Application of Neural Networks to Meltblown Process Control

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SYNOPSIS

Process modeling is essential for the control of optimization and an on-line prediction is very useful for process monitoring and quality control. Up to now, no satisfactory methods have been found to model an industrial meltblown process since it is of highly dimensional and nonlinear complexity. In this article, back-propagation neural networks (BPNNs) were investigated for modeling the meltblown process and on-line predicting the product specifications such as fiber diameter and web thickness. The feasibility of this application was successfully demonstrated by agreement of the prediction results from the BPNN to the actual measurements of a practical case. The network inputs included extruder temperature, die temperature, melt flow rate, air temperature at die, air pressure at die, and die-to-collector distance (DCD). The output of the fiber diameter was obtained by neural computing. The network training was based on 160 sets of the training samples and the trained network was tested with 70 sets of test samples which were different from the training data. This research is preliminary and of industrial significance and especially valuable for the optimal control of advanced meltblown processes.

INTRODUCTION

Meltblowing, as shown in Figure 1, is a one-step process to extrude melt filaments out of orifices and directly make microfiber nonwovens from polymers or resins with the aid of high-velocity hot air to attenuate the filaments. Meltblowing has become an important industrial technique because of its ability to produce fabrics of microfiber structure, which are ideally suited for filtration media, thermal insulators, battery separators, and oil sorbents. There is no doubt that the great market potential comes from the excellent and high-performance quality, which arises from much stricter requirements for the control over the meltblown process. Much work has been carried out in the last 20 years, mainly focused on the following:

1. Experimental studies on the relationships of processing variables, die geometry, and web structure and its properties.[1,2]
2. Improvements of the process to obtain high-quality webs for specific applications.[3,4]
3. Attempts to model the process physically and mathematically.[5,6]

The meltblowing process is similar to melt spinning, which has been investigated more comprehensively. The primary difference between meltblowing and conventional melt spinning is that the melt-blowing process uses hot air with high velocity, rather than a draw roll in melt spinning, to provide the attenuating force in the process. The force of the air rapidly attenuates the melt filaments from an approximately 400 micron diameter at the exits of die orifices down to a final fiber diameter that can be less than 1 micron. Without a draw roll, the fibers are meltblown at such high speed that it is difficult to use a mechanical windup, which makes the meltblowing process more complicated. The complexity results mostly from the instability of fiber formation caused by lack of a draw roll and the

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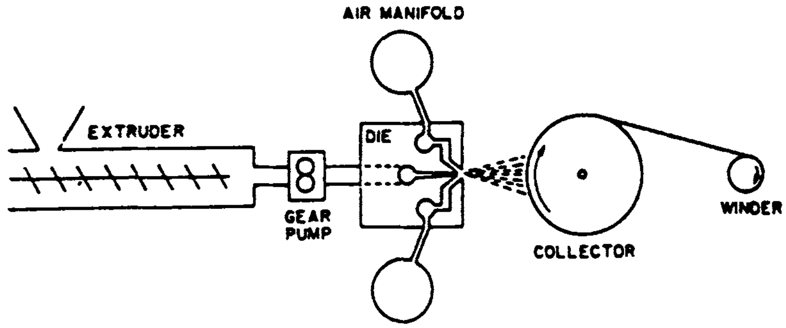

Figure 1 Schematic of the meltblown process.

effect of two convergent streams of high-velocity hot air on the fiber formation. The fiber-forming mechanism is very complicated and is related to the frontier research of different disciplinary areas, such as heat and mass transfer in a hot air jet field, the die swell of extruded melt filament under the attenuation effect of two convergent streams of high-velocity hot air, fiber forming, and breakage in the air jet field. Experimental research has been shown that the quality of the meltblown web depends on many processing variables such as die temperature, air temperature, air flow rate, extruder temperature, die-to-collector distance, polymer throughput rate, resin melt flow rate (MFR), and die geometry parameters such as die orifice diameter, *L/D* ratio, nosetip angle, air gap, and nosetip setback. Therefore, meltblowing is a highly complex, multivariable, and nonlinear process, leading to the extreme difficulty in theoretically modeling the process. Most of the previous work was to a large extent based on idealized models that were far from the practical process and of little industrial significance.

