Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 44 (2012) 1291 – 1292

Procedia Engineering

www.elsevier.com/locate/procedia

Euromembrane Conference 2012

[P2.050]
Neural networks approach for characterization of non-isothermal thermoplastic membrane

S.H.A. Fini*[1], F. Erchiqui[1,2], M. Farzaneh[1]
[1]*University of Quebec at Chicoutimi, Canada,* [2]*University of Quebec at Abitibi-Temiscamingue, Canada*

Abstract: Recent developments in computer-aided polymer processing have brought with them the need for an accurate description of the behaviour of industrial thermoplastic membranes under the combined effect of applied stress and temperature. In order to serve this purpose, we consider a non-isothermal approach to characterize the ABS (Acrylonitrile-Butadiene) membrane under biaxial deformation using the bubble inflation technique. Thereafter, Rivlin's theory of hyper-elasticity is employed to define the constitutive model of flat circular membranes. The nonlinear equilibrium equations of the inflation process are solved using finite difference method with deferred corrections. For the final step, a neuronal algorithm (ANN model) is employed to minimize the difference between calculated and measured parameters to determine material constants. The effect of experimental temperature (between -30 and 80 ^{o}C) on behaviour is considered in this work.

Characterization of constitutive material

First, we need to characterize the material using a bubble inflation technique, Joye et al. (1972), to fit the constitutive model. The experimental setup used to determine the material properties of the membrane has been described in detail in Erchiqui et al (2010) and Derdouri et al. (2000). Non-isothermal hyperelastic constants were determined by biaxial characterization; in which the membrane is subjected to free inflation (with a controlled air flow rate) while the forming pressure and bubble height were measured.

A hyperelastic material is defined as an elastic material in which the stress at each point can be derived from a scalar function W(F) called the strain energy function. In order to meet the requirements of objectivity, the strain energy function must be invariant under changes in the observer's frame of reference. It is well known that the Cauchy–Green deformation tensor meets this criterion. Thus, if the strain energy function can be written as a function of the right Cauchy–Green tensor C, it automatically meets the objectivity principle. The general stress–strain relationship is given by the formula:

(1)

$$S_{ij} = 2\frac{\partial W}{\partial C_{ij}} \qquad (1)$$

where S is the Piola–Kirchhoff stress tensor. The different models in the literature define the strain energy as a function of the strain field. We consider Rivlin's theory of isotropic materials, Rivlin (1948), which describes the energy as a function of the three Cauchy strain invariants: I1, I2, and I3. Assuming material incompressibility, the stress can be obtained from the following Mooney–Rivlin form (2):

(2)

$$W = \sum_{i+j=1}^{N} (I_1 - 3)^i (I_2 - 3)^j \qquad (2)$$

doi:10.1016/j.proeng.2012.08.758

The use of two terms in the series is sufficient to describe the hyperelastic modulus in both the uniaxial and biaxial deformation modes. The tangential stresses T1 and T2 are deduced from the aforementioned expression for the strain energy W.

Application of Artificial Neural Network (ANN)

The ANN used in this study consists of an input layer, one hidden layer, and an output layer. In the output layer, only one neuron is needed to anticipate the mechanical parameter, for a given pressure P, while the input to the ANN is the variance of the corresponding pressure. A well-known multilayered perceptron (MLP) neural network with a supervised training mode is considered and trained by a retropropagation algorithm. Simulation data is used for training the ANN, however, experimental data is used for testing the ANN (Braspenning et al, 1995). Hence, the testing data was not seen during the training process. All inputs are normalized before training. The well-known Generalized Delta Rule (GDR), also called error back propagation algorithm, is used to train the layered perceptron-type ANN. However, instead of applying the steepest descent method characterized by slow convergence and long training time, an approximation of Newton's method called Levenberg–Marquard algorithm (Marquardt, 1963) is used. This optimization technique is more powerful than the gradient descent, but requires more memory.

Experimental and Numerical Identification

The polymeric material which is ABS (Acrylonitrile-Butadiene-Styrene) was tested under biaxial deformation with bubble inflation technique. Initial sheet thickness was 1.50 mm and the diameter was 7.5 cm for ABS. The circular membranes are mounted between two metal disks containing a circular aperture and clamped on a support. When the temperature became quite uniform over the flat sheet, it was inflated using compressed air at a controlled flow rate. During the experiments, applied blowing pressure which is uniform in the membrane was measured by a pressure sensor. Height at the hemispheric pole (the node in which *r* =0), and time were recorded simultaneously using a laser measurement sensor and a data acquisition system.

Reference

Joye, D.D., Poehlein, G.W, and Denson C.D, II Trans. Soc. Rheol., **16**, pp. 421-445 (1972).

Derdouri, A. Erchiqui, F. Bendada, A. Verron, E. Peseux, B, Proceedings of the 13th International Congress on Rheology, Cambridge, UK, August 20–25, **3**, pp 394-396 (2000)

Rivlin, R.S., Phil. Trans. R. Soc., **A241**: 379–397 (1948).

Marquardt, D., SIAM Journal on Applied Mathematics, **11**, pp-431-441 (1963).

Erchiqui F and *al*, The Canadian Journal of Chemical Engineering, Vol. **88**, No. **1**, pp. 116-125 (2010).

Braspenning, P. J., F. Thuijsman and A. J. M. Weijters, Springer, 295 (1995).ISBN-3-54059488-4.

Keywords: Hyperelasitc, Non-isothermal test, Thermoplastic ABS membrane, Neural Networks