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IDENTIFICATION OF CRIMS MODEL PARAMETERS FOR WARPAGE PREDICTION IN INJECTION MOULDING SIMULATION

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ABSTRACT: Polymer injection moulding is a process widely used to produce components in a lot of different applications. One of the most critical aspects related to this process is to control the warpage of the parts after the extraction from the mould. Numerical simulations can predict a part warpage by using specific warpage models. Among numerical codes, Autodesk Moldflow Insight® uses a Corrected In Mold Residual Stress (CRIMS) model, that calculate the residual stresses develop during the moulding process. Warpage is then predicted calculating the deformations of the component induced by the considered stresses. Using experimental and numerical techniques, a new identification procedure was introduced to evaluate the six parameters of the CRIMS model included in the Moldflow® material properties database. The study was conducted on a box for an automotive application made of polypropylene. On the base of a complete rheological, thermal and physical characterization of the employed material, a numerical simulation of the process was implemented, integrating it with an optimization procedure to identify the values of the CRIMS parameters that force numerical results to fit measured deformations. As this procedure was very time consuming, requiring to run several computationally intensive simulations, artificial neural networks were employed to approximate numerical results with lower computational time. Results were verified with independent samples, showing good correspondence between experimental results and numerical calculated deformations.

KEYWORDS: injection moulding, numerical simulation, CRIMS parameters identification

1 INTRODUCTION

Shrinkage and distortion of injection moulded parts after ejection from the mould originate a significant industrial problem, as the subsequent assembly may be inhibited. The reduction in the size of part as compared to the size of the mould cavity depends on the volumetric shrinkage due to 1) contraction of the polymer chains during the polymer melt cooling, 2) crystallization of semi-crystalline polymers, and 3) relaxation of oriented polymer chains. Prediction of shrinkage and distortion has been the focus of several recent researches [1-3]. Historically, the residual strain method is the older of the two shrinkage prediction methods employed in today numerical codes. It is based on the following empirical model for shrinkage:

$$S^{//} = \sum_{i=1}^{5} a_i M_i^{//} \qquad S^{\perp} = \sum_{i=6}^{10} a_i M_i^{\perp} \tag{1}$$

where $S^{//}$ and $S^{\perp}$ are, respectively, in-plane shrinkage strains in the directions parallel and transverse to the flow direction, a_i are shrinkage coefficients and $M_i^{//}$ are respectively, measures of volumetric shrinkage, crystallization, relaxation due to mould restraint, material orientation and a constant. Similar measures $M_i^{\perp}$ hold in the transverse flow direction. In practice, the coefficients a_i are constants for a given material and are determined by means of a shrinkage characterization procedure whereby shrinkage data obtained experimentally from moulding a standard test piece are fitted to the above equations [2].

In the residual stress model, rather than calculating shrinkage strain a residual stress distribution for each element is directly calculated. This more recent model is derived from Hooke's law that, for an elastic solid, has the form:

$$\sigma_{ij} = c_{ijkl}^{e} \varepsilon_{kl} \tag{2}$$

where σ_{ij} and ε_{kl} are stress and strain tensors. The term c_{ijkl}^{e} is the tensor of elastic constants or effectively a viscoelastic relaxation modulus. For neat polymers, c_{ijkl}^{e} is defined by the modulus and Poisson's ratio of the material. Viscoelastic data are difficult to

