Artificial Neural Network Modeling for Predicting Melt Blowing Processing

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ABSTRACT: An artificial neural network model is established for predicting the fiber diameter of melt blown nonwoven fabrics from the processing parameters. An attempt is made to study the effect of the number of hidden layers and hidden layer neurons to minimize the prediction error. The artificial neural network with three hidden layers (5, 2, and 3 neurons in the first, second, and third hidden layer, respectively) yields the minimum prediction error and thus is determined as the preferred network. The square of the correlation coefficient of measured and predicted fiber diameters shows the good performance of the model. Using the established ANN model, computer simulations of the effects of the processing parameters on the fiber diameter are carried out. The results show great promise for this research in the field of computer assisted design of melt blowing technology. © 2005 Wiley Periodicals, Inc. J Appl Polym Sci 99: 424–429, 2006

Key words: artificial neural network; fiber diameter; melt blown; nonwoven

INTRODUCTION

The melt blowing process is characterized by the capability of producing nonwoven fabrics with microfiber structure. In our previous article, the physics model of polymer air drawing in the melt blowing process was established for predicting the fiber diameter.[1–3] The predicted fiber diameters showed good agreement with the experimental results.[2,3]

As a nonlinear problem, the fiber diameters can also be predicted by an alternative modeling method, that is, by using the empirical model, which includes a statistical regression model, an artificial neural network (ANN) model, and so forth. ANN models have been shown to provide good approximations in the presence of noisy data and a smaller number of experimental points, and the assumptions under which ANN models work are less strict than those for regression models.[4] Therefore, over the past decades, ANNs have been used for modeling various textile nonlinear problems.[5–8] However, the applications of ANN for predicting the fiber diameter of nonwoven fabrics are very scanty. In this article, an ANN model will be established for predicting the fiber diameter of melt blown nonwoven fabrics. The effects of the number of hidden layers and hidden layer neurons will be investigated to obtain the optimum network structure. The effects of the processing parameters on the fiber diameter will also be studied using the established ANN model.

EXPERIMENTAL

Experiments are carried out on the melt blowing nonwoven equipment of Donghua University. It is known that fiber diameters of melt blown nonwovens will be influenced by both the processing parameters and the die parameters. However, it is difficult to change the die parameters in our present experiments because dies can hardly be fabricated at the university. Therefore, only the processing parameters are considered in this investigation; in the meantime, the die parameters are fixed as follows: die width = 0.7 mm, die length = 200 mm, slot width = 0.2 mm, head width = 0.5 mm, angle between the slot and spinneret axis = 30°, and spinneret diameter = 0.3 mm. The polymer used is polypropylene with the melt flow index of 54. The processing parameters concerned are the polymer flow rate: 0.018, 0.035, and 0.070 g/s; initial polymer temperature: 230, 260, and 290°C; initial air velocity: 78, 168, and 235 m/s; and initial air temperature: 280, 310, and 340°C. A group of fundamental parameters is set up, which are the polymer flow rate of 0.035 g/s, the initial polymer temperature of 260°C, the initial air velocity of 168 cm/s, and the initial air temperature of 310°C. When one processing parameter varies, the other three are kept to the fundamental values. The experimental program is shown in Table I.

The image analysis method is employed to measure the fiber diameter. The images of nonwoven samples are acquired by the QUESTER three-dimensional

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TABLE I
Experimental Program

Testing number	Polymer flow rate (g/s)	Initial polymer temperature (°C)	Initial air velocity (m/s)	Initial air temperature (°C)
1	0.035	260	168	310
2	0.018	260	168	310
3	0.070	260	168	310
4	0.035	230	168	310
5	0.035	290	168	310
6	0.035	260	78	310
7	0.035	260	235	310
8	0.035	260	168	280
9	0.035	260	168	340

video frequency microscope and then processed by the image analysis software named Image-Pro Plus to measure the fiber diameter. Further details about the fiber diameter testing can be found in another of our articles.[3]

