\ \text{MPa}$$
$$10\% \le C_f \le 30\%$$
$$10 \le A_f \le 50$$
$$220\ ℃ \le T_{me} \le 260$$
$$60\ MPa \le P_{in} \le 80\ MPa$$
$$20\ s \le t_c \le 30\ s$$

4. To optimize the design variables of cure profile such as 1^{st} temperature rise (Rt_1), dwell temperature, dwell time (T_{dwell}), 2^{nd} temperature rise (Rt_2), & hold temperature (T_{hold}), a MOO problem has been formulated to minimize the conflicting objectives such as difference of cure degree, variance of cure degree and cure time [65].

$$\begin{aligned} \min f_1 &= t|_{\alpha_{\min}=0.9} \\ \min f_2 &= \alpha_{\max} - \alpha_{\min} \\ \min f_3 &= \frac{1}{N}\sum_{i=1}^{N}(\alpha_i - \alpha_{ave})^2 \end{aligned} \quad (8)$$

Subject to,

$$
\begin{aligned}
&373 \le T_{dwell} \le 433\\
&1 \le Rt_1 \le 5\\
&1 \le Rt_2 \le 5\\
&443 \le T_{hold} \le 463\\
&0 \le Time_{dwell} \le 90
\end{aligned}
$$

5. Summary and Conclusion

This review article has targeted the process optimization of mould filling and curing steps in the composite moulding process. Bulk and tow permeability, gate and vent location, injection pressure, and component geometry were found to be the crucial parameters for addressing the multi-phase and multi-scale problems for mould filling stage. Whereas, mould temperature, initial temperature of resin, degree of cure, heat flux, temperature gradient and temperature overshoot found to be crucial parameters for optimizing thermal profile in curing stage. To manufacture a void-free composite part with the optimized parameters different optimization techniques have been developed. The number of single objective and multi-objective optimization techniques has been developed to optimize the objectives like the degree of cure, temperature overshoot, process time, gate and vent location and mould fill time. The Nelder mead simplex method, simulated annealing, GA, NSGA-II, and MOOGA are the most used traditional techniques for optimizing the process as well as mould parameters.

Although there are number of articles found on the development of numerical models for addressing multi-scale and multi-phase problems for the complex geometries. The development of an effective optimization technique for addressing such problems is a crucial task. Nowadays, the development of a hybrid multi-objective optimization technique for optimizing the LCM process parameters is an active area of research. Till now, very few articles found on MOO for both mould filling and curing parameters using appropriate optimization techniques. Hence for optimizing the parameters of complex geometry, thick and ultra-thick component development of an effective optimization technique is needed. This may advance the use of LCM technology in the industry for manufacturing large and complex structures instead of traditional techniques.

References

1. Chang C (2015) Simulation of non-isothermal filling process in vacuum assisted compression resin transfer moulding process. *Plastics, Rubber and Composites*, 44, 162–170
2. Yang B, Jin T, Li J, Bi F (2015) Three-Dimensional Numerical Simulation of Mold Filling Process in Compression Resin Transfer Molding. *Applied Composite Materials*, 22, 209–230
3. Yang B, Jin T, Li J, Bi F (2014) Simulating the resin flow and stress distributions on mold tools during compression resin transfer molding. J*ournal of Reinforced Plastics Composites*, 33,1316–1331
4. Bodaghi M, Lomov S V, Simacek P, Correia NC, Advani SG (2019) On the variability of permeability induced by reinforcement distortions and dual scale flow in Liquid Composite Moulding: A review. *Composites Part A*. *https://doi.org/10.1016/j.compositesa.2019.03.004*
5. Mittal G, Rhee KY, Mi V, Hui D (2018) Reinforcements in multi-scale polymer composites : Processing , properties , and applications. *Composites Part B* 138, 122–139
6. Lomov S V (2011) Modelling the geometry of textile reinforcements for composites: *WiseTex. In: Compos. Reinf. Optim. Perform. Woodhead Publishing Limited*, 200–238
7. Leclerc JS, Ruiz E (2008) Porosity reduction using optimized flow velocity in Resin Transfer Molding. *Composites Part A* 39, 1859–1868
8. Andrew JJ, Srinivasan SM, Arockiarajan A, Dhakal HN (2019) Parameters influencing the impact response of fiber-reinforced polymer matrix composite materials : A critical review. *Composite Structutes* https://doi.org/10.1016/j.compstruct.2019.111007