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obtain for melts under shear rates associated with injection moulding. Therefore, the material is assumed to not sustain any stress above the transition temperature, whereas below the transition temperature the material is assumed to be elastic [2].
Unlike the residual strain model, the residual stress distribution for each element is calculated in the residual stress model. The model, however, tends to overpredict shrinkage [1]. To overcome this defect, Kennedy and Zheng [2] proposed a hybrid model where the error in prediction was corrected by measured shrinkage values from moulded parts. For unfilled materials the model has the form:

$$\begin{aligned} \sigma_c^{//} &= b_1\sigma_p + b_2\tau + b_3 \\ \sigma_c^{\perp} &= b_4\sigma_p + b_5\tau + b_6 \end{aligned} \tag{3}$$

where $\sigma_c^{//}$ and $\sigma_c^{\perp}$ are the corrected principal stresses in the directions parallel and transverse to flow respectively, σ_p is the predicted residual stress, b_i are constants to be determined and τ is a measure of orientation in the material. In order to determine the constants b_i Kennedy and Zheng [2] propose to use measured shrinkages, parallel and transverse to flow, from moulded rectangular samples and, for each sample, to run a simulation in order to calculate average values of σ_p and τ for each element in the sample model. The measured shrinkages can then be converted into equivalent stresses using the modulus of the sample and scaling the average of σ_p so as to produce the measured strain. Hence the left-hand sides of equation (3) are known. The constants are then obtained by regression using equation (3).This corrected residual in-mould stress (CRIMS) model yields a better prediction of shrinkage for several neat and filled polymers [1].
A new identification procedure is proposed in this paper to identify the constants b_i of the CRIMS model. This procedure is based on numerical and experimental data but, instead of using special purpose rectangular samples, it can be applied to any geometry. In order to demonstrate the generality of the proposed approach, the identification was conducted on an industrial case study. On the base of a complete rheological, thermal and physical characterization of the employed material, a numerical simulation of the process was implemented, integrating it with an optimization procedure to identify the values of the CRIMS parameters that force numerical results to fit measured deformations. As this procedure is very time consuming, requiring to run several computationally intensive simulations, artificial neural networks were employed to approximate numerical results with lower computational time.

2 EXPERIMENTAL

2.1 INJECTION MOULDING

The CRIMS model was calibrated on an injection moulded box for an automotive application made of polypropylene (Figure 1).

Figure 1: *Box for automotive application*

To obtain an accurate calibration of the numerical simulation, experimental tests were run at different process conditions. The experimental plan was designed according to the Design of Experiments (DOE) method, considering two factors (melt temperature and packing pressure) varying among three levels (respectively 240°C – 260°C – 280°C and 35 MPa - 40 MPa – 45 MPa). The factors and their levels were selected on the base of industrial requirements. Considering two replications, the experimental plan was composed by 18 runs. For each run, a box was moulded in a Sandretto 820 tons injection moulding machine, keeping constant all the process parameters with the exception of the two control factors.

2.2 WARPAGE MEASUREMENT

In each moulded part, the three critical dimensions shown in Figure 2 were measured to estimate the part warpage. The distances were measured using a Zeiss CMM machine, and the deformations were calculated considering the difference between the nominal dimension and the experimental result.

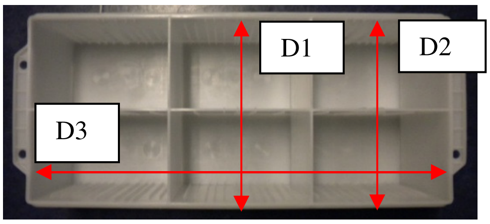

Figure 2: *Warpage measurement*

Two dimensions are related to the part width (D1 and D2) and one to the part length (D3). All the measures are referred to the external side of upper contour of the component, where the cover of the box must fit. These are the most critical dimensions to keep under control because a warpage in this area would hindered the assembly of the box with its lid.

3 IDENTIFICATION OF CRIMS COEFFICIENTS

An optimization procedure was implemented to calibrate a numerical simulation with the experimental results. The calibration consists in the identification of the values of the CRIMS model parameters that force numerical results to fit measured deformations. The differences between numerical and experimental deformations was minimized using an iterative optimization algorithm. Unfortunately, this operation is very time consuming, because for each iteration an entire simulation must be run with different values of CRIMS parameters. Therefore, in order to reduce the computational time artificial neural networks were used to locally approximate the simulation results. A numerical campaign was set-up according to the DOE method for training the artificial neural network to reproduce the results of the simulation with a large saving of computational time.