ARTIFICIAL NEURAL NETWORK MODELING

An artificial neural network is an information-processing system where processing occurs at many simple elements called neurons organized in layers and where signals are passed between neurons over connection links. Each connection link has an associated weight that multiplies the signal transmitted, and each neuron applies a transfer function to its net input (sum of weighted input signals) to determine its output signal. Figure 1 shows the structure of a multi-layer ANN. This ANN has one input layer with k neurons to process the k independent variables; $n - 1$ hidden layers with $m, p, q, \ldots$ neurons, respectively; and one output layer with r neurons to provide the r responses. The weights of the first hidden layer modify the information transmitted from the input layer to the first hidden layer; that of the second, the information transmitted from the first hidden layer to the second hidden layer; and the like. The last hidden layer's weights modify the information transmitted from the last hidden layer to the output layer. The mathematical expression of the ANN model with one input layer, $n - 1$ hidden layers, and one output layer is given by

$$\hat{\mathbf{Y}} = \Phi(\hat{\mathbf{W}}_n^T \Psi_{n-1}(\hat{\mathbf{W}}_{n-1}^T \Psi_{n-2} \cdots (\hat{\mathbf{W}}_3^T \Psi_2(\hat{\mathbf{W}}_2^T \Psi_1(\hat{\mathbf{W}}_1 \mathbf{X} + \hat{\mathbf{b}}_1) + \hat{\mathbf{b}}_2) + \hat{\mathbf{b}}_3) + \cdots \hat{\mathbf{b}}_{n-1}) + \hat{\mathbf{b}}_n) \quad (1)$$

where $\hat{\mathbf{Y}}_i^T$ is the vector of predicted responses; $\boldsymbol{X}$ is the vector of inputs; $\hat{\mathbf{W}}_1$ is a matrix containing the weights

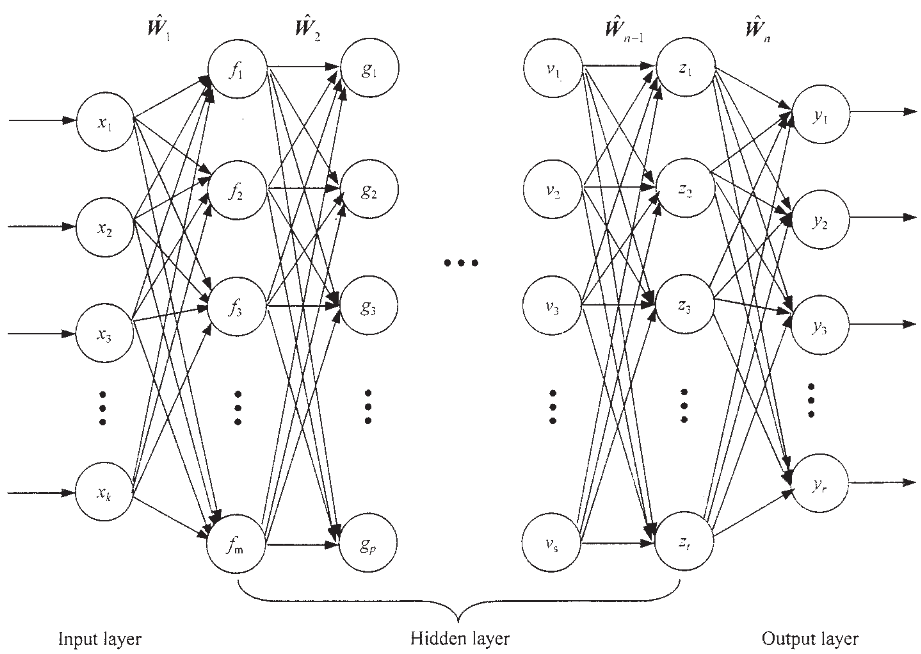

Figure 1 Structure of a multi-layer artificial neural network.

