
# PUBLISHABLE SUMMARY

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## OPTO-CLAVE

Design, implementation and validation of an automatic learning cure cycle optimisation process for the eco-efficient autoclave processing of composite materials

JTI - CleanSky

Type: Deliverable

## Publishable Project Summary

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| **PP** | Restricted to other programme participants (including the Commission Services) | |
| **RE** | Restricted to a group specified by the consortium (including the Commission Services) | |
| **CO** | Confidential, only for members of the consortium (including the Commission Services) | |

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# 2 Introduction

The OPTO-CLAVE project aimed to provide a solution for process monitoring and optimisation in autoclave composites cure. In this deliverable, the final project report is presented.

# 3 Objectives

The objective of this report is to describe the work performed in the project, including all exploitation and dissemination activities for the use of the foreground.
The report follows the layout of the electronic submission final project report form.

# 4 Work Performed

## *4.1 Final Publishable summary report*

### *4.1.1 Executive summary*

The OPTOCLAVE project developed knowledge based optimisation software called DETA-LEARN. The software performs analysis and constrained optimisation of the autoclave manufacturing process. The output is an alternative cure profile that aims to either minimise the processing time and/or the energy usage during processing.
The main functions of the software are the following:

- Analysis of the manufacturing process taking into account the autoclave dimensions, composite part geometry, materials specifications, material state models and real temperature data.
- Constrained optimization algorithm that can be tailored to the process. The optimization can be directed to shortening the cure cycle, achieving a material specification (for example final glass transition temperature) or minimizing the energy requirements for the process.
- Estimation of energy demands for the process, in kWh

The DETA-LEARN software has optimised the autoclave manufacturing of a composite stiffened panel. The process details were supplied by the Topic Manager. The optimised profile resulted in a reduction of 12% in cure time and 16% in energy consumption.

### *4.1.2 Project context and main objectives*

Autoclave processing is recognised in aerospace as the process that produces high performance composite structures of large size and complex shape. Composite parts manufactured in autoclave are widely used in order to benchmark the quality of composite parts produced using other manufacturing processes such as Resin Transfer Moulding (RTM) and Resin Infusion (RI).
Autoclave is generally recognised as an expensive manufacturing process both in terms of capital investment and in energy usage.
The need for the OPTOCLAVE project initiated from the challenge to control the temperature in large autoclaves. Temperature control in autoclaves is generally poor with temperature overshoots of >10°C being typically observed. The reason for this lack of accurate control is the convective heat transfer mechanism and the need to heat a large volume of air in order to cure the part. The slow transfer of heat through convection is coupled with the faster conduction mechanism from the metallic tool to the composite and the very fast autocatalytic polymerisation reaction.
The ultimate aim of the project is to provide software that can simulate the cure process inside the autoclave and provide information about the material state of the composite.
In order to achieve the above aim, a number of objectives were defined:

- Analyse the materials defined by the Topic Manager and develop material state models.
- Develop an optimisation algorithm for the autoclave process that takes into account the equipment constraints (for example, the maximum heating rate that can be achieved), the material state properties, the part geometry and shape, and customer specifications (for example a pre-defined time the part needs to stay at a specific temperature).

- Develop an auto-learning algorithm that can perform system identification from temperature signals and dielectric sensors embedded in the part.
- Include all the models and algorithms in one single software that can be readily used by the Topic Manager
- Install final version of the software to the Topic Manager site and train personnel in its use.

In addition to the above objectives, a further objective has been agreed between the Topic Manager and the consortium:

- Estimate the energy savings achieved by the optimized cure process that is calculated by the optimization algorithm.

### *4.1.3 Description of the main S&T results*

#### *4.1.3.1 Materials definition*

The materials selected by the Topic Manager are the following:

- Matrix system: Cytec Prism EP2400 resin system[1]
- Fabric: Saertex Unidirectional Carbon-Gelege[2] PB 214 g/m$^2$

#### *4.1.3.2 Composite part and process definition*

The process that was studied in the project was liquid infusion of the EP2400 resin through vacuum bag (a one sided tool is used). The part to be manufactured is a stiffened panel with nine T-stringers integrated into it. The part schematic is shown in Figure 1. The fabric is laid out in the tool. Metallic inserts are used to form the T-stringers. Vacuum is applied to the whole setup, including the metallic inserts.

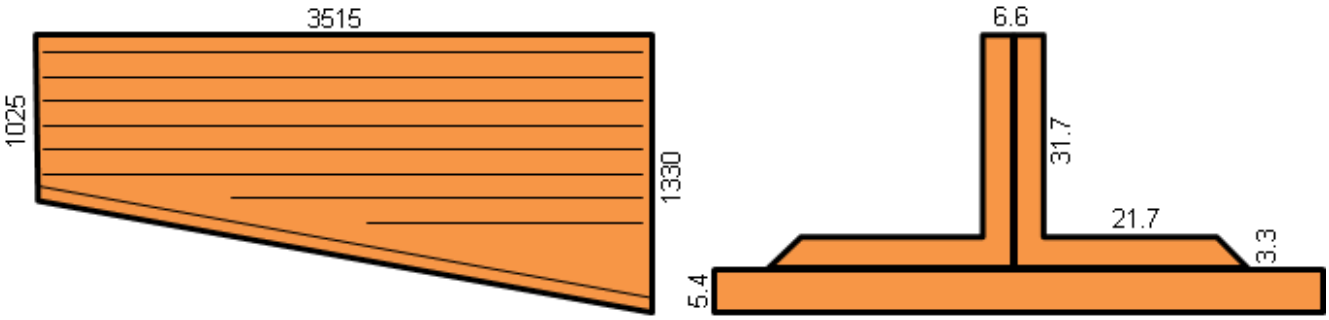


*Figure 1: Composite part sketch and main dimensions (in mm)*

The cure cycle imposed is described in Table 1. The total cure time is 427 minutes.

*Table 1: Experimental cure cycle*

| Segment name and number | Start temperature (°C) | End temperature (°C) | Heating rate (°C/min) | Duration (min) |
|---|---|---|---|---|
| 1:Initial heating | 20 | 115 | 5 | 19 |
| 2:Infusion | 115 | 115 | 0 | 178 |
| 3:Temperature increase | 115 | 180 | 2 | 32.5 |
| 4:Isothermal cure | 180 | 180 | 0 | 173.5 |
| 5:Cooling | 180 | 60 | 5 | 24 |

[1] http://www.cemselectorguide.com/pdf/PRISM_EP2400_031912.pdf
[2] http://www.saertex.com/produkt_technik/produkte/fasereigenschaften/

*4.1.3.3 Material state modelling and process modelling*

A number of material state models have been developed for the EP2400 resin system.

**Cure kinetics model**

The experimental data showed that the resin follows a different reaction mechanism when cured under isothermal or non-isothermal conditions. Therefore, two different models for isothermal and non-isothermal cure have been developed respectively:

Isothermal cure

The following equation was used in order to fit the experimental data:

$$\frac{da}{dt} = \underbrace{k_1(a_{final} - a)^{n_1}}_{n-th\ order\ kinetics} + \underbrace{k_2 a^m (a_{final} - a)^{n_2}}_{autocatalytic\ kinetics} \quad (1)$$

$$k_1 = A_1 e^{-\frac{E_1}{RT}}, \quad k_2 = A_2 e^{-\frac{E_2}{RT}} \quad (2)$$

The cure kinetics model has 7 independent parameters. Data from 7 isothermal experiments were fitted to Eq. (1). The fitting results are shown in Table 2. The exponential terms showed further temperature dependence.

*Table 2: Parameters estimation for the isothermal cure of EP2400*

| Parameter | Unit | Fitted value or equation |
|---|---|---|
| $A_1$ : pre-exponential factor | 1/min | 190794 |
| $E_1$ : activation energy for the n-th order kinetic mechanism | J/mol | 75865 |
| $A_2$ : pre-exponential factor | 1/min | 1547086 |
| $E_2$ : activation energy for the n-th order kinetic mechanism | J/mol | 29402 |
| $n_1$ : order of the n-th order kinetic mechanism | | $n_1$ = 1.4748 – 0.0014*T |
| $n_2$ : order of the autocatalytic mechanism | | $n_2$ = 0.6 for T<160°C<br>$n_2$ = 0.0161*T – 1.651 for T>160°C |
| m : order of the autocatalytic mechanism | | m = 0.0011*T + 0.4558 |

Indicative fitting results are shown in Figure 2.

