A Soft Computing Approach to Model the Structure–Property Relations of Nonwoven Fabrics

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ABSTRACT: A soft computing approach to model the structure–property relations of nonwoven fabrics for filtration use is developed. Because the number of samples is very limited, the artificial neural network model to be established must be a small-scale one. Consequently, this soft computing approach includes two stages. In the first stage, the structural parameters are selected by using a ranking method, to find the most relevant parameters as the input variables to fit the small-scale artificial neural network model. The first part of this method takes the human knowledge on the nonwoven products into account. The second part uses a data sensitivity criterion based on a distance method that analyzes the measured data of nonwoven properties. In the second stage, the artificial neural network model of the structure–property relations of nonwoven fabrics is established. The results show that the artificial neural network model yields accurate prediction and a reasonably good artificial neural network model can be achieved with relatively few data points by integrated with the input variable selecting method developed in this research. The results also show that there is great potential for this research in the field of computer-assisted design in nonwoven technology. © 2006 Wiley Periodicals, Inc. J Appl Polym Sci 103: 442–450, 2007

Key words: computer modeling; structure–property relations; simulations

INTRODUCTION

Nonwoven fabrics are polymer materials that have sheet or web structures created by bonding or entangling fibers or filaments and perforating films with mechanical, thermal, or chemical methods. Because of the superior and particular properties of nonwoven products, their uses are continuing to expand. The major end-uses of nonwoven fabrics include disposable personal hygiene products, medical products, wipes and towels, filtration media, coated fabrics, geotextiles, roofing products, and interlinings.

The filter performances and other properties of nonwoven fabrics for filtration use are highly related with their structural characteristics. Therefore, investigating the structure–property relations will be not only beneficial to better understanding of nonwoven products but also possible of achieving computer-assisted design of nonwoven fabrics. The structure–property relation of nonwoven fabrics, however, is a complicated nonlinear problem that is difficult to be modeled physically. Therefore, some researchers studied the structure–property relations of nonwoven fabrics using an experimental approach.

Ericson and Baxter[1]discussed the dependence of fabric properties of spun-bonded nonwovens on structural parameters, such as weight uniformity, filament separation, and filament directionality. Troesch and Hoffmann[2] found that the binder-to-fiber ratio and the distribution of the binder in the web have a decisive effect on the mechanical properties of nonwoven fabrics. Wyatt et al.[3] and Wei et al.[4] carried out experimental investigations of the effect of fiber structure and morphology on the mechanical properties of thermal bonded nonwoven fabrics. Their experiments confirmed that tensile strength and stiffness of the fabrics correlate with the orientation and crystallinity of fibers. Nosov and Dzhavakhishvili[5] studied the thermal resistance of needle punched nonwoven fabrics of various fiber composition, surface density, and thickness. Experiments showed that the thickness of the nonwovens exerted the greatest effect on its thermal resistance; surface density and fiber composition exerted a smaller effect. Subramaniam et al.[6] produced different needle-punched nonwoven fabrics of different weights, thicknesses, and blend compositions and found that the air permeability of nonwovens was strongly dependent on the fiber volume fraction. Pan and Wang[7] studied the relationship

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between the structure and filtration property of melt blown nonwoven fabrics experimentally. The thickness of the nonwoven fabrics was the only structural parameter considered. The relationships between the thickness and the filtration resistance and filtration efficiency were established using the curve-fitting method. Genis[8] established a relation between the fiber diameter, fabric thickness and the air permeability and a relation between the fiber diameter, fabric thickness, volume density and the sound absorption coefficient of melt blown nonwoven fabrics by multiple regression analysis of the experimental data. Lin et al.[9] investigated the effect of fiber arrangement on the mechanical properties of thermal bonded nonwoven fabrics and showed that the anisotropy of the mechanical properties of nonwoven fabrics could be improved by arranging the fibers at random. Rong and Bhat[10] used differential scanning calorimetry to analyze the binder fiber distribution of thermal bonded nonwoven fabrics and investigated the relationship of binder fiber distribution and the tensile strength of nonwovens.