on the connection links between the input layer and the first hidden layer; $\hat{\mathbf{W}}_i^T$ ($i = 2, 3, \ldots, n - 1$) is the transpose of $\hat{\mathbf{W}}_i$, which is a matrix containing weights for the links between the i-1th hidden layer and the ith hidden layer; $\hat{\mathbf{W}}_n^T$ is the transpose of $\hat{\mathbf{W}}_n^I$, which is a matrix containing weights for the links between the last hidden layer and the output layer; $\hat{\mathbf{b}}_i$ ($i = 1, 2, \ldots, n - 1$) and $\hat{\mathrm{b}}_n$ are vectors containing a special type of weights, called biases, that modify the net input for the ith hidden layers and output layer, respectively; Ψ_i is the transfer function of the neurons of the ith hidden layer; and Φ is the transfer function of the neurons in the output layer. Obtaining the weights in $\hat{\mathbf{W}}_i$ and $\hat{\mathbf{b}}_i$ ($i = 1, 2, \ldots, n$) is commonly done with the error back propagation algorithm, which is in essence similar to a least squares reduction. The neurons in the hidden layer usually use a hyperbolic tangent function as the transfer function (eq. (2)), and the neurons in the output layer use a pure linear function (eq. (3)).[4]

$$\Psi(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

$$\Phi(x) = x \tag{3}$$

A feed forward artificial neural network is created in this research. Inputs of the ANN are the polymer flow rate, initial polymer temperature, initial air velocity, and initial air temperature, while the output is the fiber diameter. The transfer functions of the hidden layer and output layer neurons are the hyperbolic tangent function and pure linear function, respectively. The ANN is trained with the help of the error back propagation algorithm using the Matlab Neural Network Toolbox. The training function used is "trainlm," which is based on the Levenberg–Marquardt optimization theory because the neural network converges much faster than by using other training functions. Ninety nonwoven samples are divided into a training set and a testing set, with 60 and 30 samples, respectively.

A key to successfully fit the ANN is to keep a testing set to test the prediction capabilities of the model. ANN models that are accurate to a high degree increase the confidence of an optimization procedure. The prediction accuracy of an ANN model is related to the type and structure of the ANN. To minimize prediction error, an attempt is made to study the effect of the number of the hidden layers and hidden layer neurons. The ANN model is designed up to three hidden layers. To obtain a stable artificial neural network, the total number of network weights and biases cannot exceed the number of training samples. According to this principle, the number of hidden layer neurons can be determined as follows. The one hidden layer ANN model has 2 to 9 neurons in the hidden

TABLE II
Average and Maximum Prediction Errors of Different ANN Structures

No.	ANN structure	Average error	Variation coefficient
1	4-5-3-3-1	2.7735	0.8828
2	4-5-3-2-1	2.7778	0.7838
3	4-5-2-3-1	2.7999	0.7252
4	4-5-2-2-1	2.7484	0.7503
5	4-4-4-3-1	2.7016	0.7676
6	4-4-4-2-1	3.0098	0.7756
7	4-4-3-4-1	2.8398	0.7850
8	4-4-3-3-1	2.8527	0.7864
9	4-4-3-2-1	2.8684	0.7816
10	4-4-2-4-1	3.0755	0.7790
11	4-4-2-3-1	3.1476	0.8532
12	4-4-2-2-1	3.2615	0.9122
13	4-3-5-3-1	3.0848	0.7601
14	4-3-5-2-1	2.7861	0.7754
15	4-3-4-4-1	3.1072	0.8121
16	4-3-4-3-1	2.7871	0.7703
17	4-3-4-2-1	2.9987	0.8062
18	4-3-3-5-1	2.7829	0.8804
19	4-3-3-4-1	3.2067	0.7742
20	4-3-3-3-1	2.7772	0.7997
21	4-3-3-2-1	3.0749	0.7921
22	4-3-2-5-1	2.7792	0.8000
23	4-3-2-4-1	3.2129	0.8467
24	4-3-2-3-1	2.8819	0.8271
25	4-3-2-2-1	3.1312	0.7542
26	4-2-5-3-1	2.9320	0.8265
27	4-2-5-2-1	2.7859	0.7771
28	4-2-4-4-1	2.9840	0.7807
29	4-2-4-3-1	3.0065	0.7739
30	4-2-4-2-1	2.7709	0.7934
31	4-2-3-5-1	3.0473	0.9145
32	4-2-3-4-1	3.2583	0.8265
33	4-2-3-3-1	3.2641	0.7806
34	4-2-3-2-1	2.8853	0.7533
35	4-2-2-5-1	3.0219	0.9776
36	4-2-2-4-1	3.0496	0.9164
37	4-2-2-3-1	2.7750	0.7674
38	4-2-2-2-1	2.7647	0.8791
39	4-5-4-1	2.9994	0.7723
40	4-5-3-1	3.0989	0.8541
41	4-5-2-1	2.9286	0.8157
42	4-4-5-1	3.1505	0.7745
43	4-4-4-1	2.8129	0.7728
44	4-4-3-1	2.7828	0.7787
45	4-4-2-1	2.8428	0.7749
46	4-3-5-1	3.0430	0.7644
47	4-3-4-1	3.0660	0.7958
48	4-3-3-1	2.7731	0.7648
49	4-3-2-1	2.7680	0.7771
50	4-2-5-1	2.7837	0.7753
51	4-2-4-1	3.0312	0.7719
52	4-2-3-1	2.8179	0.7724
53	4-2-2-1	3.1305	0.7527
54	4-9-1	2.8816	0.8215
55	4-8-1	2.8613	0.7841
56	4-7-1	2.8075	0.7991
57	4-6-1	2.7589	0.7750
58	4-5-1	2.9020	0.7730
59	4-4-1	3.1418	0.7747
60	4-3-1	2.8842	0.7800
61	4-2-1	3.4412	0.9475