Non-Isothermal cure

The modeling equation for the non-isothermal cure of the EP2400 resin system is the following:

$$\frac{da}{dt} = \underbrace{k_1(1 - a)^{n_1}}_{n-th\ order\ kinetics} + \underbrace{k_2 a^m (1 - a)^{n_2}}_{autocatalytic\ kinetics} \quad (3)$$

$$k_1 = A_1 e^{-\frac{E_1}{RT}}, \quad k_2 = A_2 e^{-\frac{E_2}{RT}} \quad (4)$$

An evolutionary algorithm was used for the modelling of the data. The modelling results are listed in Table 3.

*Table 3: Parameters estimation for the dynamic cure of EP2400*

| $A_1$ (1/min) | $E_1$ (J/mol) | $A_2$ (1/min) | $E_2$ (J/mol) | $n_1$ | $n_2$ | m |
|---|---|---|---|---|---|---|
| 292896693 | 96951.70 | 48264.24 | 50188.16 | 0.441487 | 1.555356 | 0.824029 |

Indicative fitting results are shown in Figure 3.

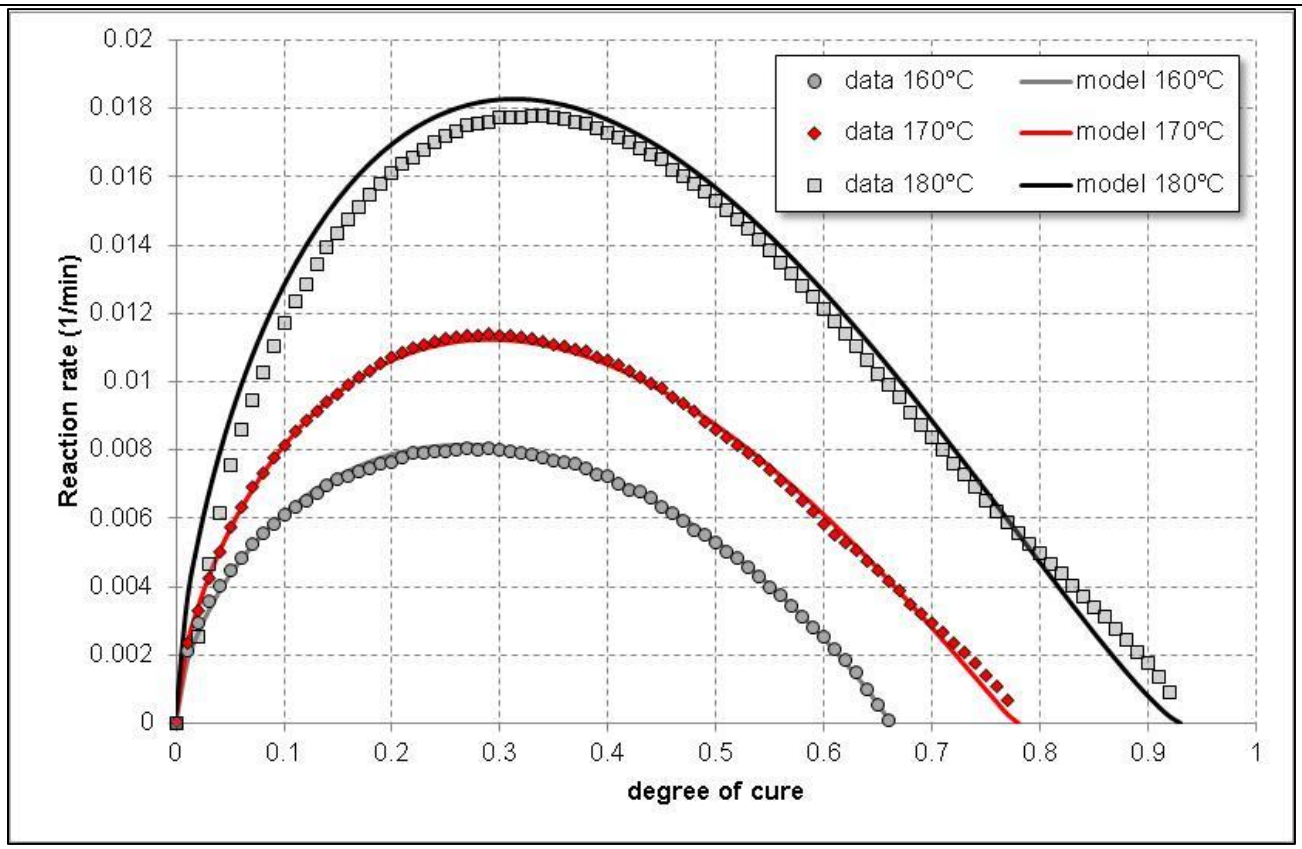


*Figure 2: Modelling of isothermal cure of EP2400 at 160°C, 170°C and 180°C*

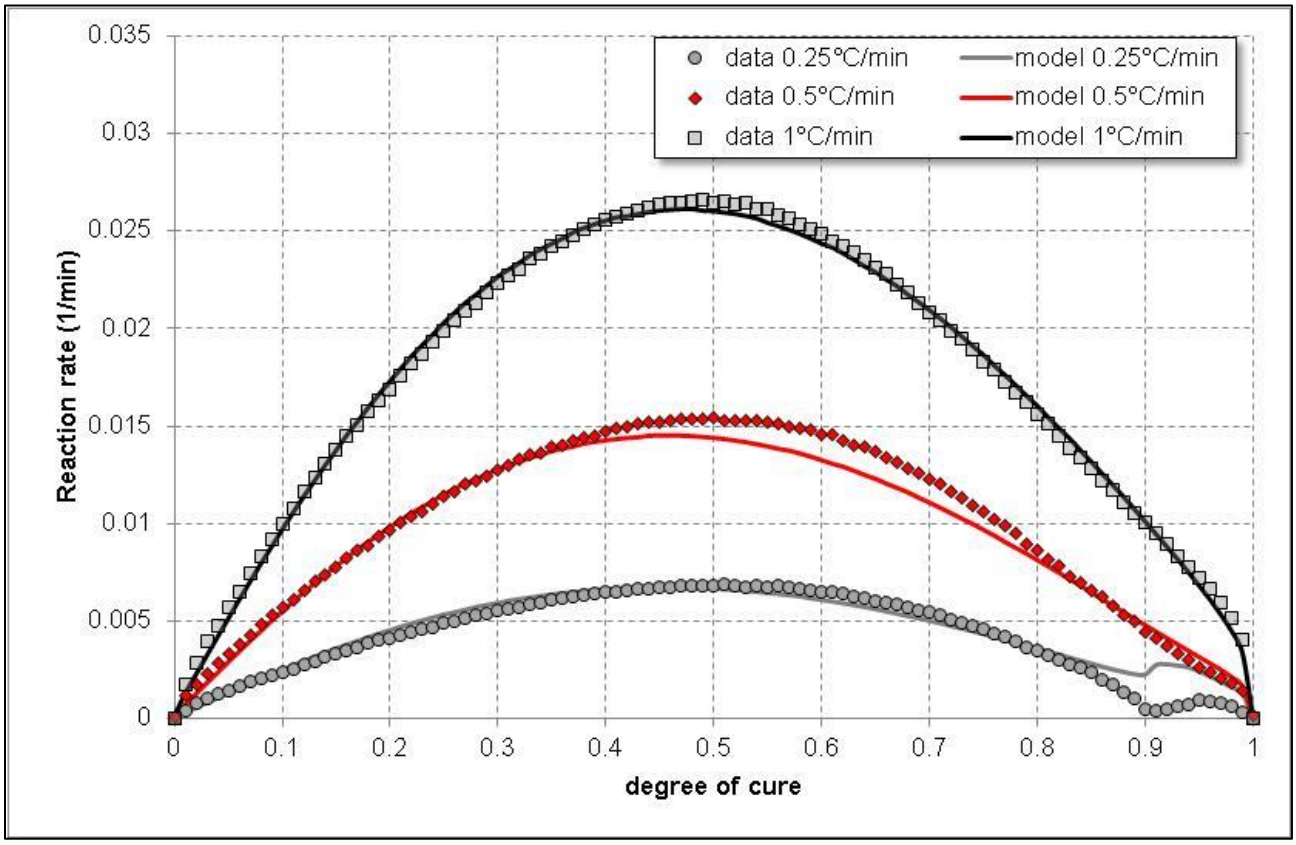


*Figure 3: Modelling of non-isothermal cure of EP2400 at low heating rates*

**Glass transition temperature modelling**

The glass transition temperature of uncured, partially cure and fully cured samples of EP2400 was measured. A representative calculation is shown in Figure 4. The onset and mid-point of the inflection are used for the calculation of the glass transition onset and the glass transition temperature respectively.