9. Breard J, Saouab A, Bouquet G (2003) Numerical simulation of void formation in LCM. *Composites Part A* 34, 517–523
10. Kuentzer N, Simacek P, Advani SG, Walsh S (2006) Permeability characterization of dual scale fibrous porous media. *Composites Part A*, 37, 2057–2068
11. Swery EE, Meier R, Lomov S V, Drechsler K, Kelly P (2015) Predicting permeability based on flow simulations and textile modelling techniques : Comparison with experimental values and verification of FlowTex solver using Ansys CFX. *Journal of Composite Materials*, 1–15
12. Dong C (2008) A modified rule of mixture for the vacuum-assisted resin transfer moulding process simulation. *Composites Science and Technology*, 68, 2125–2133
13. Mal O, Couniot A, Dupret F (1998) Non-isothermal simulation moulding process of the resin transfer. *Composite Part A*, 189–198
14. Kim J, Hwang Y, Choi K, Kim H, Kim H (2019) Prediction of the vacuum assisted resin transfer molding (VARTM) process considering the directional permeability of sheared woven fabric. *Composite Structures*, 211, 236–243
15. Hamidi YK, Altan MC (2017) Process Induced Defects in Liquid Molding Processes of Composites. *International Polymer Processing*, 32, 527–544
16. Oya Y, Matsumiya T, Ito A, Matsuzaki R, Okabe T (2019) Gate optimization for resin transfer molding in dual-scale porous media: Numerical simulation and experiment measurement. *Journal of Composite Materials*, 0, 1–15
17. Moumen A El, Tarfaoui M, Lafdi K (2019) Additive manufacturing of polymer composites: Processing and modeling approaches. *Composites Part B. https://doi.org/10.1016/j.compositesb.2019.04.029*
18. Porto J, Letzow M, Amico SC, Souza JA, Isoldi LA (2012) COMPUTATIONAL MODELING OF RTM AND LRTM. *Engineering Térmica (Thermal Engineering)*, 11, 93–99
19. Wang J, Andres E, Simacek P, Advani SG (2012) Use of Flow Simulation to Develop Robust Injection and Vent Schemes that Account for Process and Material Variability in Liquid Composite Molding Process. *Computer Modeling in Engineering & Sciences*, 88, 155–181
20. Poorzeinolabedin M, Parnas L, Dashatan SH (2014) Resin infusion under flexible tooling process and structural design optimization of the complex composite part. *JOURNAL OF MATERIALS & DESIGN*, *https://doi.org/10.1016/j.matdes.2014.08.008*
21. Amico SC, Souza JÁ, Gilson A, Lima B De (2013) Resin transfer molding process : a numerical and experimental investigation. *International Journal of Multiphysics*, 7, 125–136
22. Reia da Costa EF, Skordos AA (2012) Modelling flow and filtration in liquid composite moulding of nanoparticle loaded thermosets. *Composite Science and Technology*, 72, 799–805
23. Park CH, Lebel A, Saouab A, Bréard J, Lee W Il (2011) Modeling and simulation of voids and saturation in liquid composite molding processes. *Composites Part A*, 42, 658–668
24. Kumar AA, Sundaram R (2016) Cure cycle optimization for the resin infusion technique using carbon nanotube additives. *Carbon*, 96, 1043–1052
25. Ghauch ZG, Aitharaju V, Rodgers WR, Pasupuletti P, Dereims A, Ghanem RG (2018) Integrated stochastic analysis of fiber composites manufacturing using adapted polynomial chaos. *Composites Part A*, *https://doi.org/10.1016/j.compositesa.2018.12.029*
26. Rouison D, Sain M, Couturier M (2004) Resin transfer molding of natural fiber reinforced composites : cure simulation. *Composites Science and Technology*, 64, 629–644
27. Rouison D, Sain M, Couturier M (2006) Resin transfer molding of hemp fiber composites : optimization of the process and mechanical properties of the materials. *Composites Science and Technology*, 66, 895–906
28. Kuppusamy RRP, Neogi S (2017) Simulation of Air Entrapment and Resin Curing During Manufacturing of Composite Cab Front by Resin Transfer Moulding Process. *Archives of Metallurgy and Material*, 62, 1839–1844
29. Kuppusamy RRP (2018) Development of Liquid Composite Moulded Thermoset Composite Automotive Parts Using Process Simulations: Liquid Composite Moulding Process Simulations. *Design and Optimization of Mechanical Engineering Products IGI Global*, 24–36
30. Shi F, Dong X (2011) 3D numerical simulation of filling and curing processes in non-isothermal RTM process cycle. *Finite Elements in Analysis and Design*, 47, 764–770
31. Kiuna N, Lawrence CJ, Fontana QP V, Lee PD, Selerland T, Spelt PDM (2002) A model for resin viscosity during cure in the resin transfer moulding process. *Composites Part A*, 33, 1497–1503
32. Ruiz E, Trochu F (2006) Multi-criteria thermal optimization in liquid composite molding to reduce processing stresses and cycle time. *Composites Part A*, 37, 913–924