TABLE III
Weights and Biases of the ANN

Weights from input layer to first hidden layer				Biases for first hidden layer
$\hat{\mathbf{W}}_1$				$\hat{\mathbf{b}}_1$
−0.4264	0.2671	1.9024	−0.9482	2.1784
−0.6367	−1.2872	1.7320	−0.9719	−0.3061
2.3455	−1.2476	−2.3674	−1.8980	0.5268
−0.9351	1.4787	−2.8977	1.5969	−2.1249
−0.0292	2.1173	−2.7261	0.0117	0.9047
Weights from first hidden layer to second hidden layer				Biases for second hidden layer
$\hat{\mathbf{W}}_2$				$\hat{\mathbf{b}}_2$
1.2947	2.1154			−1.3229
1.5257	−1.4402			2.8893
−4.4797	2.7253			
−3.7432	0.4242			
1.6276	−0.5227			
Weights from second hidden layer to third hidden layer				Biases for third hidden layer
$\hat{\mathbf{W}}_3$				$\hat{\mathbf{b}}_3$
−2.5500	−0.2358	3.5658		1.5984
1.4302	−3.0965	0.5305		−0.0353
				3.5416
Weights from third hidden layer to output layer				Bias for output layer
$\hat{\mathbf{W}}_4$				$\hat{\mathbf{b}}_4$
1.4096				1.7669
1.9083				
−0.8973				

layer. The ANN model with two hidden layers contains 2 to 5 neurons in each hidden layer. And the ANN model with three hidden layers can only be 2 to 5 neurons in each hidden layer.

RESULTS AND DISCUSSION

Table II gives the average value and variation coefficient of prediction errors of different ANN structures. The format of the ANN structure in the second column of Table II is expressed as the number of neurons in the input layer, then the number of neurons in the first hidden layer, number of neurons in the second hidden layer, number of neurons in the third hidden layer, and number of neurons in the output layer, in turn. For example, 4–5-3–3-1 means that there are 4, 5, 3, 3, and 1 neurons in the input, first, second, and third hidden layers and output layer, respectively. The prediction errors of the ANN model with three, two, and one hidden layers are listed in the upper, middle, and lower part of Table II, respectively. It can be found from Table II that the average value and variation coefficient of prediction error reaches the minimum (2.7999% and 0.7252) when the ANN structure is 4–5-2–3-1. Table III shows the weights and biases of the ANN model, which is superior to other network structures in prediction error. Figure 2 shows the correlation of measured and predicted fiber diameters. The square of correlation coefficient is 0.9424, which confirms the effectiveness of the established ANN model.