All these investigations used an experimental approach to study the structure–property relations of nonwoven fabrics. And some used regression analysis to correlate the structural parameters and properties. These correlations were strongly dependent on the experimental data and thus had poor generalization. The other drawback of these investigations is that few structural parameters of nonwovens were considered. Most focused on the fiber parameters, such as fiber diameter and fiber composition. Only a few fabric structural parameters were investigated.

Consequently, it is necessary to make a mathematical approximation of inherent simplicity, i.e., to use the empirical models. The artificial neural network (ANN) is an empirical model that can provide good approximations in the presence of noisy data and smaller number of experimental points.[11] Also, the assumptions under which ANNs work are less strict than other meta-models. Therefore, various ANN models have been used to predict the properties of yarns and of woven, knitted, and nonwoven fabrics since the mid-1990s.[12–18] Chen et al.[19,20] established ANN models to predict the fiber diameter of melt-blown nonwoven fabrics from the processing parameters and compared the ANN model with physical and statistical models. However, it is still very scanty for the use of ANN on modeling the structure–property relations of nonwoven fabrics.

As a primary effort, the present work is aimed at developing a soft computing approach to model the structure–property relations of nonwoven fabrics. To link this work closely with industrial applications, the samples used are all collected from a nonwoven manufacturer in France. However, only a total of 18 samples are available; thus, the ANN model to be established based on these limited samples must be a small-scale one. Because many structural parameters affect the properties, the structural parameters have to be ranked before modeling, so as to find the most relevant parameters to fit the small-scale ANN model. These selected parameters will be the input variables of the small-scale ANN model. Consequently, this soft computing approach includes two stages. The first stage is selecting the structural parameters as the input variable of ANN model, which is achieved with a two-part ranking method. The second stage is the ANN modeling of the structure–property relations of nonwoven fabrics. Compared with previous studies, this research will establish a reasonably good ANN model that can generalize well and consider more structural parameters as the model inputs.

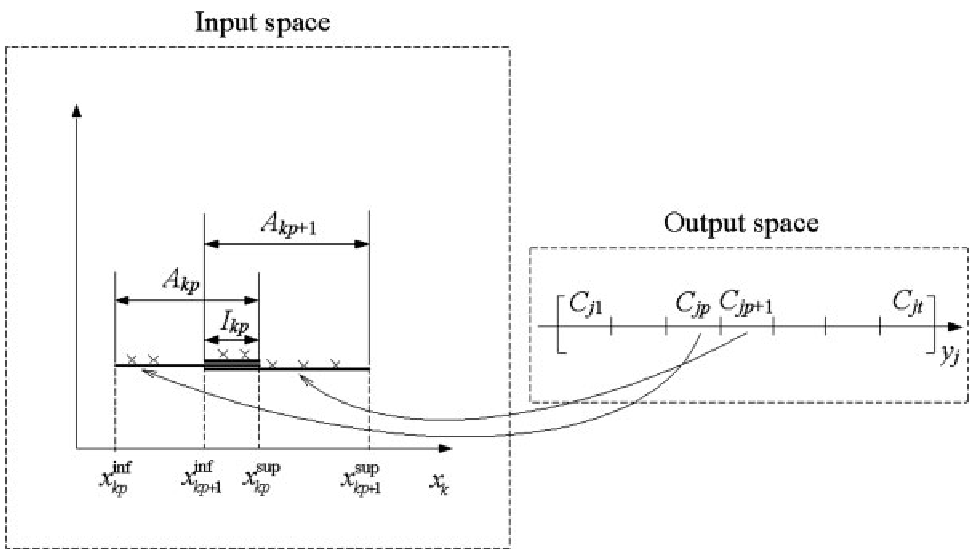

Figure 1 Relationship between input and output spaces.