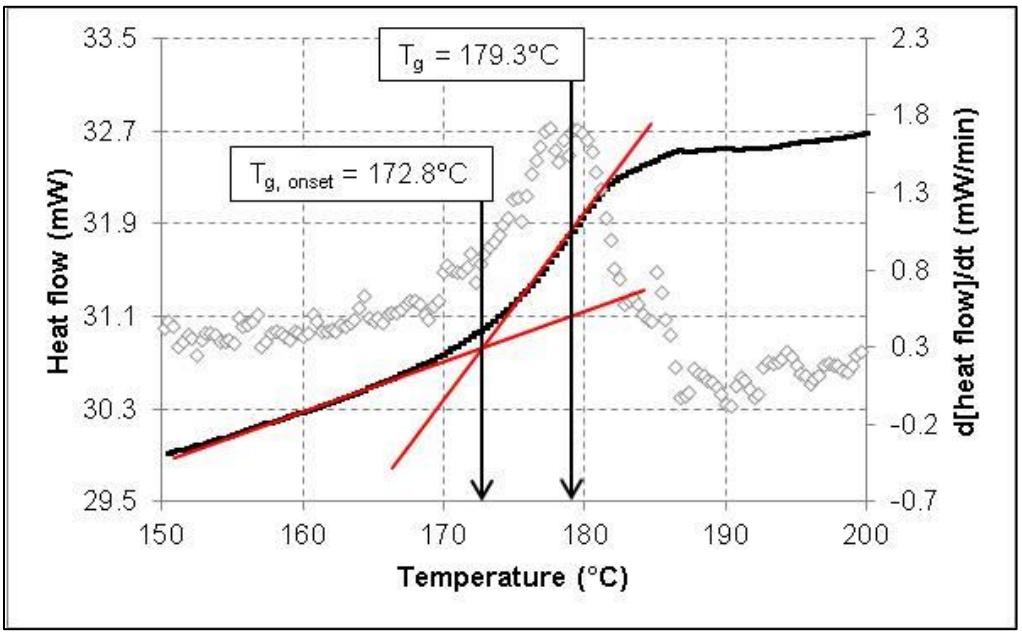


*Figure 4: Glass transition temperature calculation for the sample cured at 180°C*

The results are summarised in Table 4.

*Table 4: Glass transition temperature values*

| Temperature (°C) | unreacted | 120 | 130 | 140 | 150 | 160 | 170 | 180 | Fully cured |
|---|---|---|---|---|---|---|---|---|---|
| Degree of cure | 0.00 | 0.32 | 0.46 | 0.51 | 0.57 | 0.66 | 0.78 | 0.93 | 1.00 |
| $T_{g,\ onset}$ (°C) | -15.6 | 135.7 | 140.9 | 143.1 | 145.8 | 154.3 | 158.4 | 172.8 | 178.5 |
| $T_g$ (°C) | -12.1 | 140.5 | 145.6 | 151.1 | 154.1 | 160.8 | 166.4 | 179.3 | 192.6 |

A modified Di Benedetto equation was fitted to the data:

$$T_g(a) = \begin{cases} f(a) = T_{g,0} + \frac{(T_{g,O}-T_{g,0})\lambda_1 \frac{a}{a_O}}{1-(1-\lambda_1)\frac{a}{a_O}} & 0 \le a \le a_O \\ g(a) = T_{g,O} + \frac{(T_{g,P}-T_{g,O})\lambda_2\left(1-\frac{a}{a_O}\right)}{1-(1-\lambda_2)\left(1-\frac{a}{a_O}\right)} & a_O \le a \le 1 \end{cases} \quad (5)$$

$$\lambda_2 = -\frac{1}{1-a_O}\frac{T_{g,\infty}-T_{g,O}}{T_{g,P}-T_{g,\infty}}, \quad T_{g,P} = \frac{1}{1-p}T_{g,\infty} - \frac{p}{1-p}T_{g,O}, \quad p = \frac{\lambda_1}{1-a_O}\frac{T_{g,\infty}-T_{g,O}}{T_{g,O}-T_{g,0}} \quad (6)$$

An evolutionary algorithm was used for the modelling of the data. The modelling results are listed in Table 5. The fit to the experimental data is shown in Figure 5.

*Table 5: Parameters estimation for Eq. (5)*

| Material parameters | | Fitting parameters | | | Dependent parameters | |
|---|---|---|---|---|---|---|
| $T_{g,0}$ (°C) | $T_{g,\infty}$ (°C) | $\alpha_O$ | $T_{g,O}$ (°C) | $\lambda_1$ | $\lambda_2$ | $T_{g,P}$ (°C) |
| -12.1 | 192.60 | 0.48894 | 150.2816 | 8.46697 | 1.50400 | 137.5262 |

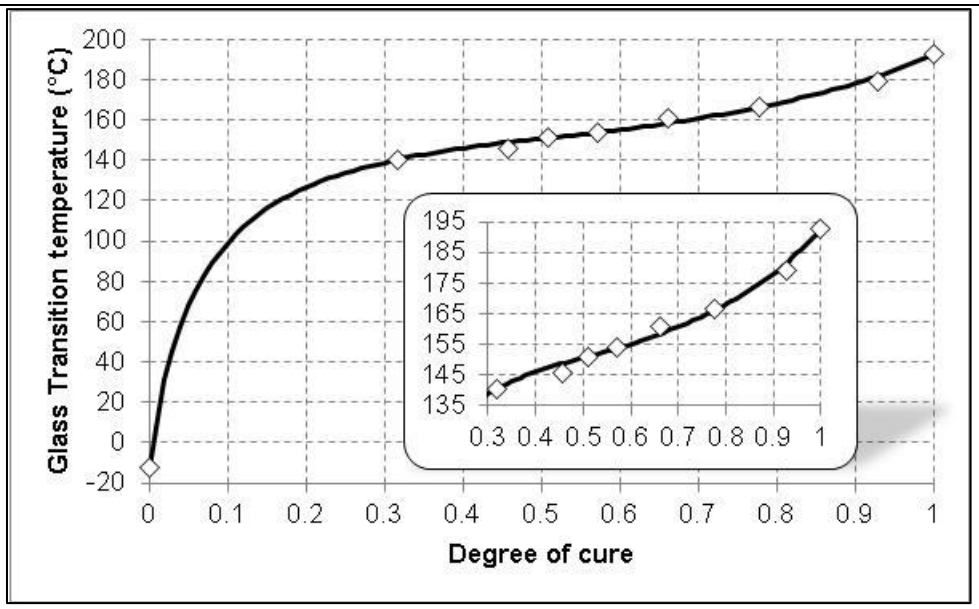


*Figure 5: Glass transition temperature model. The insert graph focuses on Tg values higher than 140°C*

## Viscosity modelling

The viscosity measurements at 90°C, 100°C, 110°C and 120°C are shown in Figure 6. Viscosity rises sharply after a period of relatively low values.

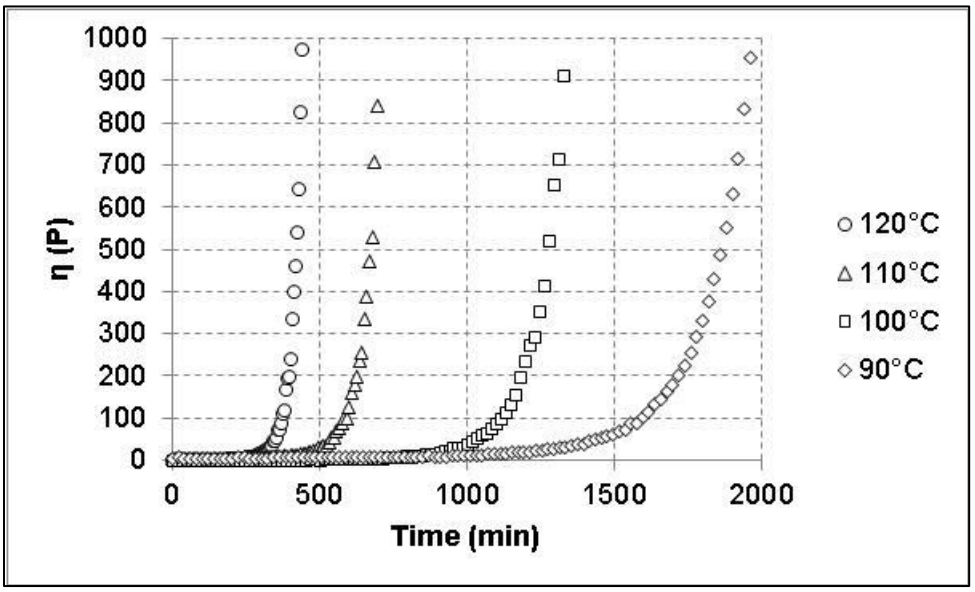


*Figure 6: Viscosity measurements at infusion temperatures*

The data were modelled using the following equation:

$$\eta(T) = \eta_0(T) e^{D\left(\frac{1}{T} - \frac{1}{T_0}\right)} \quad (7)$$

$$\frac{\eta_0(T_0)}{\gamma} = e^{\left(\left(\frac{ln\eta_0(0)}{\gamma} + \left(Ae^{-\frac{E}{RT}}\right)t\right)(1-\mu)\right)^{\frac{1}{1-\mu}}} \quad (8)$$

A combination of an evolutionary algorithm and a Generalised Reduced Gradient (GRC) Nonlinear optimisation method was used for the modelling of the data. The modelling results are listed in Table 6. The fit to the experimental data is shown in Figure 7.