With the help of the established ANN model, not only the fiber diameter can be predicted, but also computer simulations of the effects of the processing parameters on the fiber diameter can be carried out.

Figure 3 shows the effects of the polymer flow rate on the fiber diameter. As expected, lower polymer flow rates produce finer fibers. When the polymer flow rate is 0.018 g/s, the final fiber diameter is 53.6% finer than when the rate is 0.070 g/s.

Figure 4 illustrates how changes of initial polymer temperature cause changes of the rate of fiber attenuation. Observe that the higher the initial polymer temperatures, the finer the fibers will be. When the initial polymer temperature increases to 290°C, the final fiber

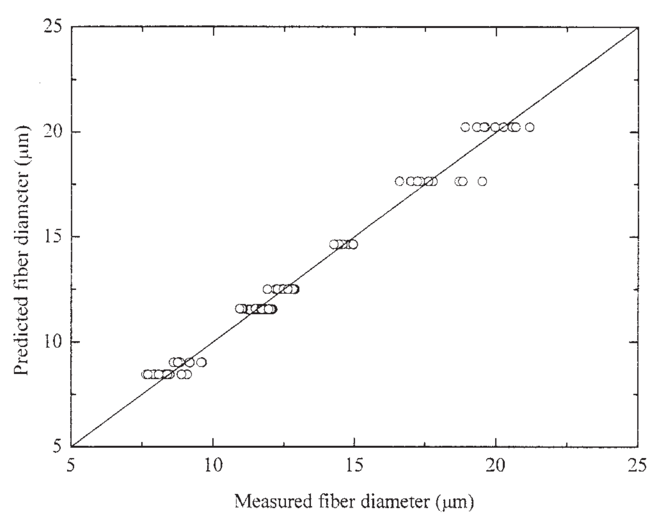

Figure 2 Correlation of measured and predicted fiber diameters.

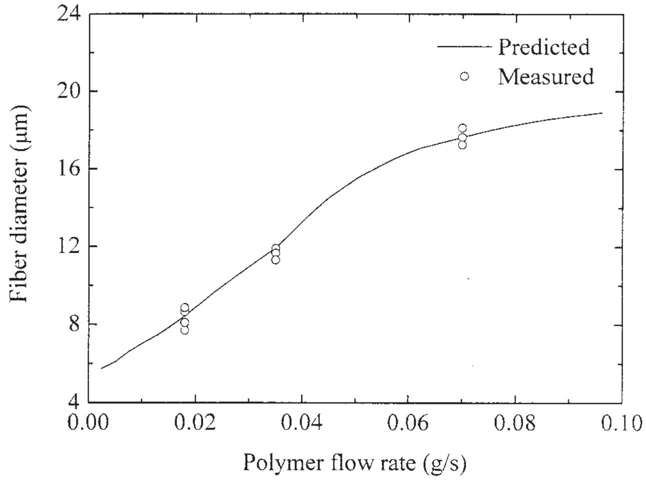

Figure 3 Effect of polymer flow rate on fiber diameter.

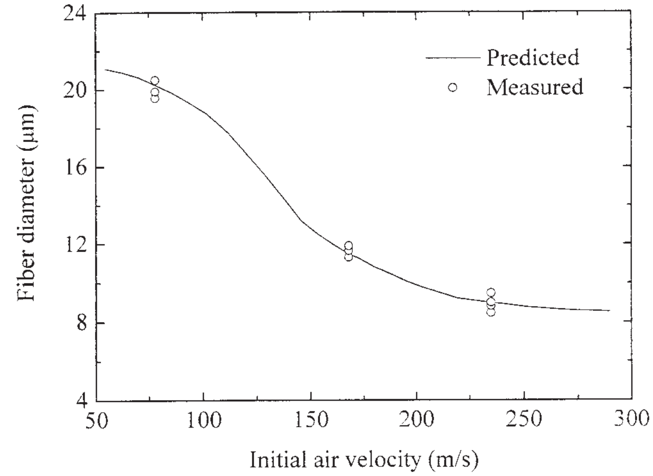

Figure 5 Effect of initial air velocity on fiber diameter.

diameter is 23.4% finer than when the temperature is 230°C.