SELECTION OF RELEVANT STRUCTURAL PARAMETERS

In this study, we develop a method to rank the structural parameters which is different from above-mentioned input variable selecting methods. This two-part method can deal with nonlinear relationships between input and output variables, without the need for a large number of data to run it. The first part takes the human knowledge on nonwoven products into account (VA_k). The second part is a data sensitivity criterion based on a distance method (S_k).

The ranking criterion is formulated as follows. Let $X_s = (x_{s1}, x_{s2}, \dots, x_{sk}, \dots, x_{sn})^T$ denote the input vector of all the structural parameters and $Y_s = (y_{s1}, y_{s2}, \dots, y_{sj}, \dots, y_{sm},)^T$ the output vector of properties. The subscript s indicates the sth sample ($s \in \{1, \dots, i, \dots, l, \dots, z\}$). All the recorded data have been normalized to eliminate the scale effects and the series of data contains z samples. To rank the relevant inputs for a given output y_j, a criterion variable F_k is defined as follows:

$$F_k = g_1 \cdot VA_k(x_k, y_j) + g_2 \cdot S_k(k \in \{1, \dots n\}, j \in \{1, \dots m\}), \quad (1)$$

where g_1 and g_2 are two positive coefficients. The criterion is designed for searching the best compromise between the human knowledge and data sensitivity.

The first part (VA_k) of the ranking criterion is determined with the aid of the human knowledge.[21] As shown in Figure 1, the universe of discourse of y_j is divided into t equivalent intervals C_{jp} ($p \in \{1, \dots, t-1\}$). The set A_{kp} is constructed with the set of input data x_k, which corresponds to the output interval C_{jp} of y_j.

The human knowledge shown in Table I is expressed with linguistic sentences, such as

Rule 1: IF x_1 is increasing AND y_1 is increasing THEN R $(x_1, y_1) = +1$
Rule 2: IF x_1 is increasing AND y_1 is decreasing THEN R $(x_1, y_1) = -1$
Rule 3: IF x_1 is decreasing AND y_1 is increasing THEN R $(x_1, y_1) = -1$
Rule 4: IF x_1 is decreasing AND y_1 is decreasing THEN R $(x_1, y_1) = +1$

Then VA_k can be calculated using the following formula:

$$\begin{cases} VA_k(x_k, y_j) = \dfrac{1}{t-1}\displaystyle\sum_{p=1}^{t-1} va_p \\ x_{kp}^{\inf} = \min\limits_{s\in\{1,\dots,z\}}\{x_{sk} | y_{sj} \in C_{jp}\} \quad \text{and} \quad x_{kp}^{\sup} = \max\limits_{s\in\{1,\dots,z\}}\{x_{sk} | y_{sj} \in C_{jp}\} \\ \text{if } I_{kp} = \phi, \begin{cases} va_p = \frac{1}{2}|R(x_k, y_j)| \times [1 + R(x_k, y_j)], & \text{if } x_{kp+1}^{\inf} \geq x_{kp}^{\sup} \\ va_p = \frac{1}{2}|R(x_k, y_j)| \times [1 - R(x_k, y_j)], & \text{if } x_{kp+1}^{\sup} \leq x_{kp}^{\inf} \end{cases} \\ \text{if } I_{kp} \neq \phi, \begin{cases} va_p = \frac{1}{2}|R(x_k, y_j)| \times [1 + R(x_k, y_j)] \times \left(1 - \frac{|I_{kp}|}{|U_{kp}|}\right), & \text{if } x_{kp+1}^{\sup} \geq x_{kp}^{\inf} \\ va_p = \frac{1}{2}|R(x_k, y_j)| \times [1 - R(x_k, y_j)] \times \left(1 - \frac{|I_{kp}|}{|U_{kp}|}\right), & \text{if } x_{kp+1}^{\inf} \leq x_{kp}^{\inf} \end{cases} \end{cases} \quad (2)$$

where R (x_1, y_1) is the relation index between the structural parameter x_1 and property y_1; va_p is the human knowledge criterion value in the interval C_{jp}; $x_{kp}^{\inf}$, and $x_{kp}^{\sup}$ are the lower bound (inferior limit) and upper bound (superior limit) of set A_{kp}, respectively; I_{kp} and U_{kp} are the intersection set and union set