Fortunately, the fast-growing neural network methodology of artificial intelligence provides a novel and powerful way to model such a complex system. In this article, the application of neural networks to the meltblown process is initially presented and discussed.

NEURAL NETWORK METHODOLOGY

A neural network is a computer system which mimics the structure of human brain and imitates intelligent behavior. It consists of many simple and highly connected neurons (processing elements or nodes) and processes information by its dynamic-state response to external inputs. It can deal with the problems of highly dimensional and nonlinear systems. The parallel distributed processing of the

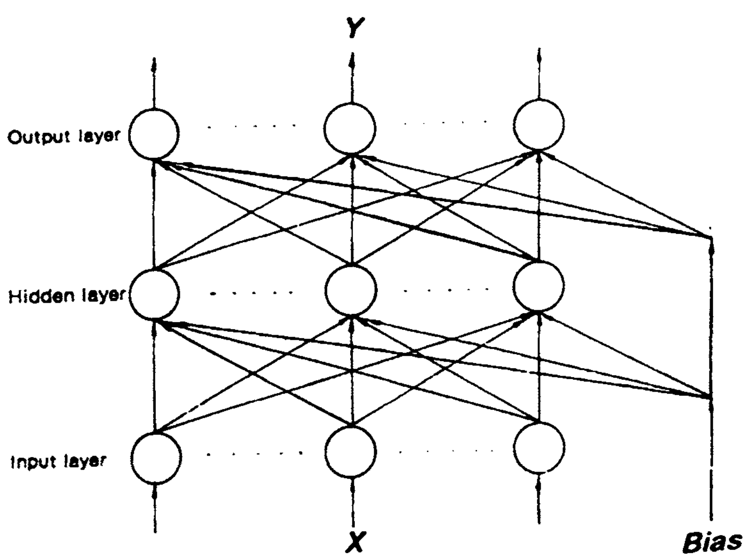

Figure 2 A typical backpropagation network.

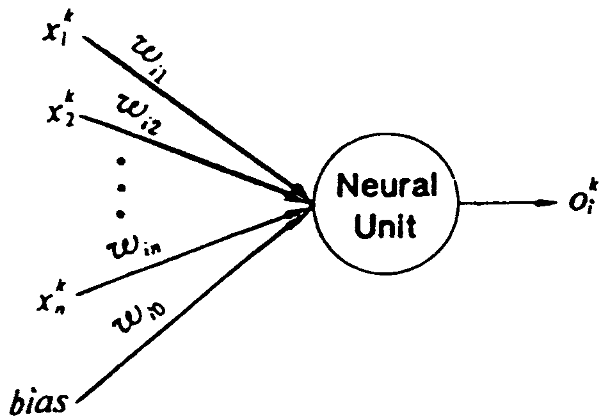

Figure 3 A neural element (a processing element).

neural networks promises high computation rates provided by the massive parallelism, a greater degree of robustness or fault tolerance due to the distributed representation, and the ability to adapt and to continue to improve performance. The learning is based on samples, so it is especially suitable for the complicated process with a nontransparent mechanism. Therefore, neural networks, as one of most active branches of artificial intelligence in recent years, have been widely used in the process industries, including fault diagnosis and pattern recognition, process control and identification, system modeling, and on-line measurement and prediction.

The architecture of a neural network depends on three key factors: network topology, node characteristics (activation functions), and the learning algorithm (learning rule). There are different types of neural networks and, among them, back-propagation neural networks (BPNNs) are the most popular and widely used in various fields. In this article, BPNNs were investigated to model the meltblown process and predict the fiber diameter.

A BPNN, as shown in Figure 2, is composed of one input layer, one output layer, and one (or more) hidden layer(s). The output of the threshold element (Bias) is equal to 1. There is no theoretical limit on the number of hidden layers but typically there are one or two. Each hidden layer has an adjustable number of nodes. The number of nodes in input and output layers depends heavily on the properties of the problem that one is studying. The weights (W_{ij}) on connections are adjustable and their initial values are generally obtained from a randomizing routine.