33. Jeyranpour F, Alahyarizadeh G, Minuchehr A (2016) The Thermo-Mechanical Properties estimation of Fullerene-Reinforced Resin Epoxy Composites by Molecular Dynamics Simulation- A Comparative Study The thermo-mechanical properties estimation of fullerene-reinforced resin epoxy composites by molecular dynami. *Polymer*, 88, 9–18
34. Jahromi PE, Shojaei A, Pishvaie SMR (2012) Prediction and optimization of cure cycle of thick fiber-reinforced composite parts using dynamic artificial neural networks. *Journal of Reinforced Plastics and Composites*, 31, 1201–1215
35. Behzad T, Sain M (2007) Finite element modeling of polymer curing in natural fiber reinforced composites. *Composites Science and Technology*, 67, 1666–1673
36. Zhang Z, Friedrich K (2003) Artificial neural networks applied to polymer composites : a review. *Composites Science and Technology*, 63, 2029–2044
37. Aleksendrić D, P C (2015) Composite materials – modelling, prediction and optimization. *Soft Computing in Design and Manufacturinf of Composite Material, https://doi.org/10.1533/9781782421801.61*
38. Park CH, Lee W Il (2011) Modeling void formation and unsaturated flow in liquid composite molding processes : a survey and review. *Journal of Reinforced Plastics and Composites*, 30, 957–977
39. Jahromi PE, Shojaei A, Pishvaie SMR (2012) Prediction and optimization of cure cycle of thick fiber-reinforced composite parts using dynamic artificial neural networks. *Journal of Reinforced Plastics and Composites*, 31, 1201–1215
40. DEB K (2004) *Optimization for engineering design*, 2nd ed. Prentice Hall
41. Parpinelli RS, Lopes HS, Freitas AA (2002) Data mining with an ant colony optimization algorithm. *IEEE Transactions on Evolutionary Computation*, *6(4),* 321–332
42. Yang X-S, Deb S (2014) Cuckoo search: recent advances and applications. *Neural Computing and Applications*, 24(1), 169–174
43. Civicioglu P, Besdok E (2013) A conceptual comparison of the Cuckoo-search, particle swarm optimization, differential evolution and artificial bee colony algorithms. *Artificial Intelligence Review*, 39(4), 315–346
44. Elsheikhi SA, Benyounis KY (2016) Review of Recent Developments in Injection Molding Process for Polymeric Materials. *Reference Module in Materials Science and Materials Engineering, https://doi.org/10.1016/B978-0-12-803581-8.04022-4*
45. Kessels JFA (2007) Optimising the flow pipe arrangement for resin infusion under flexible tooling. *Composites Part A*, 38, 2076–2085
46. Montés N, Sánchez F (2010) A new computational tool for liquid composite moulding process design based on configuration spaces. *Composites Part A*, 41, 58–77
47. Maier R, Rohaly T, Advani SG, Fickie K (1996) A FAST NUMERICAL METHOD FOR ISOTHERMAL RESIN TRANSFER MOLD FILLING. *International Journal for Numerical Methods in Engineering*, 39, 1405–1417
48. Lin M, Murphy M, Hahn H (2000) Resin Transfer Molding Process Optimization. *Composites Part A, https://doi.org/10.1016/S1359-835X(99)00054-8*
49. Li J, Zhang C, Liang R, Wang B (2008) Robust design of composites manufacturing processes with process simulation and optimisation methods. *International Journal of Production Research*, 46, 2087–2104
50. Samir J, Echaabi J, Hattabi M (2011) Numerical algorithm and adaptive meshing for simulation the effect of variation thickness in resin transfer molding process. *Composites Part B* 42,1015–1028
51. Mathur R, Fink BK, Advani SG (1999) Use of Genetic Algorithms to Optimize Gate and Vent Locations for the Resin Transfer Molding Process. *Polymer Composites*, 20
52. Jovanovic V, Manoochehri S, Chassapis C (2001) Paramer Estimation for Resin Transfer Molding. *Engineering Computations, https://doi.org/10.1108/02644400110409186*
53. Nielsen D, Pitchumani R (2001) Intelligent model-based control of preform permeation in liquid composite molding processes, with online optimization. *Composites Part A*, 32, 1789–1803
54. Chen X, Xie H, Chen H, Zhang F (2010) Optimization for CFRP pultrusion process based on genetic algorithm-neural network. *International journal of material forming*, 3, 1391–1399
55. Okonkwo K, Simacek P, Advani SG, Parnas RS (2011) Characterization of 3D fiber preform permeability tensor in radial flow using an inverse algorithm based on sensors and simulation. *Composites Part A*, 42, 1283–1292
56. Yun M, Sas H, Simacek P, Advani SG (2017) Characterization of 3D fabric permeability with skew terms. *Composites Part A*, 97, 51–59