TABLE I
Human Knowledge of Nonwoven Products

Properties structural parameters	Air permeability	Strength at break (MD)	Elongation at break (MD)
Fiber			
Length	+1	+1	+1
Count	−1	+1	+1
Nonwoven			
Thickness	−1	+1	+1
Total pore volume	+1	−1	−1
Basis weight	−1	+1	+1
Basis weight uniformity	+1	+1	+1
Fiber volume density	−1	+1	+1

generated by A_{kp} and A_{kp+1}, respectively; *and* φ is an empty set.

The data sensitivity criterion S_k in eq. (1) implies the following two hypotheses:[22]

1. IF a small variation of an input variable corresponds to a big variation of the output variable, THEN this input is considered as a sensitive variable.
2. IF a big variation of an input variable corresponds to a small variation of the output variable, THEN this input is considered as an insensitive variable.

Therefore, according to criterion S_k, an input variable is considered to be relevant if its small variation induces a great variation of an output:

$$T_k = \sum_{\substack{i \neq l \\ 1}}^{z} \frac{d(y_{ij}, y_{lj})}{d'_k(X_i, X_l)} \tag{3}$$

$$S_k = \frac{\max\limits_{k \in \{1,\ldots,n\}} (T_k) - T_k}{\max\limits_{k \in \{1,\ldots,n\}} (T_k) - \min\limits_{k \in \{1,\ldots,n\}} (T_k)}, \tag{4}$$

where $d'_k(X_i, X_l) = \sqrt{d^2(X_i, X_l) - d_k^2(X_i, X_l)}$, $d\,(X_i, X_l)$ is the Euclidean distance between X_i and X_l in the input space. $d_k\,(X_i, X_l)$ is the projection of $d\,(X_i, X_l)$ on the axis x_k; and $d\,(y_{ij}, y_{lj})$ is the Euclidean distance between y_i and y_l of the jth output variable. The smaller the T_k value, the more relevant to y_j will be the input x_k. So S_k is calculated by eq. (4) to be standardized and have the same tendency as the human knowledge VA_k (larger VA_k means more relevant).

Two methods are employed to determine the weights g_1 and g_2 in eq. (1). As shown in eqs. (5) and (6), method 1 uses the variation coefficient of VA_k and S_k as their weights g_{11}^* and g_{21}^*, respectively. The second subscript ''1'' of g_{11}^* and g_{21}^* indicates method 1. The principle of this method is as follows. A larger variation coefficient means that the corresponding criterion has stronger capability to differentiate between samples. So this criterion should be assigned a larger weight.[23] As shown in eqs. (7) and (8), method 2 uses the dispersion maximization decision principle to determine the weights g_{12}^* and g_{22}^* which means larger dispersion of a criterion corresponds to larger weight.[24] The second subscript ''2'' of g_{12}^* and g_{22}^* indicates method 2. The above weights are then normalized using eq. (9). The final weights are the arithmetic average of weights determined by the two methods, as shown in eqs. (10) and (11):

$$g_{11}^* = \frac{\sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(VA_k - \frac{1}{n}\sum_{k=1}^{n} VA_k\right)^2}}{\frac{1}{n}\sum_{k=1}^{n} VA_k} \tag{5}$$

$$g_{21}^* = \frac{\sqrt{\frac{1}{n-1}\sum_{k=1}^{n}\left(S_k - \frac{1}{n}\sum_{k=1}^{n} S_k\right)^2}}{\frac{1}{n}\sum_{k=1}^{n} S_k} \tag{6}$$

$$g_{12}^* = \frac{\sum_{\substack{i \neq k \\ 1}}^{n} |VA_i - VA_k|}{\sqrt{\left(\sum_{\substack{i \neq k \\ 1}}^{n} |VA_i - VA_k|\right)^2 + \left(\sum_{\substack{i \neq k \\ 1}}^{n} |S_i - S_k|\right)^2}} \tag{7}$$

