Pultrusion manufacturing process development: Cure optimization by hybrid computational methods

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Abstract

This paper develops a hybrid approach, based on genetic algorithms and simplex method, to optimize the accuracy of a manufacturing process by material pultrusion. The numerical model, proposed in a recent paper of the same authors, is solved by a finite difference scheme. The analysis technically shows the efficiency of the optimization algorithm.

Keywords: Pultrusion; Cure optimization; Genetic algorithms; Simplex method; Finite element method; Finite difference method

1. Introduction

Pultrusion manufacturing process is widely used to shape composite materials into parts characterized by constant cross section. During the pultrusion process fibres are impregnated into a resin bath and then the wetted reinforcement is pulled through a heated die to be correctly shaped and cured. Pultrusion is a continuous process, characterized by remarkable automation and, nowadays, it is more and more used to obtain complex parts for aeronautical, spatial and civil applications.

The influence of thermo-chemical aspects on the mechanical properties of the final product has been carefully analysed by Wilcox et al. in [1]. An experimental investigation performed by Carlsson et al. [2] has shown that mechanical, as well as, surface properties of the processed part are affected by several process parameters, such as pre-heater temperature, heating platens temperature, cooling temperature, and pull speed. Manufacturing defects, such as void and microcracks, usually related to non optimal cure profiles into the processing parts, affect linear and nonlinear behaviour of pultruded composites [3]. Several computational models [4–10] have been proposed to analyse temperature and degree of cure profiles in the processing parts, however, very few works have been focused on the optimization of the above profiles.

An optimization procedure based on a Galerkin weighted residual finite element formulation was proposed by Coelho et al. in [11]. The simulated annealing method was used to avoid local minima and then the solution was refined using a successive quadratic programming (SPQ) procedure. An objective function based on economic criteria
was implemented, using opportune constraints for the minimum value of the degree of cure and the temperature peak into the composite material. A different approach, based on the combination of numerical model and mathematical procedures, was proposed by Li et al. [12] and by Joshi et al. [13]. Several process parameters, such as heating platens temperatures, pull speed, resin bath temperature, and cooling temperature, were considered to optimize material cure, taking into account that the processing material temperature can not exceed the degradation temperature of the considered resin system. The above method has shown to be quite efficient, although the output of the solution was affected by the combination of the process parameters considered at the first step of the optimization procedure.

In this paper a hybrid method, based on the use of genetic algorithms and of the simplex method, for pultrusion process optimization, is proposed. Objective function is evaluated and minimized by an iterative procedure based on the combination of above techniques with a finite difference model [14]. The finite element model, developed in [14], is then used to validate and analyse the obtained solution.

2. Governing equation

The optimization method, briefly outlined in Section 1, is applied, as already mentioned, to a pultrusion manufacturing process. This Section provides a concise description of the analytic model. Specifically, the heat transfer model, for the heated die, writes as follows:

\[
ρdc_p,d \frac{∂T}{∂t} = \frac{∂}{∂x} \left( k_x, d \frac{∂T}{∂x} \right) + \frac{∂}{∂y} \left( k_y, d \frac{∂T}{∂y} \right) + \frac{∂}{∂z} \left( k_z, d \frac{∂T}{∂z} \right).
\]  

(2.1)

where \( T \) is the temperature, \( ρ_d \) is the die material density, \( c_{p,d} \) is the die material specific heat, \( k_{x,d}, k_{y,d}, \) and \( k_{z,d} \) are the thermal conductivities into the die, respectively, in \( x, y, \) and \( z \) direction.

Assuming \( x \) as the pull direction, energy conservation equation, for the composite material, writes:

\[
ρc_{p,c} \left( \frac{∂T}{∂t} + v_x \frac{∂T}{∂x} \right) = k_x,c \frac{∂}{∂x} \left( \frac{∂T}{∂x} \right) + k_y,c \frac{∂}{∂y} \left( \frac{∂T}{∂y} \right) + k_z,c \frac{∂}{∂z} \left( \frac{∂T}{∂z} \right) + ρ_f V_r Q.
\]

(2.2)

being \( ρ \) the density, \( c_p \) the specific heat, \( k_x, k_y, \) and \( k_z \) the thermal conductivities (in \( x, y, \) and \( z \) direction respectively), which are assumed to be constant. Moreover, using the subscripts \( r, f, \) and \( c \) to indicate the resin, fibre and composite material, respectively; \( V_r \) is the resin volume fraction, \( v_x \) is the pull speed, and \( Q \) is the specific heat generation rate due to resin exothermic cure reaction.