The inputs enter in the first layer and its outputs are exactly same as its inputs, and their weighted sums (see Fig. 3) of first layer outputs become the inputs to the second layer (first hidden layer), which are transferred through a transfer function or activation function, generally using a sigmoid function (see Fig. 4), to obtain the neuron outputs. The weighted sum of these outputs forms the inputs to the next layer (or output layer). Forward calculation is conducted in the same way as for the second layer until the outputs of the neural network are finally reached. This is so-called feed-forward calculation of BPNNs and can be expressed by the following equations:

For the input layer,

$$o_i^k = x_i^k$$

where x_i^k is the input of the ith node in the input layer for sample k and o_i^k is its output.

For the hidden layer,

$$net_i^k = \sum_{l=1}^{n} w_{il} \cdot o_l^k + w_{i0}$$

$$o_i^k = f(net_i^k)$$

$$f(a) = \frac{1}{1 + e^{-a}}$$

where net_i^k is the input of node i for sample k; w_{il}, the connection weight from the previous layer node l to node i; o_l^k and o_i^k, the outputs of the previous layer node l and current layer node i, respectively; w_{i0}, the threshold value of node i; and n, the node number of the previous layer.

During the training (or learning) sequence, the final outputs of neural networks are calculated feed-forward as described above. They are compared with the actual outputs of training samples from measurement to yield an error profile. The error profile is propagated back through the network by a learning rule to update the weights on the connections. In this article, an improved back-propagation al-

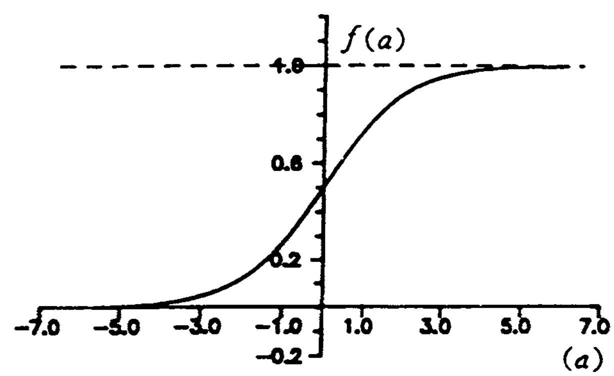

Figure 4 Sigmoid function.

Table I $L_{27}(9 \times 3^9)$ **Table**

Test No.	Column No. 1	2	3	4	5	6	7	8	9	10
1	1	1	1	1	1	1	1	1	1	1
2	1	2	2	2	2	2	2	2	2	2
3	1	3	3	3	3	3	3	3	3	3
4	2	1	1	1	2	2	2	3	3	3
5	2	2	2	2	3	3	3	1	1	1
6	2	3	3	3	1	1	1	2	2	2
7	3	1	1	1	3	3	3	2	2	2
8	3	2	2	2	1	1	1	3	3	3
9	3	3	3	3	2	2	2	1	1	1
10	4	1	2	3	1	2	3	1	2	3
11	4	2	3	1	2	3	1	2	3	1
12	4	3	1	2	3	1	2	3	1	2
13	5	1	2	3	2	3	1	3	2	1
14	5	2	3	1	3	1	2	1	2	3
15	5	3	1	2	1	2	3	2	3	1
16	6	1	2	3	3	1	2	2	3	1
17	6	2	3	1	1	2	3	3	1	2
18	6	3	1	2	2	3	1	1	2	3
19	7	1	3	2	1	3	2	1	3	2
20	7	2	1	3	2	1	3	2	1	3
21	7	3	2	1	3	2	1	3	2	1
22	8	1	3	2	2	1	3	3	2	1
23	8	2	1	3	3	2	1	1	3	2
24	8	3	2	1	1	3	2	2	1	3
25	9	1	3	2	3	2	1	2	1	3
26	9	2	1	3	1	3	2	3	2	1
27	9	3	2	1	2	1	3	1	3	2