$$g_{22}^* = \frac{\sum_{\substack{i \neq k \\ 1}}^{n} |S_i - S_k|}{\sqrt{\left(\sum_{\substack{i \neq k \\ 1}}^{n} |VA_i - VA_k|\right)^2 + \left(\sum_{\substack{i \neq k \\ 1}}^{n} |S_i - S_k|\right)^2}} \tag{8}$$

$$g_{11} = \frac{g_{11}^*}{g_{11}^* + g_{21}^*} \quad g_{21} = \frac{g_{21}^*}{g_{11}^* + g_{21}^*} \quad g_{12} = \frac{g_{12}^*}{g_{12}^* + g_{22}^*} \quad g_{22} = \frac{g_{22}^*}{g_{12}^* + g_{22}^*} \tag{9}$$

$$g_1 = \frac{1}{2}(g_{11} + g_{12}) \tag{10}$$

$$g_2 = \frac{1}{2}(g_{21} + g_{22}) \tag{11}$$

After calculating VA_k, S_k, and the weights g_1, g_2, the criterion variable F_k of each input x_k for a given output y_j can be determined. The larger the F_k value, the more relevant to y_j will be the input x_k. Then all the F_k are ranked in a descending order. Accordingly, the relevancies of all input variables are in the same order as the value of F_k ranked. That is, the input corresponding to the first F_k of this rank will be the most relevant input to output y_j, and the like.

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.[11]

Seven structural parameters and three properties of nonwoven fabrics will be used as the inputs and outputs of the ANN model. Each property is modeled, respectively.

For lack of plentiful samples, small-scaled ANN models are established in this study. As far as our model is concerned, five inputs and one output are preferred. A feedforward artificial neural network is created using the Matlab Neural Network Toolbox. There are one hidden layer with two neurons (more hidden neurons will cause too many unknown weights, while the number of samples is quite limited) and one output layer with one neuron in the ANN. 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. To avoid overfitting, the Bayesian framework is employed in the training procedure. In this framework the weights and biases of the network are assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. We can then estimate these parameters using statistical techniques.[24] The training function used is ''trainbr,'' which updates the weight and bias values according to Levenberg–Marquardt optimization. It minimizes a linear combination of squared errors and weights, then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization. To test the ANN model, all the experimental data are split into a training set (with 17 data points) and a testing set (with 1 data point). All combinations of 17 and 1 data points are used to train and test the ANN. Altogether there are 18 cases being trained and tested. Finally, the average of all the 18 ANN results is compared with the experimental data.

EXPERIMENTAL

To make this work closely linked with industrial applications, the samples used are all collected from a nonwoven manufacturer in France. The method of nonwoven manufacturing is dry laid for web forming and thermal bonding for web bonding. The fiber used is polyester with a round cross section. There are seven structural parameters: fiber length, fiber count, total pore volume (tp), basis weight uniformity, thickness (tk), basis weight (bw), and fiber volume density (fvd) of nonwoven fabrics. The total pore volume of nonwoven fabrics is defined as the percentage of all the pores in a nonwoven sample and is calculated with the following formula:

$$\mathrm{tp} = [1 - \mathrm{bw}/(\mathrm{tk} \times \text{fiber density} \times 1000)] \times 100\% \quad (12)$$

The basis weight uniformity is the patchiness or mass nonuniformity of nonwoven samples. A monochromatic LED light source (Philips Lumileds Lighting, San Jose, CA) and a digital camera (Uniq Vision, Santa Clara, CA) are used to get the images of nonwovens. The basis weight uniformity is determined with the help of image analysis method.[26] The fiber volume density of nonwoven fabrics is defined as the total length (km) of fibers in a unit volume (m^3) of nonwoven fabrics:

$$\mathrm{fvd} = \mathrm{bw}/(\mathrm{tk} \times \text{fiber count} \times 0.0001) \quad (13)$$

The properties of nonwoven fabrics investigated are the air permeability, strength at break along the machine direction (MD), and elongation at the break along the machine direction (MD). The air permeability is measured on an air permeability tester (Textest AG, Schwerzenbach, Switzerland). The strength at break and elongation at break are measured on a universal tensile tester (Instron Deutschland GmbH, Darmstadt, Germany). All the structural parameters (inputs) and properties (outputs) are shown in Table II.