3.1 NUMERICAL SIMULATIONS

Numerical simulation were implemented in Autodesk Moldflow Insight®. The 3D model of the box was discretized using a dual domain mesh with 36700 elements. The hot runners system was modelled, as well as the cooling system, according to the industrial mould design.

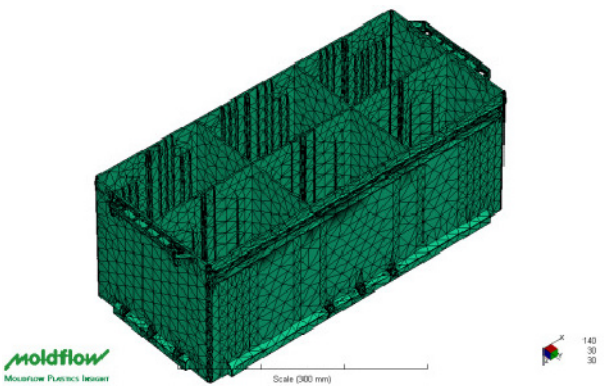

***Figure 3:** 3D meshed model of the part*

Simulations were set up to replicate the real process, taking in account rheological and thermal properties of the moulded polypropylene. A complete material characterization was conducted and all the thermal, rheological, mechanical and physical properties of the polymer were implemented in the material database. In order to compare numerical and experimental deformations, warpage results were calculated at the nodes of the model which are positioned correspondingly to the point measured in the moulded box. Figure 4 shows an example of scaled warpage result.

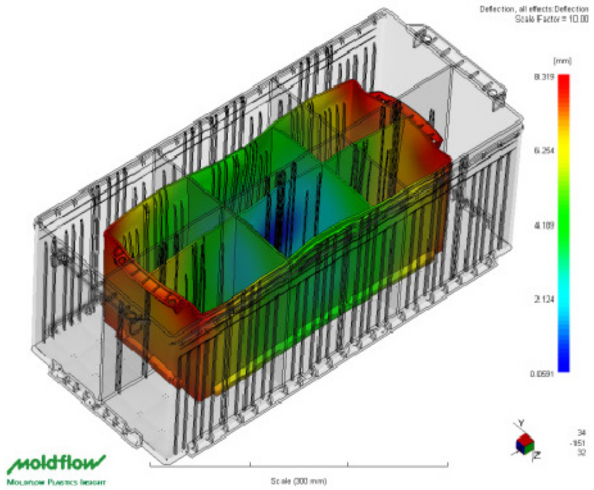

***Figure 4:** Example of scaled warpage results*

3.2 NEURAL NETWORKS

An artificial neural network (ANN) was used to reproduce the numerical simulation with a significant reduction in computational time [4]. In order to do so, one ANN was trained for each of the nine process conditions considered, as the ANN must approximate the simulation results for different values of the CRIMS parameters but warpage results were influenced by the variation of process parameters. As it is exemplified in Figure 5, the trained neural networks approximated the three deformations for each set of the six CRIMS parameters,.

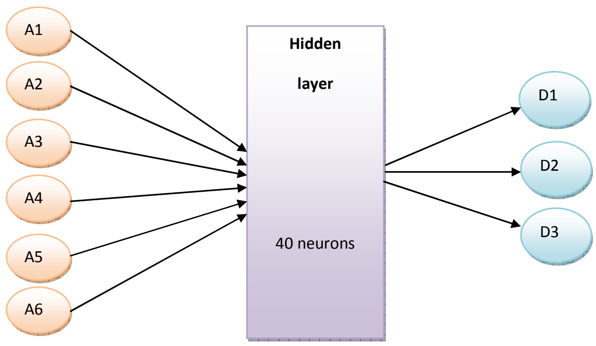

***Figure 5:** Neural Network structure*

To train the networks, a DOE plan was used, considering the CRIMS parameters as factors, varying in typical range values, and the three deformations as results. For each of the 9 process condition, 49 numerical simulations were conducted, and the results were used to train the 9 ANNs.