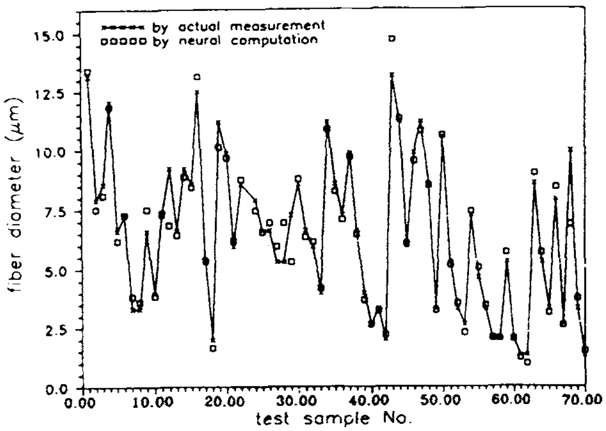

Figure 5 Comparison of predicted fiber diameter to actual measurement.

gorithm was used for training the network. The weights were adjusted in such a way that minimized the mean square error J:

$$Min\ J = \frac{1}{2} \sum_{i=1}^{P} E_i$$

where P is the number of training samples and E_i is the sum of the square error of training sample i:

$$E_i = \sum_{j=1}^{N_{out}} (t_j^i - y_j^i)^2$$

where N_{out} denotes the number of the nodes in the output layer, t_j^i is the prediction value of the jth output of sample i, while y_j^i is the actual value of the jth output of sample i. The weight change on iteration $q(\Delta W_q)$ was calculated according to

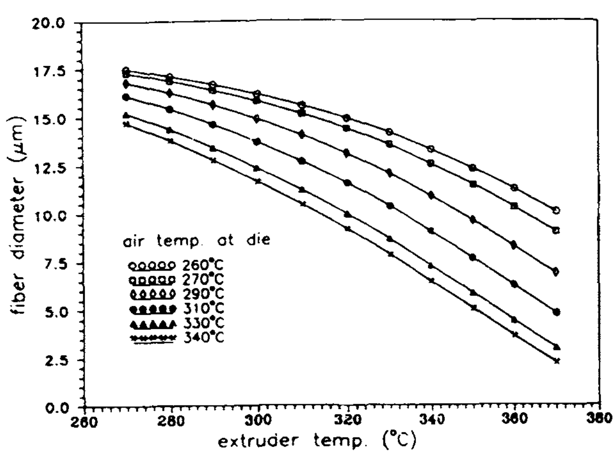

Figure 6 The effect of extruder temperature on fiber diameter.

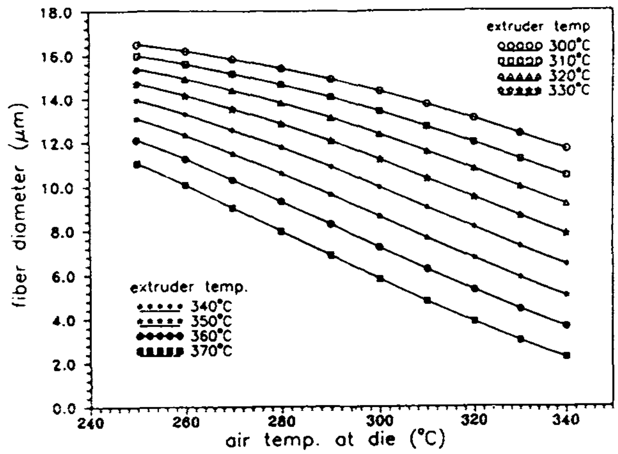

Figure 7 The effect of air temperature at die on fiber diameter.

$$\Delta W_q = -\eta M_q + \alpha \Delta \mathbf{W}_{q-1}$$

where M_q is the overall gradient; α, the momentum factor aiding in convergence; and η, the step size, determined through the Golden Section. The search interval was determined by a scanning and bracketing procedure. However, as the iteration gets closer to the optimum, the conjugate gradient was introduced to improve the convergence rate. The iteration was based on