The computer system used is a personal computer with a central processing unit of Pentium IV (3.0 GHz), an internal memory of 512 MB and a hard disk of 160 GB.

The operating system is Windows XP. The technical computing software of Matlab is employed in the modeling process.

RESULTS AND DISCUSSION

As mentioned above, there are altogether 18 samples in this investigation. First, the structural parameters of nonwovens are selected with regard to each property using the method put forward earlier in the section, Selection of Relevant Structural Parameters. Tables III–V give the ranking results of structural parameters for the three properties of nonwovens.

As far as the air permeability is concerned, Table III shows that the weights $g_1 = 0.5585$ for VA_k and $g_2 = 0.4415$ for S_k, which shows that the two criterions have almost equal importance while the human knowledge criterion is a little more important. It can be seen from Table III that the most relevant structural parameter is the fiber volume density of nonwovens, followed by the thickness and basis weight uniformity of nonwovens. Note that the criterion S_k is insufficient to explain the ranking. For example, considering S_k (only the measured data), the thickness of nonwovens is the most irrelevant parameter. By adding a more general knowledge about the products (human knowledge), the thickness increases to the second place, which coincides with our general knowledge on the close relationship between the air permeability and the thickness of nonwovens.

The ranking order for the strength at break (MD) is shown in Table IV. For this property, the weights $g_1 = 0.4542$ for VA_k and $g_2 = 0.5458$ for S_k. It can be found from Table IV that the most relevant structural parameter is the fiber volume density, followed by the fiber count and basis weight uniformity of nonwovens.

TABLE II
Experimental Results of Structural Parameters and Properties of Nonwoven Fabrics

	Structural parameter							Property		
Sample no.	Fiber length (mm)	Fiber count (dtex)	Total pore volume (%)	Basis weight uniformity (%)	Thickness (mm)	Basis weight (g/m^2)	Fiber volume density (km/m^3)	Air permeability ($l/m^2/s$)	Strength at break (N)	Elongation at break (%)
1	40	2.0	90.46	87.68	0.17	21	791855	1193.89	39.30	8.70
2	40	2.0	89.72	88.70	0.21	25	763126	765.28	51.30	8.60
3	40	2.0	89.71	85.59	0.25	29	743590	668.06	67.60	8.80
4	40	2.0	88.34	87.43	0.24	33	881410	488.61	69.90	10.10
5	40	2.0	87.94	87.98	0.35	48	879121	389.71	97.20	9.80
6	40	2.0	85.00	86.85	0.34	63	1187783	364.72	133.00	9.40
7	120	4.1	90.12	85.98	0.11	15	332594	1698.00	27.50	21.30
8	120	4.1	88.85	87.84	0.13	20	375235	1361.00	41.70	24.20
9	120	4.1	86.41	88.56	0.16	30	457317	930.00	68.70	15.10
10	120	4.1	84.30	90.64	0.18	39	528455	715.00	91.00	18.40
11	120	4.1	80.37	96.74	0.24	65	660569	267.00	186.00	15.60
12	120	4.1	85.19	99.14	0.45	92	498645	258.00	220.00	18.20
13	120	3.3	94.53	82.25	0.265	20	150943	756.00	27.60	21.80
14	120	3.3	88.50	83.12	0.189	30	317460	722.00	53.90	33.20
15	120	3.3	91.15	86.42	0.442	54	244344	360.00	99.10	34.90
16	120	3.3	89.52	82.04	0.498	72	289157	214.00	154.00	33.00
17	120	3.3	89.48	81.56	0.544	79	290441	187.50	172.00	33.80
18	120	3.3	87.83	80.05	0.643	108	335925	131.00	154.00	24.20