Figure 5 gives the effect of the initial air velocity on the fiber diameter. It can be seen that higher initial air velocities will cause the fibers to be attenuated finer. The final fiber diameter corresponding to initial air velocity of 235 m/s is 55.1% finer than that corresponding to the velocity of 78 m/s.

Figure 6 shows an insignificant effect of the initial air temperature on the fiber diameter. When the initial air temperature increases from 280 to 340°C, the fiber diameter only decreases about 4.8%. Therefore, high initial air temperature contributes little to the polymer drawing, which gives us insights on reducing the energy consumption of the melt blowing process.

In addition, the established ANN model can be used for compromising the processing parameters according to the required fiber diameter to obtain the optimal combination of the parameters and make the processing have a better cost-effectiveness ratio.

CONCLUSIONS

An artificial neural network model is established for predicting the fiber diameter of melt blown nonwoven fabrics from the processing parameters. An attempt is made to study the effect of the number of hidden layers and hidden layer neurons to minimize the prediction error. The artificial neural network with three hidden layers (5, 2, and 3 neurons in the first, second, and third hidden layers, respectively) yields the minimum prediction error and, thus, is determined as the preferred network. The square of the correlation coefficient of measured and predicted fiber diameters

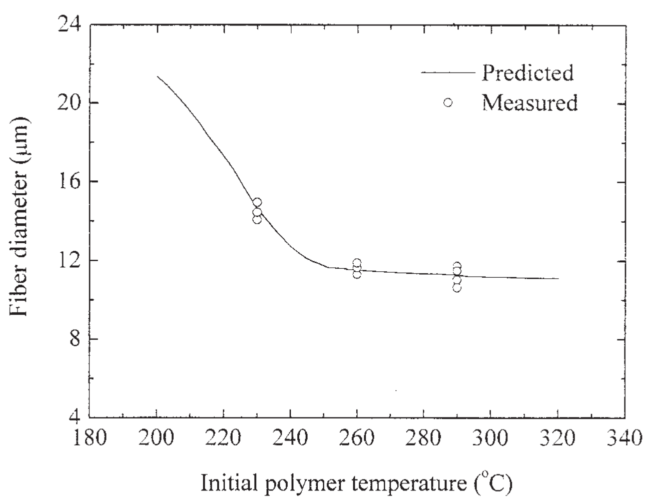

Figure 4 Effect of initial polymer temperature on fiber diameter.

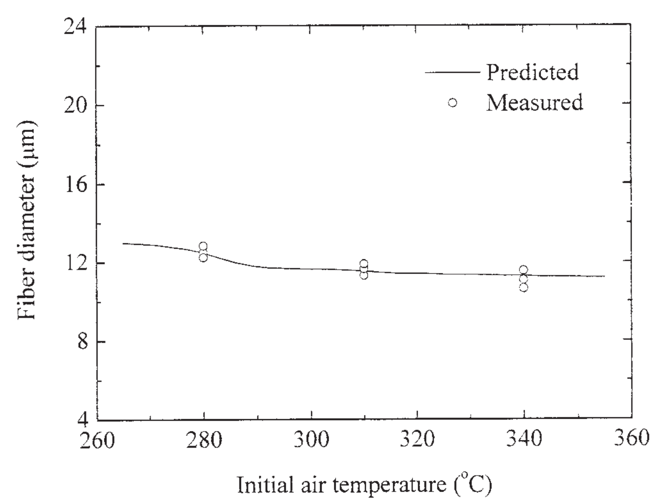

Figure 6 Effect of initial air temperature on fiber diameter.

shows the good performance of the model. Using the established ANN model, computer simulations of the effects of processing parameters on the fiber diameter are carried out. The results show great promise for this research in the field of computer assisted design of melt blowing technology.

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