3.3 IDENTIFICATION

To identify those CRIMS parameters that force the numerical results to fit the experimental deformations, an optimization procedure was implemented in modeFrontier®, a multi-objective optimization software (Figure 6). To minimize the difference between numerical and experimental results in all the 9 different set of process conditions, a genetic optimization algorithm was employed [5]. For each iteration and for the corresponding values of the six input factors, the neural networks previously trained approximated the numerically calculated deformations, in order to compare them to the experimentally measured deformations.

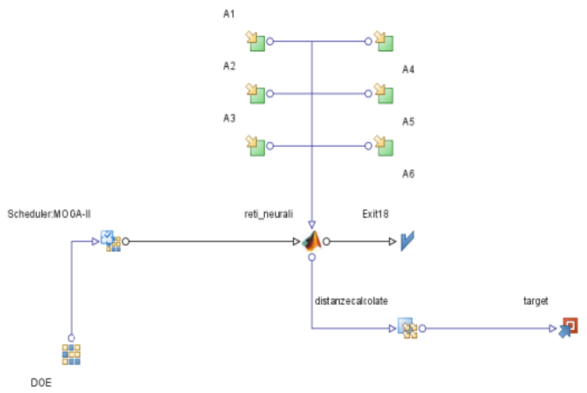

Figure 6: *modeFrontier optimization workflow*

Eventually, the identification procedure converged to the optimal CRIMS parameters. An example of the results of the calibrated numerical simulation is reported in Figure 7, regarding the deformation D1. Similar results were obtained for the other two deformations.

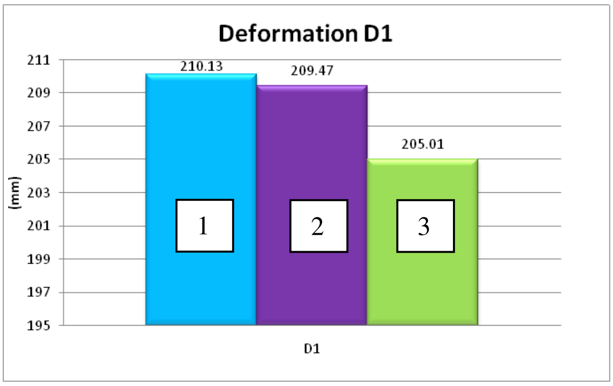

Figure 7: *Deformation D1 (1) measured, (2) calibrated and (3) uncalibrated*

3.4 VALIDATION

The identified CRIMS parameters were then validated at a different set of process conditions, with values of melt temperature and packing pressure within the range of variability used in the previous DOE plan. The moulded components were measured and compared with the deformations calculated by the numerical code which was set using the same process conditions and the identified CRIMS parameters. The results of this comparison are reported in Table 1. They show a good correspondence between experimental and calculated deformations.

Figure 8: *Validation results*

	Calculated deformation (mm)	Measured deformation (mm)	Error
D1	209.0	210.1	-0,313%
D2	207.2	208.4	-0,542%
D3	472.3	473.4	-0,231%

4 CONCLUSION

A new identification procedure is proposed in this paper to identify the parameters of the CRIMS model. This procedure is based on numerical and experimental data but, instead of using special purpose rectangular samples, it can be applied to any geometry. In order to demonstrate the generality of the proposed approach, the identification was conducted on an industrial case study. On the base of a complete rheological, thermal and physical characterization of the employed material, a numerical simulation of the process was implemented, integrating it with an optimization procedure to identify the values of the CRIMS parameters that force numerical results to fit measured deformations. As this procedure is very time consuming, requiring to run several computationally intensive simulations, artificial neural networks were employed to approximate numerical results with lower computational time. Results were verified with independent samples, showing good correspondence between experimental results and numerical calculated deformations.

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