*Table 6: Parameters estimation for Eq. (7)*

| A (P/min) | E (J/mol) | γ (P) | μ | $\ln\eta_0(0)$ (P) | D |
|---|---|---|---|---|---|
| 2036079 | 61963.6 | 1.76805 | 0.577255 | 0.496872 | 5000 |

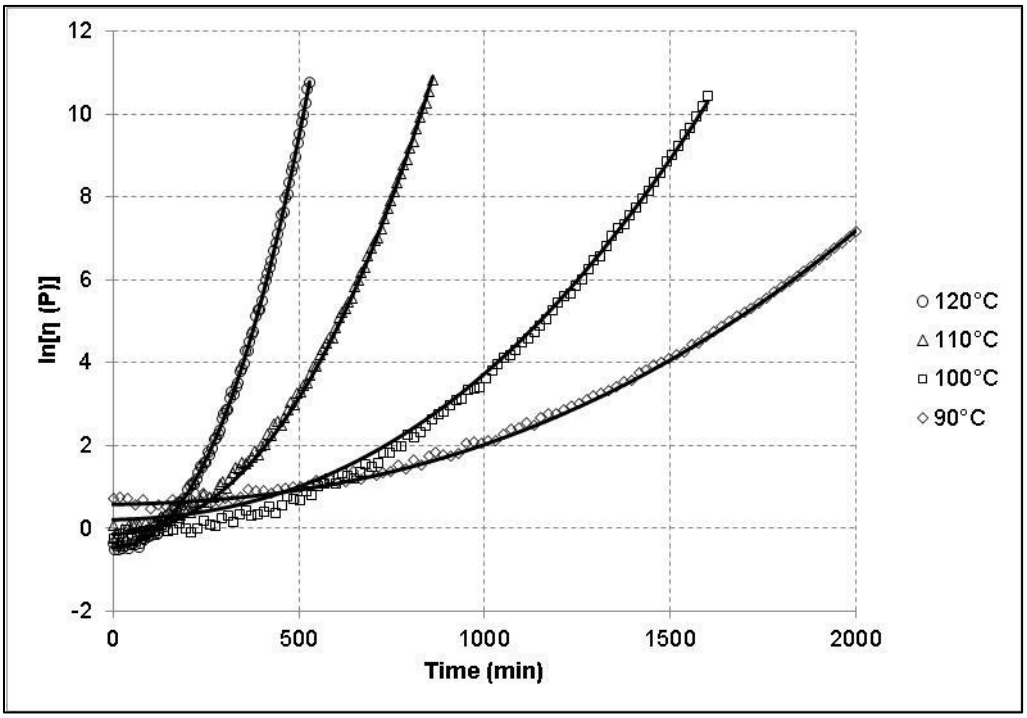


*Figure 7: Viscosity modelling results*

**Fabric permeability**

The measurement of permeability of the fabric architecture used in the part was made in a simple rectangular heated cell having two heated plates (top and bottom) of dimensions 70 x 40 mm. In the cell electrical contact sensing points were installed every 20 mm along the length of the rectangle as shown in Figure 8.

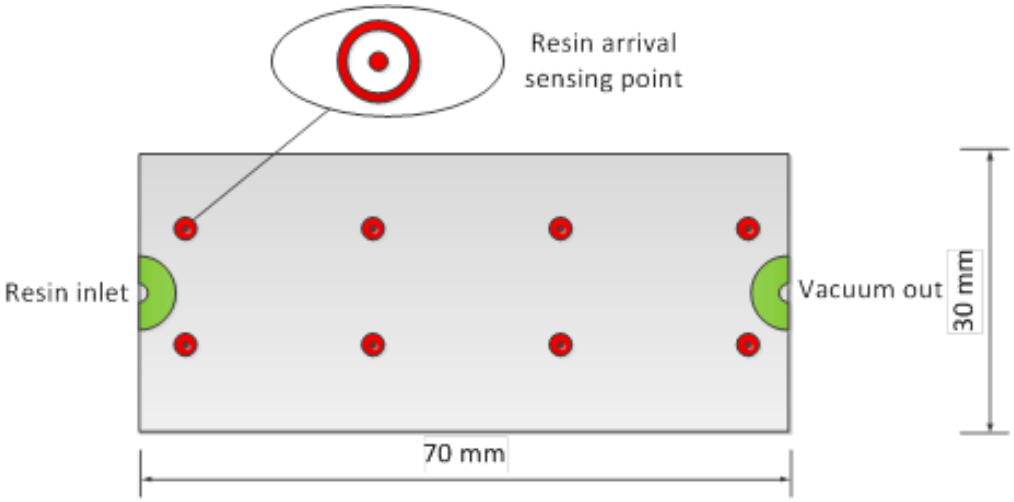


*Figure 8: Layout of resin arrival sensing points within the heated cell for fabric permeability measurement*

Dry perform typical of the stiffened panel's skin architecture was cut (42 plies) and placed in the cell. The fabric was pressed on the bottom tool plate of the cell surface by a vacuum bag, while the top plate ensured homogeneous temperature across the fabric thickness. An infusion pressure of 75kPa was applied to the cell. The resin was pre-heated to 90°C before infusion, so that the resin viscosity was estimated to be 178 mPa.s (using Eq.(7)). The times of resin arrival at the sensing points were measured by an accurate analogue input board.
Permeability was estimated using the following equation:

$$K_x = \frac{x^2 \eta \phi}{2 t_{fill}(P_o - P_b)} \quad (7)$$

where x is the maximum length of the resin path within the heated cell (x = 60 mm), η is the resin viscosity (η = 178 mPa.s), ϕ is the porosity of the perform (taken as 0.70), $t_{fill}$ is the time to cover the length x ($t_{fill}$ = 14.8 sec) and $P_o$-$P_b$ is the pressure gradient across the part ($P_o$-$P_b$ = 70 kPa).
The results of the test and the permeability calculation are shown in Table 7.

*Table 7 Measurements of permeability of the fabric used for the composite stiffened panel*

| Distance (mm) to inlet along each line | 5 | 25 | 45 | 65 |
|---|---|---|---|---|
| Time of arrival (sec) at line 1 | 1.0 | 5.9 | 10.8 | 15.8 |
| Permeability ($m^2$) | $2.02 \times 10^{-10}$ | | | |
| Time of arrival (sec) at line 2 | 0.9 | 6.1 | 10.9 | 16.1 |
| Permeability ($m^2$) | $1.97 \times 10^{-10}$ | | | |

#### *4.1.3.4 Modelling approach for process optimisation*

The process optimisation procedure developed for the project has two distinct steps:

**Heat transfer mechanism estimation through the MISO-NARX system identification technique**.
The system identification procedure is shown in Figure 9. The temperature of the tool, $T_t$ and the exothermic heat of the polymerisation reaction are the input parameters. The temperature of the part, $T_p$ is compared to the estimated temperature of the part, $\check{T}_p$. The minimisation of the error $T_p$ - $\check{T}_p$ is the objective function for the optimisation in the second step.