57. Nikbakt S, Kamarian S, Shakeri M (2018) A Review on Optimization of Composite Structures Part I: Laminated Composites. *Composites Structures, https://doi.org/10.1016/j.compstruct.2018.03.063*
58. Nikbakht S, Kamarian S, Shakeri M (2019) A Review on Optimization of Composite Structures Part II: Functionally Graded Materials. Compos Struct. https://doi.org/10.1016/j.compstruct.2019.01.105
59. Henz BJ, Mohan R V, Shires DR (2007) A hybrid global – local approach for optimization of injection gate locations in liquid composite molding process simulations. Compos Part A 38:1932–1946
60. Li J, Zhang C, Liang R, Wang B (2008) Robust design of composites manufacturing processes with process simulation and optimisation methods. *International Journal of Production Research, https://doi.org/10.1080/00207540600806455*
61. Advani SG, Sas HS, Šimác P (2015) A methodology to reduce variability during vacuum infusion with optimized design of distribution media. *Composites Part A*, 78, 223–233
62. Carlone P, Palazzo GS (2014) A Simulation Based Metaheuristic Optimization of the Thermal Cure Cycle of Carbon-Epoxy Composite Laminates. *AIP Conference Proceedings, https://doi.org/10.1063/1.3589483*
63. Ruiz E, Trochu F (2005) Comprehensive Thermal Optimization of Liquid Composite Molding to Reduce Cycle Time and Processing Stresses. *Polymer Composites, https://doi.org/10.1002/pc.20077*
64. Wang J, Simacek P, Advani SG (2016) Use of Centroidal Voronoi Diagram to find optimal gate locations to minimize mold filling time in resin transfer molding. *Composites Part A*, 87, 243–255
65. Matsuzaki R, Yokoyama R, Kobara T, Tachikawa T (2019) Multi-Objective Curing Optimization of Carbon Fiber Composite Materials Using Data Assimilation and Localized Heating. *Composites Part A, https://doi.org/10.1016/j.compositesa.2019.01.021*
66. Achim V, Ratle F, Trochu F (2009) Evolutionary operators for optimal gate location in liquid composite moulding. *Applies Soft Computing*, 9, 817–823
67. Tifkitsis KI, Mesogitis TS, Struzziero G, Skordos AA (2018) Stochastic multi-objective optimisation of the cure process of thick laminates. *Composites Part A*, 112, 383–394
68. Moayyedian M, Abhary K, Marian R (2017) Optimization of injection molding process based on fuzzy quality evaluation and Taguchi experimental design. *CIRP Journal of Manufacturing Science and Technology, https://doi.org/10.1016/j.cirpj.2017.12.001*