Heat generation rate \( Q \):

\[
Q = \frac{dH(t)}{dt} = H_{tr} R_r(α),
\]

(2.3)

where \( H(t) \) is the amount of heat evolved during the curing process up to time \( t \), \( H_{tr} \) is the total heat of reaction, and \( R_r \) is the rate of resin reaction, related to the degree of cure \( α \) and the absolute temperature, according to the Arrhenius equation, as follows:

\[
R_r(α) = \frac{dα}{dt} = K_0 \exp \left( -\frac{ΔE}{RT} \right) (1 - α)^n,
\]

(2.4)

being \( K_0 \) the pre-exponential constant, \( ΔE \) the activation energy of the resin reaction, \( R \) the gas universal constant, and \( n \) the order of the reaction (kinetic exponent).

Finally, the concentration of the resin species, into the forming die, is given by the following transport equation:

\[
\frac{∂α}{∂t} = R_r(α) - v_x \frac{∂α}{∂x}.
\]

(2.5)

3. Optimization techniques

3.1. Genetic algorithms

In engineering sciences there are several problems which need to select a solution among several possible combinations. Such problems are usually defined as NP-HARD problems; an analytical solution cannot be achieved,
while the computational cost increases with the number of variables, in some cases with an increase greater than the polynomial one. In such cases good results can be achieved using heuristic methods, such as ants models, genetic algorithms, neural networks, simulated annealing and tabu search method. Advantages of the above methods are the independence from the characteristics of the specific problem, the ability to explore the whole space of solutions, to overcome local minimum points and to use the experience for new searches.

Genetic algorithms (GA), proposed by J.J. Holland in 1975, are a class of stochastic search methods, based on the principles of the natural selection. Applications of genetic algorithms in engineering problems can be found in [15–17]. Mathematical foundations of population dynamics with selective internal structure are reported in [18–20], while optimization methods are dealt with in Chapter 4 of [21].

Genetic algorithms operate on a population of individuals, defined chromosomes, which represent possible solutions to the specific problem. Each chromosome is characterized by a fitness score, which measure the goodness of the considered solution. Individuals with a relatively higher fitness score have higher probability of reproducing, obtaining a new population of individuals characterized by the features of different parents. Individuals with a bad fitness score have lower probability of reproduction and then are extinguished. Being favoured the crossover between the best individuals of the current population, the more interesting areas of the search space are analysed looking for the solution. Repeating the above procedure, after several generations, good features of the parents are extended to the whole population.

The robustness of the genetic algorithms is due to the genes mix, which allows the local minimum to be overcome. For each individual, the fitness score is evaluated using the fitness function, which represents the mathematical description of the considered problem.

The reproduction of a given population, taking into account that the first population is randomly generated, is based on the following operations: selection, crossover and mutation. During the selection, the individuals of the current population are copied into a mating pool; individuals characterized by higher fitness score are copied more times than individuals characterized by lower fitness score. Several selection techniques can be used. The simplest one is the uniform selection, which is useful for debugging and testing, but is not a very effective search strategy. According to the roulette wheel selection, each chromosome is placed on a roulette wheel and occupies an area proportional to the probability of being selected. This technique preserves genes which could show their capacity in successive generation, since even individuals with a lower fitness score can reproduce and algorithm convergence is fast. Another selection method is the population decimation: individuals are sorted according to their fitness value and only chromosome whose fitness score is better than a previously defined cut off score are selected for reproduction. This technique is very simple and fast in convergence; however, individuals with some good genes can extinguish for a relatively low fitness score. The tournament selection is based on the competition between couples of individuals of the current generation. The winner of each competition is the chromosome with higher fitness score; this individual reproduces, while the loser can be chosen for other fights. The tournament selection, however, is characterized by a relatively slower convergence.

After the selection, genes of the chosen individuals are mixed; this operation is defined crossover. In literature three methods of crossover are defined: one point, two points, and uniform crossover. The single point crossover is widely used in literature to obtain a relatively fast convergence. According to this technique, two chromosomes are randomly chosen and, after probabilistic considerations, their genes can be exchanged starting from a casual point. According to the two points (or multi points) crossover, chromosomes can be considered as circles, the procedure is similar to the one point crossover, but the two parents exchange only genes limited by the two points. Using the uniform crossover, each individual of the current generation gives the gene associated with a specific position to one of the two sons, according to probabilistic consideration and the other son takes the respective gene from the other parent. Crossover is considered the most important genetic operation, because it influences directly algorithm convergence; however, an excessive use of crossover can cause premature convergence to a local maximum.

