Predicting the Filtration Properties of Melt Blowing Nonwoven Fabrics Using Neural Network Intelligent Technique Model

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Abstract—The filtration properties of melt blowing nonwovens are affected by the pore structure of nonwovens which is strongly related to the processing parameters. However, it is difficult to establish physical models on the relationship between the processing parameters and filtration properties. In this work, the ANN model is established for predicting the filtration properties of melt blowing nonwovens from the processing parameters. The results reveal that the ANN method is really an effective and viable modeling technique. This method can exactly predict the filtration properties because the results are good enough.

Keywords—melt blowing, nonwoven, filtration performance, processing parameter, artificial neural network model.

Ⅰ. INTRODUCTION

The melt blowing process [1-3], originally developed in 1950s, can produce nonwoven fabrics with microfiber structure. Fiber diameters can be as little as 1-10 μm, even 0.5 μm. The melt blowing nonwoven fabrics are highly efficient filter materials whose filtration efficiency can be over 99.9%. In the melt blowing process, a molten stream of polymer is extruded from the die and rapidly attenuated into microfibers by the air jet with high velocity and high temperature. The melt blowing nonwoven fabrics are characterized by high porosity, tiny pore diameter and ultrafine fibers, which make these fabrics well serve the function of high efficiency filter materials used in various fields. The melt blowing nonwoven fabrics has acted as the filtering materials for filtering out leukocytes from the transfusion blood to prevent the adverse reaction and speed of viruses. The filtration properties of melt blowing nonwoven fabrics are affected by the structure of nonwovens which is related to the processing parameters. However, it is rather difficult to establish a physics model to describe the process-property relation of melt blowing nonwoven fabrics.

In recent years, artificial neural network (ANN) model has been used in many engineering fields to predict material properties. Within the textile industry alone, numerous applications have been reported [4-7]. In the previous papers, many researchers found that prediction performance was the best for ANN model, followed by the statistical and physics models. It has been seen from the literature that predictions by ANN model have more promising results compared to conventional prediction methods such as regression or correlation analyses, especially for non-linear and complex relationships among system variables. In this paper, we attempt to predict filtration performance of melt blowing nonwoven fabrics with ANN model. The results show that processing parameters have an important effect on filtration performances.

Ⅱ. EXPERIMENTAL RESULTS

A. Materials

The polymer used is S904 polypropylene with a melt flow index of 54.

B. Processing parameters

The experiments of melt blowing nonwovens equipment were carried out at our university. The melt blowing process parameters of concern were as following: the polymer throughput rate, air initial velocity,
die-to-collector distance, air pressure, and number of layers etc., and the variation ranges of the parameters are 0.0015--0.0035g/min/hole, 90-198m/s, 8-14cm, 13-23 Pa, 4-15 layer, respectively.

C. Testing conditions

The experimental samples were subject to conditioning at 65% RH and 20±5°C for 24 hours and then the testing was carried out.

D. Program and results

The filtration property under study is the filtration resistance. The experimental program and results are shown in Table 1.

<table>
<thead>
<tr>
<th>No.</th>
<th>Polymer throughput rate (g/min/hole)</th>
<th>Air initial velocity (m/s)</th>
<th>Die-to-collector distance (cm)</th>
<th>Air pressure (Pa)</th>
<th>Number of layers</th>
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<td>18.6</td>
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</tbody>
</table>

