Estimation of the Ends Pressure Drop in an Online Capillary Rheometer—Using the Neural Network Approach

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ABSTRACT: Using an online or inline capillary rheometer as a tool of rheology measurement would come into the ends pressure drop problem. In order to derive the actual pressure drop of the capillary, another capillary with the same diameter and different length is needed (according to Bagley correction) but would result in a more complex mechanism. In this study, a neural network approach is proposed to estimate the ends pressure drops in an online capillary rheometer. The back propagation learning algorithm is used for network training. The shear rate, the die pressure, and the ratio of diameters of the reservoir to the capillary are taken as the neural network inputs, and the ends pressure drop is taken as the output. Two hundred of training sets that are made from a laboratory capillary rheometer are used for network training. The trained neural network can be consequently applied to real-time assessment of the ends pressure drops in the online capillary rheometer. It is concluded that using the proposed method for calculating the ends pressure drop is effective. Besides, the simplicity of the mechanism provides good portability for both online polymer characterization and quality control in processing. © 1999 John Wiley & Sons, Inc. J Appl Polym Sci 73: 2183–2186, 1999

Key words: capillary rheometer; online; inline; neural network; ends pressure drop

INTRODUCTION

In the polymer processing industries, more and more stringent requirements on the product quality control are demanded. Lots of efforts have focused on the improvement of stability of the processing machines, instrumentation, and take-up devices. Since the relative advanced technology have achieved an acceptable extent, the intent to lower down the production costs and off-standard products turns to how to properly control the polymeric properties under processing. An efficient control should always be based on a precise measurement. In most forming processes (like extrusion and injection), polymers are processed under the molten state. An online rheometer to measure the rheological properties, which can be used as the index of the end-product quality, would be required.

Using a precise online rheometer to measure the rheological properties of a polymer can also determine in real-time the structure (like molecular weight and molecular weight distribution) of a polymer under processing. Besides, online measurements provide more reliable data than that of offline measurements.[1] It's because the rheological properties of polymers are dependent on shear history and heating history. Online measurement would still provide much more savings in time and manpower than offline measurement.[2]

The online capillary rheometer,[3] in which the polymeric melt is continuously forced through a cir-

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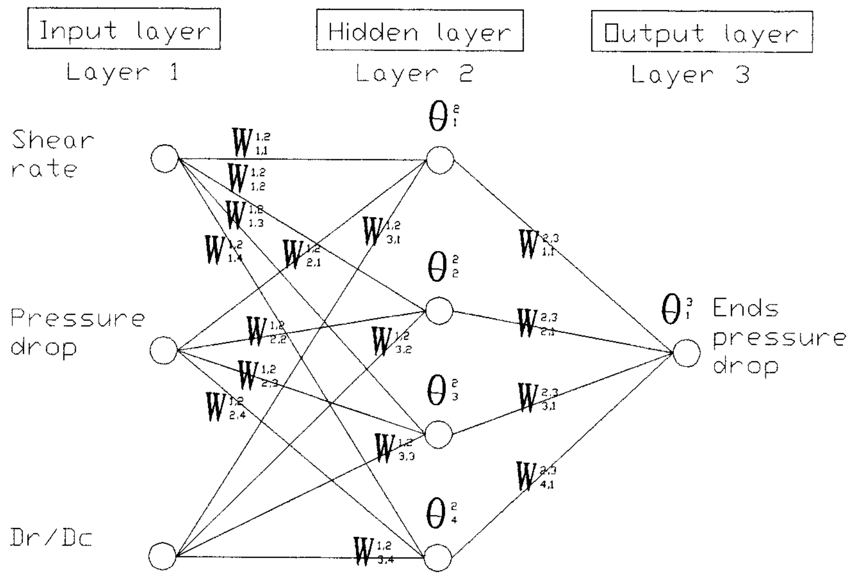

Figure 1 Neural network structure used in this article.

cular pipe in processing, is the most popular rheometer due to its compactness and simple construction. Rheological properties can be determined by measuring its pressure drops and flow rates. Göfftert[4] developed an online rheometer called a bypass rheograph that has been using in laboratories and industries for a long time, in which the pressure transducer is installed in the reservoir in front of the capillary; therefore the ends pressure drop problem arises. The solution to this problem, undoubtedly, is to use the Bagley correction.[5] In order to derive the actual pressure drop of the capillary, another capillary with the same diameter and different length is needed, consequently resulting in a more complex mechanism.