$$\Delta W_q = \eta M_q' + \alpha \Delta W_{q-1}$$

$$M_q' = M_q + \beta M_{q-1}'$$

$$\beta = \frac{\| M_q \|^2}{\| M_{q-1} \|^2}$$

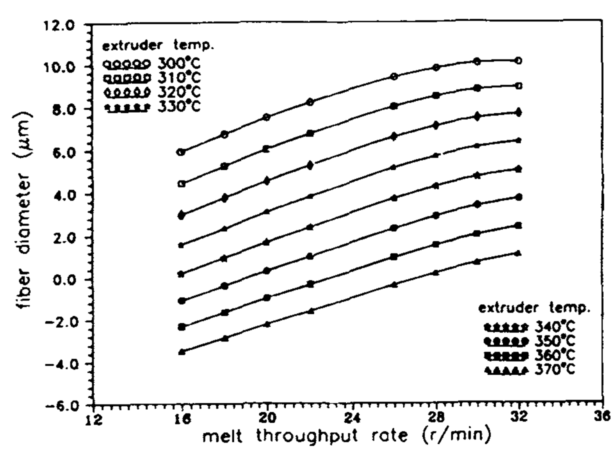

Figure 8 The effect of melt throughout rate on fiber diameter.

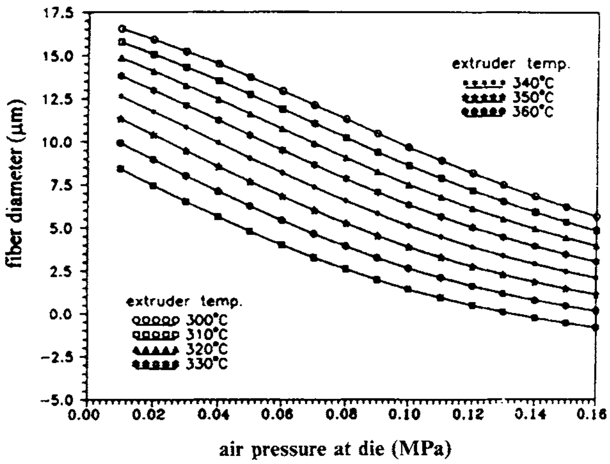

Figure 9 The effect of air pressure at die on fiber diameter.

where M' is the overall conjugate gradient. If the objective J was less than the preset positive tolerance, then the training procedure stopped.

To build up a practical neural network, the first task is to study the process and analyze its cause–effect relationships between various variables and to determine the inputs and outputs, then to obtain sufficient training samples for the training sequence. The sample acquirement is a time-consuming process, which is very important because neural networks learn and obtain their problem-solving ability from the training samples.

The input variables in this research consisted of die temperature, air temperature at die, polymer melt throughput rate, extruder temperature, air pressure at die, and die-to-collector distance. The output was the fiber diameter. By comparison of several network topology structures (6-3-1, 6-4-1, 6-5-1, 6-6-1, 6-4-3-1, etc.) and different transfer functions (sigmoid, quadratic), the network 6-4-1 (six nodes in the input layer, four nodes in the hidden layer, two nodes in the output layer) was chosen as the final structure, using a sigmoid function as its transfer function. Because of the wide distribution of the data of meltblown processes, it was necessary to pretreat the original input and output data. An improved normalization method, as shown below, was presented to improve prediction precision. For input data,

$$X = a + (1 - a)\frac{(X_{\text{in}} - X_{\min})}{(X_{\max} - X_{\min})}$$

For output data,

$$Y = b + (1 - b)\frac{(Y_{\text{out}} - Y_{\min})}{(Y_{\max} - Y_{\min})}$$

where a and b are adjustable constants between 0 and 1, X and Y are, respectively, the input and output vectors after normalization, the subscripts of "in" and "out" are, respectively, the actual input and output vectors, and "min" and "max" are, respectively, the minimum and maximum values of input or output vectors.

For measuring the mean difference between the predicted and actual outputs for the testing patterns, the following root mean square error (rms) was used:

$$\text{rms} = \frac{\sum_{p=1}^{P} \sqrt{\sum_{j=1}^{N_{\text{out}}} (y_j^p - t_j^p)^2}}{P}$$

The whole training procedure was to adjust all weights on connections of the network according to the learning rule. The iteration went on until the computed outputs reached the required precision of agreement to the actual outputs.