III. THE ARTIFICIAL NEURAL NETWORK MODEL

A. The artificial neural networks model with back-propagation learning scheme

Artificial neural networks [8] have been applied to different textile problems. Among many artificial neural network schemes, multi-layer feed-forward neural networks with back-propagation learning algorithms based on gradient descent have been widely used, since they offer unlimited approximation power for non-linear mapping. Therefore, in this study, an ANN was used with the back-propagation learning scheme to predict the filtration performances of melt blowing nonwoven fabrics. The back-propagation neural network is essentially a network of simple processing elements working together to produce a complex output. These elements or nodes are arranged into different layers as input, hidden and output. The output from a back propagation neural network is computed using a procedure known as the forward pass. The input layer propagates a particular input vector’s components to each node in the hidden layer. Hidden layer nodes compute output values, which become inputs to the nodes of the output layer. The output layer nodes compute the network output for the particular input vector. The forward pass produces an output vector for a given input vector based on the current state of the network weights. Since the network weights are initialized to random values, it is unlikely that reasonable outputs will result before training. The weights are adjusted to reduce the error by propagating the output error backward through the network. This process is where the back propagation neural network gets its name and is known as the backward pass. The training set is repeatedly presented to the network and the weight values are adjusted until the overall error is below a predetermined value. Since the Delta rule follows the path of greatest descent along the error surface, local minima can impede training. The momentum term compensates for this problem to some degree. One of the most crucial aims of the back propagation network is to minimise the error function by using the gradient steepest descent method. The error function is:

$$E = \frac{1}{2} \sum_k (Y_{dk} - Y_k)^2$$  \hspace{1cm} (1)

where $Y_{dk}$ is the desired output and $Y_k$ is the calculated output value of the output layer, respectively. The weights updated themselves by using error function as:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}}$$  \hspace{1cm} (2)
Here is the learning rate and determines the performance of the learning capability of network and \( w \) is the weight. Sigmoid function was used as activation function in this study. Sigmoid function is as follows:

\[
f(x) = \frac{1}{1 + e^{-x}}
\]

(3)

In this work, three layered network structure was used which composed of input hidden and output layers. The learning rate and momentum were optimised at 0.1 and 0.8, respectively. The model built in this study can be seen in Figure 1.

B. Back-propagation algorithm

In the ANN structure, all the neurons in one layer are connected to neurons in the next layer. The error between the correct output and the ANN output is minimised using the back-propagation learning method. The structure of ANN is given in Figure 1, and the back-propagation algorithm is briefly explained in the following steps. The algorithm has five steps: (1) A training set containing known input-output pairs is defined. (2) All the weights, \( w_{ij} \) are arbitrarily assigned at the first iteration. (3) At each layer of the network, the outputs of the neurons are calculated in a forward direction. (4) At the output layer, the output of the ANN was compared to the given target values in the training set, resulting in an error term. (5) This error term is back-propagated through the network by updating the weights according to a desired algorithm. The program continues for a given number of iterations, or until an accepted error is achieved.

C. Practicing model

We use 10 groups of datum as direct practice and 2 groups as test and verification. The algorithm of model is momentum regulation and the reading ratio is adjusted to itself. When the BP network is being practiced, its parameters could be defined according to the structure. The number can be defined according to the deviation produced in practice on every neural unit of BP. The practice results shows that the optimal number of units in hidden layer is equal to the average of unit number in output layer and input layer. Therefore, the practice time could be shortening and the precise prediction result could be output.

IV. RESULT AND DISCUSSION

As above mentioned, the deviation of specimen is 0.000102 after the BP network running 3000 times. The compare of analogy value to actually experimental value in practice group, as well as the compare of predictive value to actually experimental value in test or verification group in the light of BP network, is shown in Table 2. The prediction result shows that BP network can predict...
filtration properties of melt blowing nonwovens fabrics well for the result is rather exact. Meanwhile, the coincidence of study practice specimen is good as well as the predictive value of two-test and verification specimen groups approximates to their experimental value.

VI. CONCLUSIONS

We use the ANN model to predict filtration properties of melt blowing nonwoven fabrics. Our findings indicate that the filtration properties of melt blowing nonwoven are determined by the polymer throughput rate, air initial velocity, die-to-collector distance, air pressure, and number of layers etc. The predicted and experimental values agree well, indicating that the neural network is an excellent method for predictors. On the basis of the results obtained, with the help of the ANN model analysis, we can predict the filtration properties of melt blowing nonwoven fabrics easily and accurately.

REFERENCES