Mutation is the genetic operation which allows zones of the search space not covered by the current generation to be explored. For each gene of a new individual, a random number is generated in [0, 1]; if this number results minor than the probability of mutation, then the gene can mutate. If relatively faster convergence can be achieved using crossover, mutation is a really useful operation when the search space is very large.

In some cases, reproduction can result in a new generation characterized by lower fitness scores; this is not always considered negative in terms of evolution; however, some of the best individuals can be lost. Elitism allows preservation of the best individual in the current generation, which is directly copied in a successive generation.
Several convergence criteria can be used to stop the algorithm: fitness limit (if fitness value is smaller than a predefined value), generation number, time limit, stall generation (if the best fitness score is constant for a certain number of generations), and stall time limit. GAs are considered as very effective optimization algorithms; however, in several cases, better results can be achieved using hybrid (heuristic and analytical) approach. In this way advantages of a different method are combined to obtain a better result with reduced computational cost.

In this paper GAs are combined with the simplex method. A description of the simplex method is given in the following:

3.2. Simplex method

Simplex algorithm is one of the earliest and best known optimization techniques. From a theoretical point of view, a simplex is defined as the geometrical entity in $\mathbb{R}^n$ characterized by $n$ dimensions, with $(n + 1)$ vertexes and a minimum number of edges, whose dimension is $(n - 1)$, equal to $(n + 1)$. Typical examples are triangle in the two-dimensional space $\mathbb{R}^2$ and tetrahedron in three-dimensional space $\mathbb{R}^3$.

Consider a simplex in the $\mathbb{R}^n$ space and a function $f(x)$, defined as follows:

$$f : \mathbb{R}^n \rightarrow \mathbb{R}.$$  

At the $k$th step, each vertexes of the modified simplex is defined by the following vectors:

$$x_i^k = (x_{i1}, x_{i2}, \ldots, x_{in})^T, \quad i = 1, \ldots, n + 1.$$  

(3.2)

The vertex of the simplex characterized by the maximum value of the $f(x)$ function, at the $k$th step, defined as $x_h^k$ and the vertex characterized by the minimum value of the $f(x)$ function at the same step, defined as $x_l^k$, can be written as follows:

$$f \left( x_h^k \right) = \max \left\{ f \left( x_1^k \right), \ldots, f \left( x_{n+1}^k \right) \right\},$$  

(3.3)

and

$$f \left( x_l^k \right) = \min \left\{ f \left( x_1^k \right), \ldots, f \left( x_{n+1}^k \right) \right\}.$$  

(3.4)

The center point of all the vertexes, except $x_h^k$, defined as $x_{n+2}^k$, can be written as follows:

$$\sum_{i=1}^{n+1} \left( x_{i,j} - x_{h,j} \right) \right) / n.$$  

(3.5)

Detailed computing are based on the following algorithms:

Reflection: the vertex $x_h^k$ is reflected with respect to the center point $x_{n+2}^k$, obtaining the new vertex $x_{n+3}^k$, as follows:

$$x_{n+3}^k = x_{n+2}^k + \alpha \left( x_{n+2}^k - x_h^k \right),$$  

(3.6)

where $\alpha > 0$ is the reflection coefficient.

Expansion: if $f(x_{n+3}^k) \leq f(x_l^k)$, then the vector $x_{n+3}^k - x_{n+2}^k$ is expanded, obtaining the new vertex $x_{n+4}^k$, as follows:

$$x_{n+4}^k = x_{n+2}^k + \gamma \left( x_{n+3}^k - x_{n+2}^k \right),$$  

(3.7)

where $\gamma > 1$ is the expansion coefficient. Specifically, if $f(x_{n+3}^k) > f(x_l^k)$, then $x_h^k$ is substituted by $x_{n+4}^k$ and the procedure restart from step 1, with $k = k + 1$, else $x_{n+3}^k$ is substituted by $x_{n+3}^k$ and the procedure restart from step 1, with $k = k + 1$. 