EXPERIMENTAL

The experiments were carried out using the No. 1 Production Line of Beijing CHALLEN Nonwoven Tech. Corp. PP pellets were from Xingdu Plastic Inc. in Beijing with MFR 60. The ambient temperature is 25 ± 2.5°C. The web fiber diameter was the average of 100 random fibers of 10 web samples (60 × 15 mm) using an XSZ60 biomicroscope.

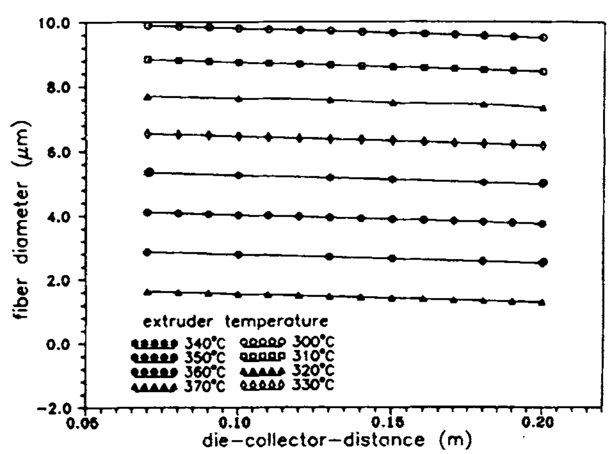

Figure 10 The effect of die-collector-distance on fiber diameter.

As mentioned above, neural networks learn on the basis of actual samples, so it is necessary to obtain sufficient training samples to build up effective ones. To do so efficiently and comprehensively, an interval orthogonal test method was presented to design the experiments for collecting training samples. The melt temperature and gas temperature were divided into several match intervals, and for each interval, the orthogonal test method [$L_{27}(9 \times 3^9)$, see Table I] was used for the experimental design.

RESULTS AND DISCUSSION

One hundred sixty sets of data were used as training samples and the trained neural network was tested by 70 sets of data which were different from the training samples. The test results (Fig. 5) show a good agreement to the actual measurement. The maximum absolute error between the predicted fiber diameter and the actual value was less than 1.5 μm. It has reached the precision of the actual measurement used in this study. If higher precision is required, more accurate training samples (or measurement) should be provided.

Using the tested neural network, we could predict the effect of process variables on fiber diameter. The effect of extruder and air temperature is shown in Figures 6 and 7. The fiber diameter decreased as air temperature and extruder temperature increased. That is due to the more easy melt flow at elevated temperatures. Figure 8 shows the relationship between the melt throughput rate and fiber diameter. As the melt throughput increased, the diameter increased. As shown in Figure 9, the increase in air pressure resulted in a decrease in fiber diameter. That is due to the fact that the higher the air pressure the higher the attenuating force on the melt filaments, which leads to a decrease in fiber diameter. Figure 10 shows that the filament attenuation is completed within a die-to-collection distance of 0.07 m. All these prediction results are consistent with the previous findings, which indicates that neural networks can be used to extract and describe the intrinsic relationships of a highly complicated process from sufficient discrete system data and that the BPNN is effective for modeling and predicting meltblown processes.

The outputs of a neural network are not limited to the fiber diameter. They can be web thickness, basic weight, and other web specifications according to the different production processes and requirements. The most valuable result of this research is not only a development of a practical neural network for the CHALLEN meltblown line, but also a technique which has been proved to be suitable for modeling and on-line predicting of the meltblowing process. It is valuable for the optimal control of the process and of practical significance to advanced meltblown processes. Further research is suggested to consider the effect of different raw materials and ambient temperature, because they may influence the performance of meltblown webs significantly.

CONCLUSIONS

The BPNN developed in this research is suitable for on-line modeling and predicting the meltblown process. It is very practical and useful for the process optimum and quality control not only for the meltblowing process but also for other nonwoven processes such as the spunbonding process, spunlace process, and so on. The enhanced normalization method presented above notably improved the network's prediction precision for the meltblown process. The interval orthogonal test method is a very effective and efficient way to obtain the comprehensive training samples of neural networks.

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