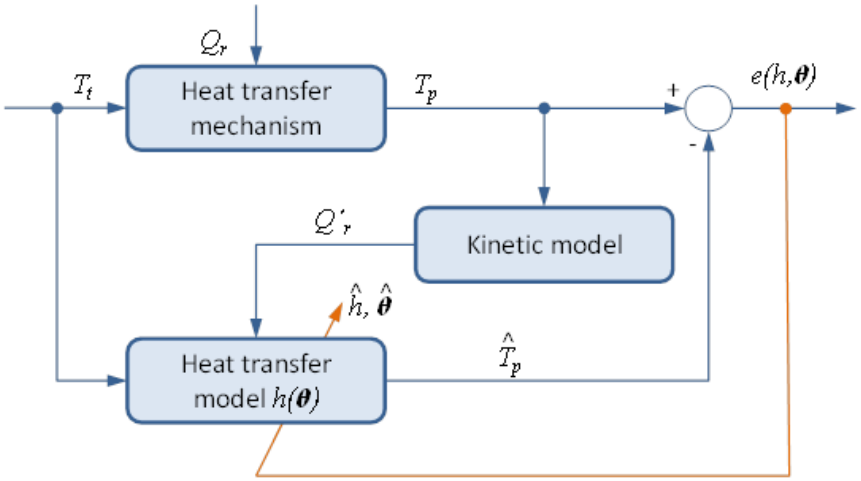


*Figure 9: Schematic diagram of the system identification procedure in the OPTOCLAVE project*

In order to account for non nonlinear dynamical relationships between the system inputs $T_t$, $Q_r$ and output $T_p$, a stochastic Multiple-Input Single-Output (MISO) Nonlinear Auto-Regressive with eXogenous excitation (NARX) model structure of polynomial form will be adopted. The MISO-NARX polynomial model has the following mathematical formulation:

$$y[t] = \theta_0 + \sum_{i_1} \theta_{i_1}\varphi_{i_1}[t] + \sum_{i_1,i_2} \theta_{i_1 i_2}\varphi_{i_1}[t]\varphi_{i_2}[t] + \cdots + \sum_{i_1,\ldots,i_l} \theta_{i_1 \ldots i_\ell}\varphi_{i_1}[t] \ldots \varphi_{i_\ell}[t] + e[t] \quad (8)$$

where t designates the normalized discrete time (t = 1,2…N), N is the data length, y[t] the model output (in the case of OPTOCLAVE this is the part temperature, $T_p$), and e[t] the model error. The model error is assumed to be a zero-mean uncorrelated sequence. The terms $\varphi_i[t]$ are delayed versions of either the output y[t] (autoregressive terms) or one of the inputs $u_i[t]$ for i = 1,2…(exogenous terms). The model parameters are denoted by $\theta_i$. The Auto-Regressive order, $n_y$, designates the maximum delay appearing in the model with regard to y[t]. A more compact formulation of Eq. (8) is:

$$y[t] = \vartheta_0 + \sum_{i=1}^{L} \vartheta_i \cdot p_i[t] + e[t] \quad (9)$$

In this form, $p_i[t]$, designates the i-th regressor. In most cases, $p_i[t]$, is a monomial consisting of products of various $\varphi_i[t]$. L stands for the number of regressors. The model parameter corresponding to the i-th regressor is designated as $\vartheta_i$. The minimum mean-square one-step-ahead prediction $\hat{y}[t]$ of the NARX model is given by:

$$\hat{y}[t] = \sum_{i=0}^{L} \vartheta_i \cdot p_i[t] \quad (10)$$

The NARX model is linear. Therefore, linear regression analysis techniques can be used for the parameter estimation methodology. Forward orthogonal least squares estimator will be used for OPTOCLAVE. The following variables are defined:

$$w_0[t] = p_0[t] = 1 \quad (11)$$

$$w_i[t] = p_i[t] - \sum_{r=0}^{i-1} a_{ri} w_r[t], i = 1, \ldots, L \quad (12)$$

$$a_{ri} = \frac{\sum_{t=1}^{N} p_i[t] \cdot w_r[t]}{\sum_{t=1}^{N} w_r^2[t]}, 0 \le r \le i-1 \quad (13)$$

The auxiliary model may be obtained as:

$$y[t] = \sum_{i=0}^{L} g_i \cdot w_i[t] + e[t] \quad (14)$$

where $w_i[t]$ and $g_i$ are the i-th regressor and the corresponding parameter of the auxiliary model, respectively. Each auxiliary coefficient $g_i$ can be estimated sequentially and independently:

$$\hat{g}_0 = \frac{1}{N}\sum_{t=1}^{N} y[t] \quad (15)$$

$$\hat{g}_i = \frac{\sum_{t=1}^{N} y[t] \cdot w_i[t]}{\sum_{t=1}^{N} w_i^2[t]}, i = 1, \ldots, L \quad (16)$$

Once the parameters $\hat{g}_i$ have been estimated, the parameters $\vartheta_i$ of the original model of Eq. (10) can be computed as:

$$\hat{\vartheta}_i = \sum_{j=i}^{L} \hat{g}_j v_j \quad (17)$$

with

$$v_i = 1, v_j = -\sum_{r=i}^{j-1} a_{rj} v_r, i < j \leq L \quad (18)$$

According to this procedure, the determination of the model structure is accomplished via the Error Reduction Ratio (ERR) criterion:

$$ERR_{\ i} = \frac{\sum_{t=1}^{N} \hat{g}_i^2 \, w_i^2[t]}{\sum_{t=1}^{N} y^2[t]} \times 100\% \quad (19)$$

The quantity ERR provides an indication of which term should be included in the model by assessing the percentage contribution of the $w_i[t]$ regressor to the reduction of the total mean-squared prediction error.
In OPTOCLAVE, the simulation of the process is also important. For this reason, the structure selection procedure will be modified by combining the ERR criterion with the Normalized Mean Square Simulation Error. The resulting, combined, *Structure Determination Criterion (SDC)* will be of the form[3]:

$$SDC_i = aERR_i + \beta\delta(NMSE)_i \quad (20)$$

where α and β are selected constants and $\delta(NMSE)_i$ denotes the reduction in the Normalized Mean Square Simulation Error when the i-th term is added to the model. NMSE is defined as follows:

$$\tilde{e}[t] \stackrel{\Delta}{=} y[t] - y_{sim}[t] \quad (21)$$

$$NMSE \ = \frac{\|\tilde{e}[t]\|^2}{\|y[t]\|^2} \times 100\% \quad (22)$$

where $y_{sim}[t]$ is the model-based simulated signal, y[t] is the actual signal, ẽ[t] is the simulation error and || || is the Euclidean norm. The selection procedure incorporates those terms which provide a significant SDC reduction.

**Cure cycle optimisation through the use of Genetic Algorithms and linear optimisation techniques.**

The determination of the optimum reference temperature profile, in terms of minimizing the cure cycle duration without affecting the quality of the composite part, constitutes an automatic learning problem that has to be handled through a proper formal optimisation procedure. This requires an effective mathematical formulation of the whole optimisation problem.

Problem formulation

The optimisation problem aims to find a value for the parameter vector, **θ**, that minimises a function L(**θ**), while satisfying a set of constraints, $g_i(\boldsymbol{\theta})$ and $q_i(\boldsymbol{\theta})$:

$$\begin{aligned} \widehat{\boldsymbol{\theta}} &= \operatorname{argmin}_{\theta} \ L(\boldsymbol{\theta}) \\ \boldsymbol{\theta} &\in \left\{\boldsymbol{\theta}: g_i(\boldsymbol{\theta}) \geq 0, i = 1, \cdots, n, q_j(\boldsymbol{\theta}) = 0, j = 1, \cdots, m\right\} \end{aligned} \quad (23)$$

The optimised parameter vector

In OPTOCLAVE the parameter vector represents the cure cycle profile. The cure cycle profile is considered as a series of sequential linear segments of the form:

[3] S.A. Billings, S. Chen, and M.J. Korenberg, "Identification of MIMO non-linear using a forward-regression orthogonal estimator", International Journal of Control, Vol. 49, no 6, pp 2157-2189, 1989

$$\{T_1(t) = T_0 + c_1 \cdot t, T_i(t) = T_{i-1}(\Delta t_{i-1}) + c_i \cdot t, \quad t \in [0, \Delta t_i] : i = 2, \cdots, p\} \quad (24)$$

where $\Delta t_i$ and $c_i$ are the time duration and the slope[4], respectively, of the i-th segment, while $p$ stands for the number of segments. Given an initial temperature, $T_0$ the cure cycle is fully defined in terms of the parameter vector $\boldsymbol{\theta}$**:**

$$\boldsymbol{\theta} \stackrel{\text{def}}{=} [\, \boldsymbol{c}^T \;\; \boldsymbol{t}^T]^T, \boldsymbol{c} \stackrel{\text{def}}{=} [c_1 \; \cdots c_p]^T, \boldsymbol{t} \stackrel{\text{def}}{=} [\Delta t_1 \; \cdots \Delta t_p]^T \quad (25)$$

The cure cycle profile is written as follows:

$$T(t, \boldsymbol{\theta}) = \sum_{i=1}^{p} [\, T_i(t, \boldsymbol{\theta}) - T_i(t, \boldsymbol{\theta}) \cdot u(t - t_i(\boldsymbol{\theta})) - c_i \cdot r(t - t_i(\boldsymbol{\theta}))] \quad (26)$$

where:

$$t_i(\boldsymbol{\theta}) \stackrel{\text{def}}{=} \sum_{j=1}^{i} \Delta t_j \quad (\, i = 1, \cdots, p), u(t) \stackrel{\text{def}}{=} \begin{cases} 1, & t > 0 \\ 0, & t \le 0 \end{cases}, r(t) \stackrel{\text{def}}{=} \begin{cases} t, t > 0 \\ 0, t \le 0 \end{cases} \quad (27)$$

The loss function

The loss function reflects the purpose of the optimisation procedure, which in the context of the OPTOCLAVE project is the reduction of the manufacturing time. This is directly connected with the duration $t_{\text{tot}}$ of the cure cycle:

$$t_{\text{tot}}(\boldsymbol{\theta}) = \sum_{i=1}^{p} \Delta t_i \quad (28)$$

Therefore, the loss function is defined as:

$$L(\boldsymbol{\theta}) \stackrel{\text{def}}{=} t_{tot}(\boldsymbol{\theta}) = \sum_{i=1}^{p} \Delta t_i. \quad (29)$$

Constraints

In order to ensure that the manufactured part will maintain its performance characteristics, a series of constrains have to be considered during the optimisation procedure. The constraints related to the process are set by the Topic Manager.