In this work, a neural network approach is proposed to calculate the ends pressure drop in an online capillary rheometer. The neural network is designed using the back propagation learning algorithm[6,7] with the shear rate, the die pressure, and the diameter ratio of the reservoir and the capillary taken as the neural network inputs and the ends pressure drop taken as the output. Two hundred training sets that are made from a laboratory capillary rheometer are used for network training. The trained neural network is applicable to real-time assessment of the ends pressure drop of a single capillary rheometer. It is concluded, according to the experimental results, that the use of proposed method for calculating online the ends pressure drop is efficient. Besides, the simplicity of the mechanism provides good portability for both online polymer characterization and quality control in processing.

SELECTION OF NEURAL NETWORK INPUT VARIABLES

According to Bagley correction,[8] the ends pressure drop can be determined from the intercept of the straight line, which is at a fixed shear rate, in the plot of pressure drop versus length-to-diameter ratio. A different shear rate would result in a different ends pressure drop in a fixed geometry die. Thus, the shear rate and the capillary pressure drop are considered as two of the neural network inputs. The effects of the capillary geometry (including the diameters ratio of the reservoir to the capillary D_r/D_c and the entry angle of the capillary) on the ends pressure drop should also be considered. In this study, a fixed entry angle with 90° was used to simplify the neural network structure. Hence, the inputs used in the network are concluded as the shear rate, the capillary pressure drop, the diameter ratio of the reservoir, and the capillary.

NEURAL NETWORK STRUCTURE

The neural network structure is designed, as is shown in Figure 1. One hidden layer is introduced between the input and output layers to include the mutual effects between the input variables. The back propagation algorithm is used for network learning. The well-known back propagation algorithm is a kind of supervised learning network, in which the gradient descent technique is employed to minimize the cost function of the mean square difference between the desired and actual neural network output. The network weight is adjusted by shifting itself towards a convergent result. The outputs can be inferred by using the network structure with measured inputs in practical applications. It is suitable for prediction, as is used for estimating the ends pressure drop in this work.

Four neurons in the hidden layer are selected by trial and error. The output of the jth neuron in layer n with respect to $n = 2$ for the hidden layer and $n = 3$ for the output layer is calculated by the sigmoid function, as shown in eq. (1).

$$A_j^n = f(\text{net}_j^n) = \frac{1}{1 + e^{-\text{net}_j^n}} \quad (1)$$

where net_j^n is the summation function of the jth neuron in layer n and can be expressed as

$$\text{net}_j^n = \sum_i (W_{i,j}^{n-1,n} A_i^{n-1}) - \theta_j^n, \; n = 2, 3 \quad (2)$$

in which A_i^{n-1} is the ith input of the network (which is given) if $n = 2$.

$W_{i,j}^{n-1,n}$ is the weight between the ith neuron in layer $n - 1$ and the jth neuron in layer n, and θ_j^n is the threshold of the jth neuron in layer n. In the learning procedure, the initial weights and the initial thresholds are firstly randomized and then are adjusted to new ones in terms of eqs. (3) and (4), respectively, in every iterative cycle.

$$W_{i,j}^{n-1,n} = W_{i,j}^{n-1,n} + \Delta W_{i,j}^{n-1,n}, \; n = 2, 3 \quad (3)$$

$$\theta_j^n = \theta_j^n + \Delta \theta_j^n, \; n = 2, 3 \quad (4)$$

where $\Delta W_{i,j}^{n-1,n}$ and $\Delta \theta_j^n$ represent adjustments in $W_{i,j}^{n-1,n}$ and in θ_j^n, respectively, and can be expressed in terms of eqs. (5) and (6).

$$\Delta W_{i,j}^{n-1,n} = \eta \delta_j^n A_i^{n-1} \quad (5)$$

$$\Delta \theta_j^n = -\eta \delta_j^n \quad (6)$$

where δ_j^n is the error signal term of jth neuron in layer n that is expressed by eq. (7) for the hidden layer and eq. (8) for the output layer.