Contraction: if \( f(x_{n+3}^{(k)}) > f(x_{n+2}^{(k)}) \), for all \( i \neq h \), the vector \( (x_n^{(k)} - x_{n+2}^{(k)}) \) is contracted, obtaining the new vertex \( x_{n+5}^{(k)} \), as follows:

\[
x_{n+5}^{(k)} = x_{n+2}^{(k)} + \beta (x_h^{(k)} - x_{n+2}^{(k)}),
\]

where \( 0 < \beta < 1 \) is the contraction coefficient. Vertex \( x_h^{(k)} \) is substituted by \( x_{n+5}^{(k)} \) and the procedure restarts from step 1.

Reduction: if \( f(x_{n+3}^{(k)}) > f(x_h^{(k)}) \), all vectors \( x_i^{(k)} \) are modified as follows:

\[
x_i^{(k)} = x_i^{(k)} + \frac{1}{2} (x_i^{(k)} - x_1^{(k)}), \quad i = 1, \ldots, n + 1
\]

and the procedure restarts from the step 1.

The algorithm stops when the following equation is satisfied:

\[
\left( \frac{\sum_{i=1}^{n+1} \left[ f(x_i^{(k)}) - f(x_{n+2}^{(k)}) \right]^2}{\sqrt{n+1}} \right)^{\frac{1}{2}} \leq \epsilon,
\]

where \( \epsilon \) is the algorithm tolerance.

According to the above procedure, the reflection coefficient \( \alpha \) is used to project the vertex with the maximum value of the \( f(x) \) function, with respect to the centre of the simplex. The coefficient of expansion is used to lengthen the search vector if the vertex obtained by the previous reflection is characterized by a value of the \( f(x) \) function, which is minor than the previously evaluated minimum. The coefficient of contraction is used to reduce the search vector when the vertex obtained by reflection is more than the second maximum value of the \( f(x) \) function before the reflection. Using the above operations, shape and dimensions of the simplex are modified according to the specific topographical shape of the function \( f(x) \). Additional technical details of optimization iterative schemes are given in Chapter 4 of the already cited book [21].

4. Optimization of the pultrusion process

The cure optimization of a C-section work piece is developed in this Section. The geometry of the model and its spatial discretization in the cross-section for the finite difference and finite element model can be found in Fig. 1(a), 1(b), and 1(c) of [14]. Only half model has been considered for symmetry reason. A more detailed description of the model, as well as the numerical finite element and finite difference formulation of the problem, can be found in [14].

Recent results on the above mathematical methods can be recovered in [22–24], and in the literature therein cited.

In this paper the optimization technique has been applied taking into account only the heating platens temperatures as optimization variables, all the other parameters, such as pull speed or cooling channel temperature have been assumed as constants. The objective function considered is based on the variance of the degree of cure, evaluated in the exit cross-section, with respect to a target value.

Objective (fitness) function writes:

\[
f = \sum_{i=1}^{N} \frac{(\alpha_d - \alpha_i)^2}{N - 1},
\]

where \( \alpha_d \) is the desired value of the degree of cure, \( \alpha_i \) is the degree of cure of the \( i \)th node of the final cross-section of the composite, and \( N \) is the number of nodes into the composite cross-section. In this way the parameters combination is evaluated to obtain a uniform and satisfactory distribution of the degree of cure.

At the first step of the developed procedure, the finite difference model [14] is implemented into a genetic algorithm. GA generates an initial population of individuals, where each chromosome represents a combination of heating platens temperatures. Temperature and degree of cure profiles into the processing material are then evaluated using the finite difference model. Fitness score of each chromosome is then calculated using the degrees of cure in the final section.
### Table 1
Genetic and hybrid optimization results