- Number of segments in the cure cycle: A maximum number of 10 segments is defined. Also, the duration of a segment cannot be less than a pre-defined value, $\Delta t_{min}$.
- Heating and cooling rate: The maximum heating rate is set to 2°C/min. The minimum heating rate is set to 0.5°C/min. The maximum cooling rate is set to 5°C/min. These constraints were defined by the specific autoclave used in the project.
- Maximum process temperature: The Topic Manager defined that the temperature should not exceed 185°C.
- Maximum reaction rate: A maximum reaction rate is set in order to avoid any catastrophic exothermic events during the manufacturing process
- Viscosity during infusion: A critical viscosity value is set for a minimum duration during infusion in order for the material to successfully infuse into the tool and impregnate the fibres.
- Glass transition temperature: The Glass Transition temperature of the final part defines the maximum degree of cure that the material needs to have reached by the end of the cure. Eq. (5) is used for the derivation of the maximum degree of cure from the target glass transition temperature.

[4] In the case of an isothermal segment, $c_i = 0$

#### *4.1.3.5 Application of the auto-learning algorithm*

The algorithm is applied to three distinct phases of the process:

- The infusion phase, in which the resin flows from the resin pot to the tool and impregnates the fibres (fibre wetting).
- The gelation phase, in which the part temperature rises in order to advance the degree of cure past the critical range for an exothermic event.
- The final temperature phase, in which the resin attains the final set of properties (degree of cure and glass transition temperature).

Temperature data from a number of thermocouples embedded in the part during processing are acquired during the 'training' cycles for the heat transfer model development. The heat transfer model translates the autoclave set-point profile to a time-temperature profile at each thermocouple location. This time-temperature profile can then be used to predict the time evolution of resin properties at these locations (space-level estimation of properties). The numerical procedure used for the space-level estimation of resin properties is presented in Figure 10.

The kinetic model of the resin system (Eq. (1) and Eq. (3)) provides the degree of cure at time t+Δt at the specific location given that the degree of cure and the temperature at the time t are known. The chemical structure model transforms the degree of cure to the glass transition temperature (Eq. (5)). The chemorheology model provides the resin viscosity at the specific location (Eq. (7)). The numerical procedure described here is implemented in DETA-LEARN.

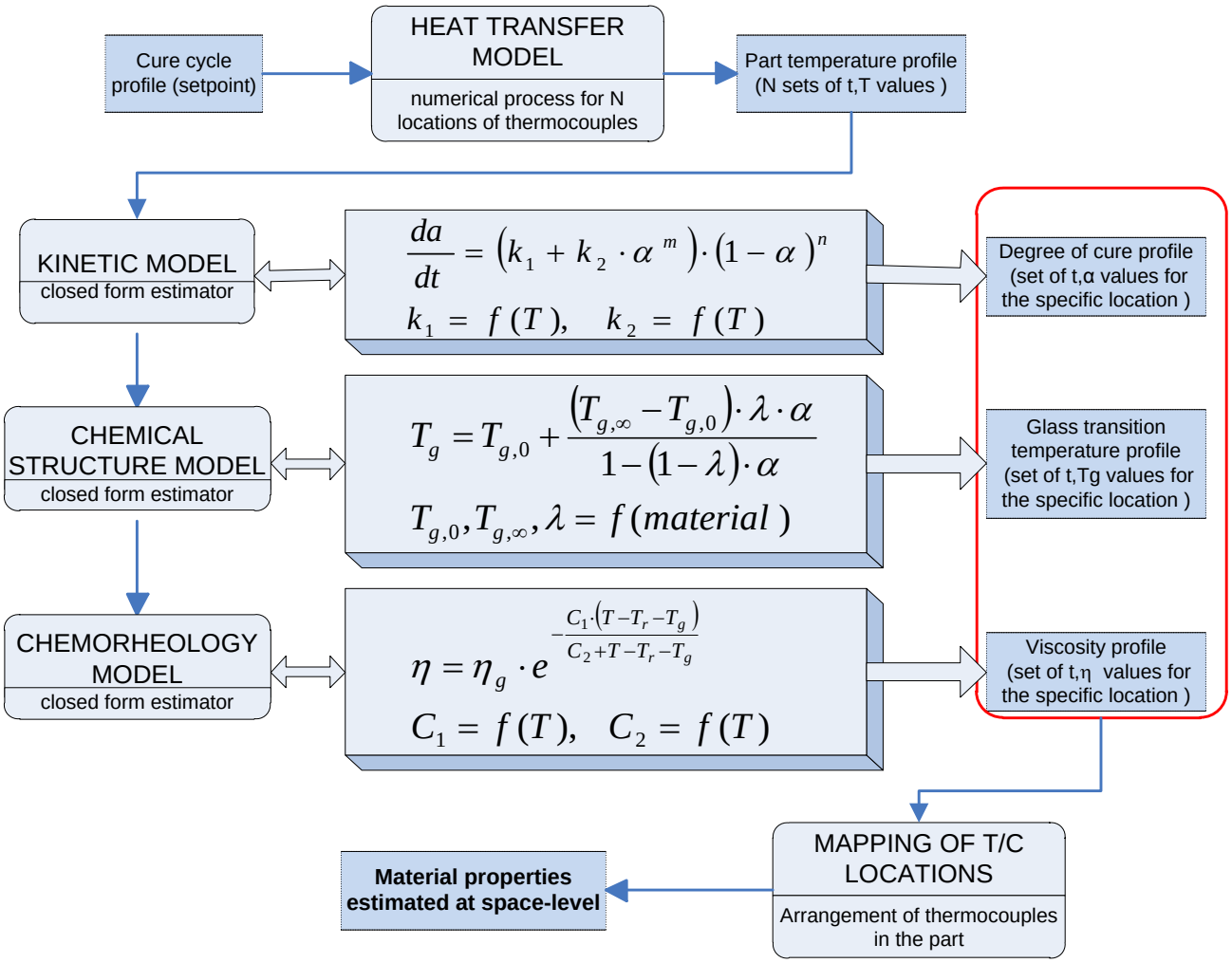


*Figure 10: Flow diagram of the numerical procedure used for the space-level estimation of material properties during the autoclave process cycle*

*4.1.3.6 DETA-LEARN software development*

Organisation of software architecture

The DETA-LEARN software is divided in two distinct modules:

- the heat transfer model training module
- the cure profile optimization module

The software operation leads in each run to one of the modules as selected by the operator at the introductory screen.

DETA-LEARN heat transfer model training module

The aim of the DETA-LEARN heat transfer training module is the extraction of the heat transfer model using experimental data consisting of the user defined reference autoclave temperature profile (set point) to the part temperature responses. The heat transfer model is obtained based on available input (reference temperature profile) and output (part temperatures) measurements using the forward regression NARX modelling procedure described in section 4.1.3.4 above.

The DETA-LEARN training software inputs and outputs are shown in Table 8.

*Table 8: DETA-LEARN training module inputs and outputs*

| INPUTS | OUTPUTS |
|---|---|
| 1. Experimental data | 1. Heat transfer model |
| 2. Experimental data sampling period | |
| 3. Number of the part temperature responses | |
| 4. Maximum model order | |
| 5. Maximum time shifting | |

INPUTS:

1. Experimental data (text input file): The experimental data which are utilized in the DETA-LEARN training software for the estimation of the heat transfer model consists of:
    a. The imposed autoclave reference temperature profile.
    b. The corresponding part temperature responses.

    The user should store the experimental data in a *.txt file (e.g. “data.txt”). The constructed data.txt file is an input file for the DETA-LEARN training software.
2. Experimental sampling period (numeric input): The sampling rate of the experimental data.
3. Number of the part temperature responses (numeric input): The number of the part temperature responses stored in the experimental data text file (without the imposed reference profile).
4. Maximum model order (numeric input): The maximum NARX model order considered by the DETA-LEARN training software.
5. Maximum time shifting (numeric input): The maximum time shifting of the NARX model regressors considered from the DETA-LEARN training software.