69. Gupta A, Kelly PA, Bickerton S, Walbran WA (2019) Simulating the effect of temperature evaluation on clamping force requirements during rigid-tool Liquid Composite Moulding process. *Composites Part A*, 43, 1–9
70. Oya Y, Yamamoto G, Sato J, Matsumiya T, Okabe T, Matsuzaki R, Yashiro S, Obayashi S (2016) Multi-objective optimization for resin transfer moulding process. *Composites Part A, https://doi.org/10.1016/j.compositesa.2016.09.023*
71. Tarasov I V, Shevtsov SN, Evlanov V, Orozaliev EE, Tarasov V, Evlanov V (2015) Model-Based Optimal Control of Polymeric Composite Cure in Autoclave System. *IFAC-Papers Online. Elsevier Ltd.*, 204–210
72. Seretis G, Kouzilos G, Manolakos D, Provatidis C (2018) Multi-Objective Curing Cycle Optimization for Glass Fabric / Epoxy Composites Using Poisson Regression and Genetic Algorithm. *Materials Research*, 21
73. Ruiz E, Trochu F (2006) Multi-criteria thermal optimization in liquid composite molding to reduce processing stresses and cycle time. *Composites Part A*, 37, 913–924
74. Struzziero G (2015) Optimisation of the VARTM process. https://doi.org/10.13140/RG.2.1.4994.9921
75. Struzziero G, Skordos AA (2016) Multi-objective optimisation of the cure of thick components. *Composites Part A*, https://doi.org/10.1016/j.compositesa.2016.11.014
76. Li K, Yan S, Zhong Y, Pan W, Zhao G (2018) Multi-Objective Optimization of the Fiber-reinforced Composite Injection Molding Process using Taguchi method, RSM, and NSGA-II. *Simulation Modelling Practice and Theory, https://doi.org/10.1016/j.simpat.2018.09.003*
77. Sonmez FO, Akbulut M (2007) Process optimization of tape placement for thermoplastic composites. *Composites Part A, https://doi.org/10.1016/j.compositesa.2007.05.003*
78. Dolkun D, Zhu W, Xu Q (2018) Optimization of cure profile for thick composite parts based on finite element analysis and genetic algorithm. *Journal of Composite Materials, https://doi.org/10.1177/0021998318771458*
79. Shevtsov, S. N., Zhilyaev, I., & Parinov, I. A. (2012). Optimization of the Composite Cure Process Based on the Thermo-Kinetic Model. *Advanced Materials Research*, 569(September), 185–192. https://doi.org/10.4028/www.scientific.net/AMR.569.185
80. Chen, X., Xie, H., Chen, H., & Zhang, F. (2010). Optimization for CFRP pultrusion process based on genetic algorithm-neural network *International Journal of Material Forming*, *3*, 1391–1399