<table>
<thead>
<tr>
<th>Case</th>
<th>Heating temperatures (°C)</th>
<th>Fitness score</th>
<th>T Peak (°C)</th>
<th>$\alpha_m$</th>
<th>$\sigma_{\text{std}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference</td>
<td>177 177 177</td>
<td>3.1E−4</td>
<td>205.8</td>
<td>0.9153</td>
<td>0.0087</td>
</tr>
<tr>
<td>(F.D.M.)</td>
<td>177 177 177</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G.A.OPT.</td>
<td>176.5 155.9 194.6</td>
<td>1.1E−5</td>
<td>195.1</td>
<td>0.9044</td>
<td>0.0034</td>
</tr>
<tr>
<td>(F.D.M.)</td>
<td>164.7 163.9 188.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HYB.OPT.</td>
<td>125.1 167.2 196</td>
<td>5.6E−7</td>
<td>209</td>
<td>0.9015</td>
<td>0.001</td>
</tr>
<tr>
<td>(F.D.M.)</td>
<td>134.2 152.2 199.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reference</td>
<td>177 177 177</td>
<td>4.9E−4</td>
<td>208.7</td>
<td>0.9195</td>
<td>0.0098</td>
</tr>
<tr>
<td>(F.E.M.)</td>
<td>177 177 177</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>G.A.OPT.</td>
<td>176.5 155.9 194.6</td>
<td>7.8E−5</td>
<td>194.6</td>
<td>0.9075</td>
<td>0.0045</td>
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<tr>
<td>(F.E.M.)</td>
<td>164.7 163.9 188.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HYB.OPT.</td>
<td>125.1 167.2 196</td>
<td>7.1E−6</td>
<td>209.3</td>
<td>0.9023</td>
<td>0.0013</td>
</tr>
<tr>
<td>(F.E.M.)</td>
<td>134.2 152.2 199.7</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A suitable penalty factor has been included in the fitness function to take into account the degradation temperature of the resin system: if the temperature peak of the processing material exceeds the resin degradation temperature, fitness score shall be modified, reducing the probability of reproduction of the specific chromosome. The value of the penalty factor is very important, cause a reduced value could not assure the satisfaction of the condition imposed on the temperature peak, while an excessive value could reject near optimal solution.

The proposed heuristic approach allows to investigate the entire search domain, avoiding local minima, in a limited number of generations. When solution converges to an enough good (but not optimal) solution, the simplex method is applied, using the same fitness function and penalty factor. The need for this strategy can be well understood taking into account that simplex method is strongly influenced by the starting point and it does not assure that local minima are avoided; however, it results very faster, with respect to genetic algorithms, starting from a near optimal solution.

The resin bath temperature, the cooling temperature, the resin degradation temperature, and pull speed are assumed, respectively, as 45°, 50°, 240° and 2.299 mm/s. Heating platens temperatures are defined as $T_1$, $T_2$, and $T_3$ for the heating platens on the top of the die, from die entrance to die exit, $T_4$, $T_5$, and $T_6$ for to the heating platens on the bottom of the die, in the same order. The range of the heating platens temperatures, for the first generation, has been assumed as [140, 220]. The lower limit has been defined, for the specific resin system, taking into account that the activation of resin reaction is related to the amount of heat provided to the part by the platens, while the upper limit has been defined taking into account the degradation temperature. The above range is not to be considered as a rigid constrain for the search domain, indeed, also external zones can be explored; however, a suitable definition of domain limits results in relatively faster convergence of the algorithm.

In the present investigation, the desired value of the degree of cure has been assumed as 0.9. In Table 1 mean value of the degree of cure in the final cross-section, its standard deviation, temperature peak value and fitness score, obtained using the finite difference model, are summed up for the reference case (assuming the temperature of all the heating platens as 177°), after the genetic optimization and at the end of the hybrid optimization. Finite difference model results are then compared with results provided by the finite element model.

As evidenced, the heating temperatures evaluated using the above procedure allows to obtain the desired distribution of the degree of cure in the exit section. The highest mean value of the degree of cure was found for the reference case, characterized also by a relatively high value of the temperature peak and standard deviation. However, remarkable temperature gradients, in the processing materials, have been evidenced by FEM simulation. This indicates that heating temperatures are not correctly setted, taking into account the used pull speed.

A relatively more accurate result has been obtained using the genetic optimization and the solution refinement by the simplex method. At the end of the whole procedure, indeed, the degree of cure in the exit section has resulted very close to the desired value. Differences between the temperatures of the heating platens placed on the top and on the
Table 2