OUTPUTS:

1. Heat transfer model (text output file): The estimated heat transfer model parameters are stored in a *.txt file, which constitutes the output of the DETA-LEARN training software. The output file will be used as an input to the DETA-LEARN cure profile optimisation software.

The user interface of the heat transfer model training module is shown in Figure 11.

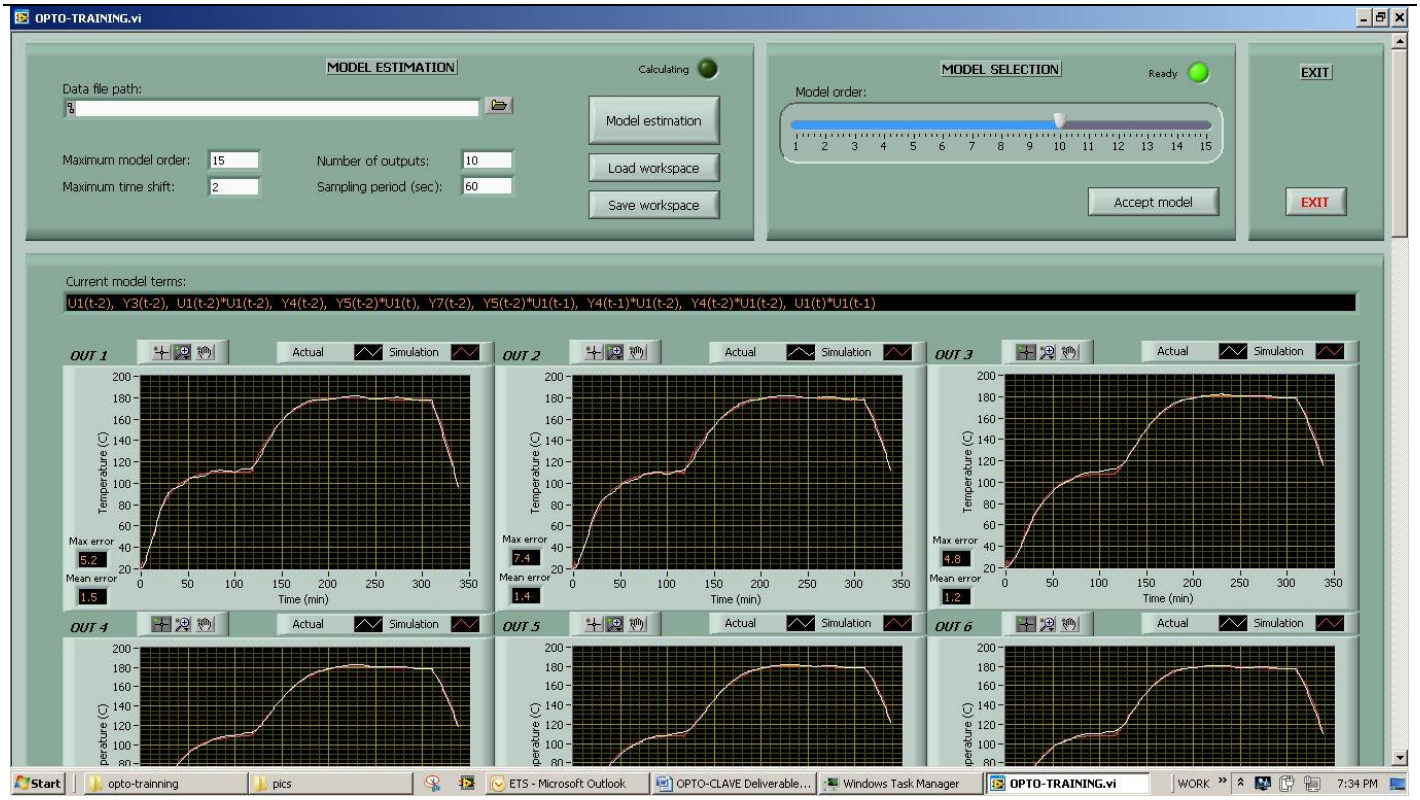


*Figure 11: User interface of the DETA-LEARN heat transfer model training software during model selection*

DETA-LEARN cure profile optimization mode

The DETA-LEARN cure profile optimisation module aims to define the optimum cure profile for the economic and energy efficient processing of composite materials.
The operation is divided into the following stages:

A. Definitions and constraints of the optimisation procedure
B. Optimisation of the infusion phase
C. Optimisation of the gelation phase
D. Optimisation of the final temperature phase
E. Summary

In stage A the operator selects the autoclave type, the part ID and the material system and loads the heat transfer model related to the autoclave, tooling and part concerned in the process. Also, the basic requirements for the part performance are given here. The constraints of the cure profile optimisation are also provided.

In stage B the infusion phase setpoint (time-temperature profile loaded to the autoclave control system) is determined. The infusion temperature and the dwell time can be either user defined or selected between several options according to the fabric wettability criterion. The operator is able to review the properties (viscosity and temperature) during infusion at all thermocouple locations. The resin properties at the pot exit provide the baseline for all further calculations.

In stage C the gelation phase setpoint (time-temperature profile loaded to the autoclave control system) is determined. A series of heating rates from the infusion temperature to the final cure temperature are tested according to the constraints defined in stage A. An automated process for the determination of the optimum profile was designed. The heat transfer model application yields the part temperature distribution across the gelation phase. The kinetic and chemorheology model implementation allows the operator to review the viscosity, degree of cure, reaction rate and $T_g$ at the thermocouple locations during the gelation phase. The

gel point is determined and the spread of gel times is estimated while all relevant constraints are assessed. The operator accepts the optimum profile in this phase in order to move to the next stage.

In stage D the final temperature phase setpoint (time-temperature profile loaded to the autoclave control system) is determined and the overall optimised cure profile is presented. The attainment of target properties at the final cure temperature is examined and the duration of the final phase is estimated. The heat transfer model application yields the part temperature distribution across the complete cure profile. The kinetic and chemorheology model implementation allows the operator to review the degree of cure, reaction rate and $T_g$ at the thermocouple locations during the complete cure profile. The spread of the final properties ($T_g$ and degree of cure) across the part are estimated and all relevant constraints are assessed.

In stage E the operator provides the nominal process reference profile as baseline for the evaluation of optimisation benefits. Also the operator provides geometrical details of the autoclave and of the part in order to perform energy calculations in the manufacturing process. At the final panel of the software operation there is presentation of the benefits resulting from the adoption of the optimised process in terms of process time and energy. All relevant cure profile optimisation results can be saved to file for later processing and review.

The software was developed in order to run in a standard PC platform (running Windows XP or later operating system) with minimum processor speed 1.5 GHz and 2 GB RAM. The display settings of the monitor should allow a resolution of 1360 x 768 pixels as a minimum. An initial estimate of the run time required for calculations (based on 12 thermocouples over a 4 hour cure process) is that the code will develop the heat transfer model in around 5 minutes and will execute calculations for cure profile optimisation in few seconds.

To illustrate the level of complexity in the software development, the user interface of DETA-LEARN for the performance of stage A in the cure profile optimisation process is shown in Figure 12.

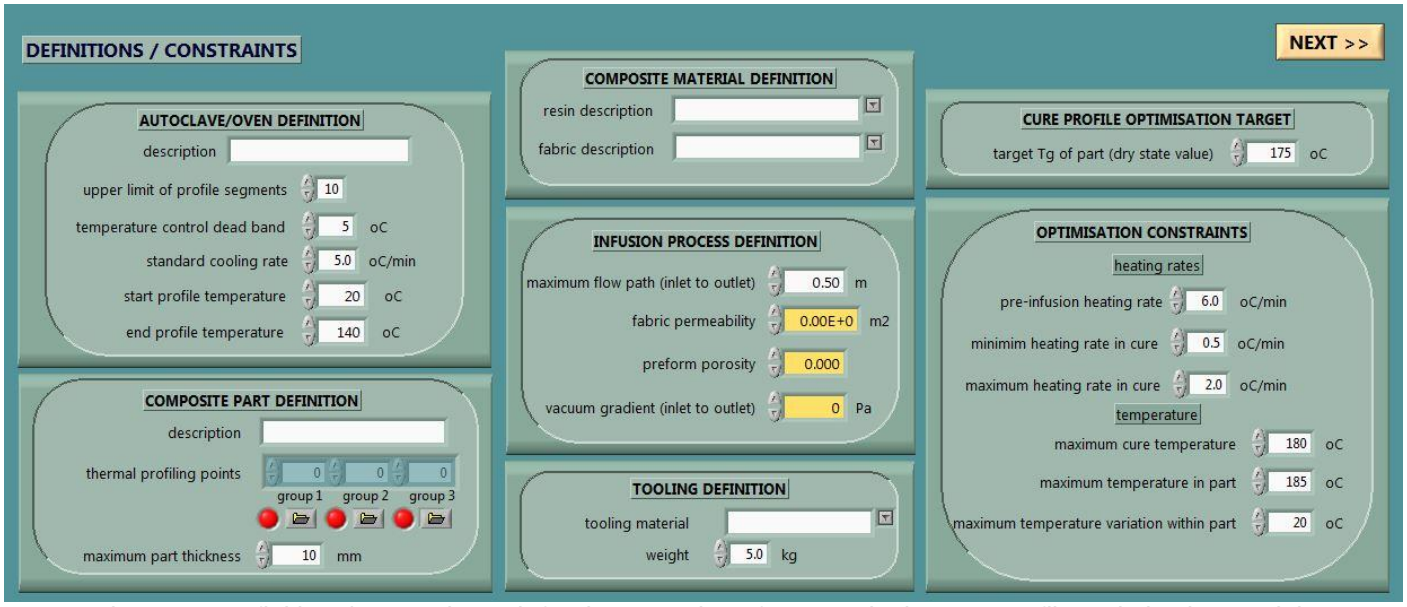


*Figure 12: Definitions/Constraints tab for the operation of stage A in the cure profile optimisation module*