Table I Three Sets of Test Geometry in the Training Experiments

Measurement	I	II	III
Length-to-diameter ratio of capillary	16	16	4
Capillary length (mm)	16	25	2
Capillary diameter (mm)	1	1.5	0.5
Capillary entry angle (degree)	90	90	90
Diameter ratio of the reservoir and the capillary	15	10	30

$$\delta_j^n = A_j^n(1 - A_j^n) \sum_i W_{j,i}^{n,n+1} \delta_i^{n+1}, \; n = 2 \quad (7)$$

$$\delta_j^n = A_j^n(1 - A_j^n)(T_j - A_j^n), \; n = 3 \quad (8)$$

where T_j is the output training data of the jth neuron in the output layer. η is the learning rate used to control the degree of the minimized error function; in this case, a value of 0.7 was selected. The procedure of deriving new weights and thresholds would go on until the convergent consequence is drawn. Finally, the convergent solutions are used for recall.

MAKING TRAINING SETS

In order to produce the training sets for training purposes, a series of experiments were implemented in a laboratory capillary rheometer. Two hundred data result from rheological tests of low-density polyethylene (LDPE) at 20 temperatures from 160 to 200°C with three different sets of D_r/D_c were used. The test geometry used for three different sets of D_r/D_c are shown in Table I. Part of the data tested in Rosand capillary rheometer is listed in Tables II and III that provide for network training.

RESULTS

The neural network program was written by using Turbo C. An IBM compatible computer with an Intel 80586/166 MHz processor was used.

One hundred sets of test data, which differ from the training set, were made for verification. Comparisons of the prediction results and the actual results are shown in Figure 2. A nearly linear relation can be seen in the plots. The maximal error is 10.9%. Though it is acceptable, it can

Table II Experimental Data of LDPE at 180°C Used for Training Purposes

Shear Rate (1/s)	Die Pressure Drop (MPa)	Ends Pressure Drop (MPa)
4599	20.2	3.58
3642	19.2	3.42
2697	17.0	3.10
2230	16.0	2.73
1768	14.8	2.57
1311	13.1	2.26
860.3	11.3	1.94
638.4	10.2	1.62
419.5	8.55	1.36
333.1	8.13	1.23
247.4	7.38	1.01
205.0	6.51	0.92
162.8	6.12	0.83
121.1	4.95	0.63
79.7	4.15	0.39
39.1	3.04	0.22

Test geometry: length-to-diameter ratio, 16/1 (mm/mm); entry angle, 90°.

also be improved by increasing the training sets or by modifying the network structure in the practical applications.

Table III Experimental Data of LDPE at 170°C Used for Training Purposes

Shear Rate (1/s)	Die Pressure Drop (MPa)	Ends Pressure Drop (MPa)
4816	22.2	4.31
3792	21.4	3.94
2790	19.1	3.47
2298	17.4	3.21
1813	16.3	2.89
1337	14.7	2.61
871.4	12.9	2.20
643.7	11.4	1.96
420.6	9.70	1.61
333.0	8.80	1.46
246.5	8.43	1.34
203.8	7.62	1.13
161.5	6.94	1.03
119.7	6.01	0.88
78.6	4.77	0.73
38.3	3.50	0.42

Test geometry: length-to-diameter ratio, 16/1 (mm/mm); entry angle, 90°.

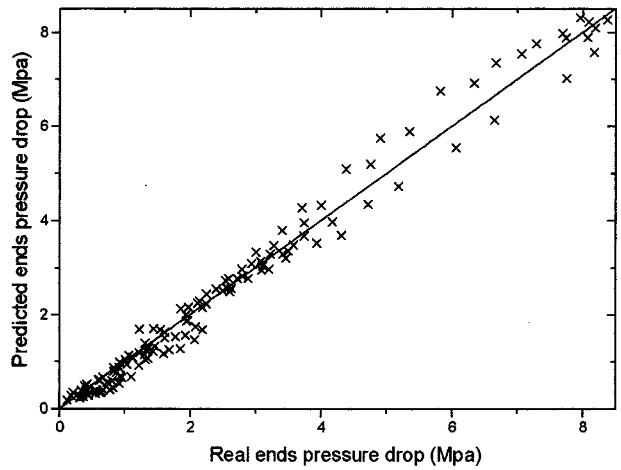

Figure 2 Predicted ends pressure drop versus real ends pressure drop.

CONCLUSIONS

In this work, a neural network approach for online calculating the ends pressure drops in a single capillary is proposed. It is concluded, according to the experimental results, that using the proposed method for calculating online the ends pressure drop is efficient. It can be used further to calculate the true shear stress; hence, the true viscosity for online or inline rheology assessment can be accomplished. Besides, a simple and portable sensor is conducted for online or inline melt characterization.

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