<table>
<thead>
<tr>
<th>Sel</th>
<th>Cros</th>
<th>Mut rate</th>
<th>Heating temperatures (°C)</th>
<th>Fitness score</th>
<th>T peak (°C)</th>
<th>α_m</th>
<th>α_std</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
<td>Sc</td>
<td>0.01</td>
<td>176.5 155.9 194.6 164.7 163.9 188.2</td>
<td>1.1E−5</td>
<td>195.1</td>
<td>0.9044</td>
<td>0.0034</td>
</tr>
<tr>
<td>T</td>
<td>Sc</td>
<td>0.01</td>
<td>172.8 155.9 196.8 167.4 161.7 186.4</td>
<td>1.9E−5</td>
<td>196.8</td>
<td>0.9027</td>
<td>0.0044</td>
</tr>
<tr>
<td>U</td>
<td>Sc</td>
<td>0.01</td>
<td>176.5 155.9 196.8 167.4 161.7 186.4</td>
<td>2.3E−5</td>
<td>196.8</td>
<td>0.9024</td>
<td>0.0055</td>
</tr>
<tr>
<td>S.U.</td>
<td>Sc</td>
<td>0.01</td>
<td>175.6 155.9 192 167.4 161.7 191.2</td>
<td>6.3E−6</td>
<td>194.7</td>
<td>0.9037</td>
<td>0.0027</td>
</tr>
<tr>
<td>R</td>
<td>S.P.</td>
<td>0.01</td>
<td>176.5 155.9 196.8 167.4 161.7 186.4</td>
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<td>196.8</td>
<td>0.9040</td>
<td>0.0048</td>
</tr>
<tr>
<td>R</td>
<td>T.P.</td>
<td>0.01</td>
<td>172.5 155.9 196.8 182.7 160.2 185.4</td>
<td>2.1E−5</td>
<td>196.8</td>
<td>0.8980</td>
<td>0.0073</td>
</tr>
<tr>
<td>R</td>
<td>Sc</td>
<td>0.05</td>
<td>165 155.9 196.8 181.3 161.7 186.4</td>
<td>1.2E−5</td>
<td>196.8</td>
<td>0.8970</td>
<td>0.0069</td>
</tr>
<tr>
<td>R</td>
<td>Sc</td>
<td>0.1</td>
<td>176.5 152.8 196.8 167.3 161.7 187.7</td>
<td>1.7E−5</td>
<td>196.8</td>
<td>0.9030</td>
<td>0.0042</td>
</tr>
</tbody>
</table>

bottom of the die can be explained taking into account the asymmetry of half cross section of the processing part, a relatively higher temperature of the bottom plate near die entrance can be related to the slow heat conduction into the composite material, while the lower temperature of the central plate in the bottom, with respect to the central plate on the top, can be explained taking into account the heat generated by the resin cure reaction. FEM simulations evidenced that temperature gradients into the processing materials have been considerably reduced using both genetic or hybrid optimization.

In Table 2 the influence of genetic operation, i.e. selection method, crossover strategy, and rate of the uniform mutation, is summed up. The robustness of the proposed genetic optimization procedure is underlined by the similar results obtained using different genetic operations. Selection method has been studied assuming crossover as scattered and mutation rate as 0.01.

As evidenced, the best fitness score has been achieved using a stochastic uniform selection. However, this selection method results slower in convergence with respect to other selection strategy; taking into account the successive refinement of the solution by the simplex method, roulette wheel can be assumed as optimal selection procedure. The effectiveness of the scattered crossover is evidenced by better value of the fitness score, related to a more uniform distribution of the degree of cure. This can be explained taking into account that scattered crossover involves a complete genes mix between the two parents and good individuals can be obtained easily. The optimal value of the mutation rate can be assumed as 0.01, indeed, slow convergence and high standard deviation of the degree of cure have been found using relatively higher rate values.

5. Conclusions

An effective procedure, for a constrained optimization of the degree of cure in the pultrusion manufacturing process has been developed. The method, based on a hybrid approach, obtained by the combination of genetic algorithms and simplex method, has been applied to the finite difference model proposed and validated in [14]. The robustness of the method is proved by reliable results provided by the genetic algorithms, using all the genetic operation. In particular, the optimal compromise between the convergence time and the fitness score value has been obtained using
the roulette wheel selection, the scattered crossover, and 0.01 as rate of the uniform mutation. Solution refinement has been achieved using the simplex method. In this way, a minor computational time has been obtained, with respect to a pure genetic optimization. In the present investigation, optimization procedure has been applied to obtain a part characterized by a good quality, i.e. an uniform distribution of the degree of cure with a satisfactory mean value, at the exit of the forming die, however it can be effectively applied, using opportune defined fitness functions, also for post die shaping pultrusion. In this manufacturing process, indeed, the processing part is completely formed out of the forming die and material cure is completed using U.V. rays or other heating sources. The distribution of the degree of cure at the die exit results one of the main process parameters to obtain an optimized product. Future perspectives of research are mainly based on the implementation of other process parameters, such as pull speed, into the proposed procedure and on the analysis of the material properties and part cross-section on the optimized temperatures.

References