The use of graphs and logical checks is extensive in the software development. As an example, the user interface of DETA-LEARN for the performance of stage C in the cure profile optimisation process is shown in Figure 13.

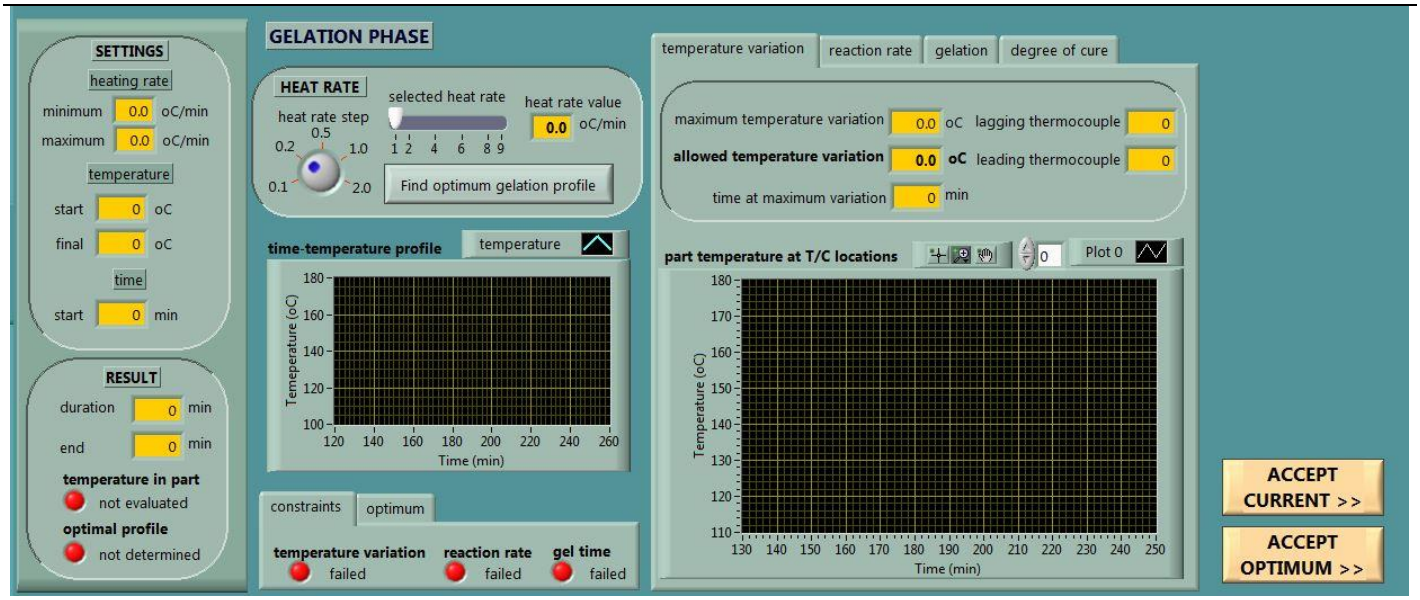


*Figure 13: Gelation phase tab for the operation of stage C in the cure profile optimisation module*

Finally, the summary page involves the assessment of benefits incurred by the optimised profile in terms of time and energy consumption. A specific model for the calculation of energy consumption has been developed (as described in Annex I) and the model is implemented to the DETA-LEARN cure profile optimisation module. The user interface of the DETA-LEARN for the performance of stage E in the cure profile optimisation process is shown in Figure 14. The results from the optimisation of the cure process for a large stiffened panel are displayed. The application of the software tool in the process of the particular component yields reduction of time by 12.8% and reduction of energy consumption by 15.9%.

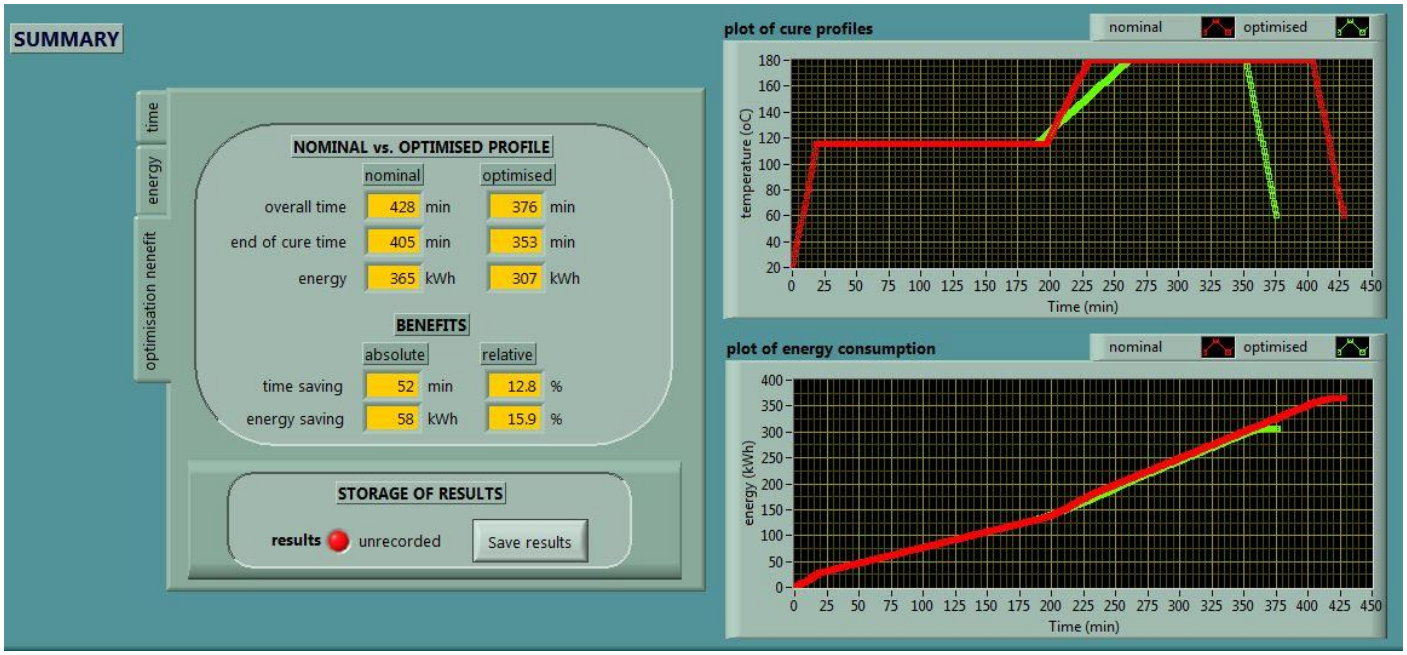


*Figure 14: Summary tab for the operation of stage E in the cure profile optimisation module on the processing of large stiffened panels*

### *4.1.4 Potential impact and main dissemination activities*

The application of the developed methodology in the optimisation of manufacturing processes should benefit the composite part design teams as well as the composite processing units as it provides a clear trend of

the processing route across all stages of manufacturing. The optimisation of infusion processes can be performed on the basis of determination (experimental or theoretical) of fabric and resin properties. The definition of cure profile at the post-infusion stage can be made in such a way to avoid exothermic effects in the most time-effective method. The attainment of the final properties of the composite part is guaranteed at the shortest time and at reduced energy consumption.

During the project dissemination activities were not performed. The dissemination of the project remains the intention of the partners and any future dissemination action will be performed after the approval of the Topic Manager.

## 5 Summary

The publishable report contains the executive summary and an extensive description of all the project activities and achievements.