TABLE III
Ranking of Structural Parameters for Air Permeability

		Human knowledge							Data sensitivity						Ranking	
	Input	R	VA	g_{11}^*	g_{12}^*	g_{11}	g_{12}	g_1	S_k	g_{21}^*	g_{22}^*	g_{21}	g_{22}	g_2	F_k	Rank
1	Fiber length	1	0	0.9684	0.7436	0.5905	0.5265	0.5585	0.4559	0.6716	0.6686	0.4095	0.4735	0.4415	0.2013	7
2	Fiber count	−1	0						0.5401						0.2385	6
3	Total pore volume	1	0.1721						0.4451						0.2926	5
4	Basis weight uniformity	1	0.3127						0.7233						0.4940	3
5	Thickness	−1	0.9820						0						0.5484	2
6	Basis weight	−1	0.6439						0.2202						0.4569	4
7	Fiber volume density	−1	0.4999						1						0.7207	1

TABLE IV
Ranking of Structural Parameters for Strength at Break (MD)

		Human knowledge							Data sensitivity						Ranking	
	Input	R	VA	g_{11}^*	g_{12}^*	g_{11}	g_{12}	g_1	S_k	g_{21}^*	g_{22}^*	g_{21}	g_{22}	g_2	F_k	Rank
1	Fiber length	1	0	0.7200	0.5669	0.5007	0.4076	0.4542	0.5640	0.7180	0.8238	0.4993	0.5924	0.5458	0.3078	5
2	Fiber count	1	0.1852						0.7710						0.5049	2
3	Total pore volume	−1	0.3490						0.5428						0.4548	4
4	Basis weight uniformity	1	0.4837						0.4683						0.4753	3
5	Thickness	1	0.5079						0.0921						0.2810	7
6	Basis weight	1	0.6667						0						0.3028	6
7	Fiber volume density	1	0.1249						1						0.6025	1

TABLE V
Ranking of Structural Parameters for Elongation at Break (MD)

		Human knowledge							Data sensitivity						Ranking	
	Input	R	VA	g_{11}^*	g_{12}^*	g_{11}	g_{12}	g_1	S_k	g_{21}^*	g_{22}^*	g_{21}	g_{22}	g_2	F_k	Rank
1	Fiber length	1	0.6667	1.1129	0.7010	0.6330	0.4957	0.5644	0	0.6451	0.7132	0.3670	0.5043	0.4356	0.3763	6
2	Fiber count	1	1						0.1174						0.6156	1
3	Total pore volume	−1	0.1642						0.6871						0.3920	4
4	Basis weight uniformity	1	0.2664						0.7961						0.4971	2
5	Thickness	1	0.1332						0.7110						0.3849	5
6	Basis weight	1	0.0753						0.6774						0.3376	7
7	Fiber volume density	1	0						1						0.4356	3

The ranking order for the elongation at break (MD) is shown in Table V. In this case, the weights $g_1 = 0.5644$ for VA_k and $g_2 = 0.4356$ for S_k. It can be seen from Table V that the most relevant structural parameter is the fiber count, followed by the basis weight uniformity and fiber volume density of nonwovens.

For designing the ANN model of structure–air permeability relation, the five inputs selected are the fiber volume density, thickness, basis weight uniformity, basis weight, and total pore volume of nonwovens according to the result of Table III. Table VI gives the experimental values, predicted values and errors for the air permeability. The predicted values are the average of 18 results. The average error −0.78% proves the effectiveness of the ANN model.

The five inputs selected for the strength at break (MD) are the fiber volume density, fiber count, basis weight uniformity, total pore volume, and fiber length according to the result of Table IV. Table VII gives the experimental values, predicted values and errors for the air permeability. The predicted values are the average of 18 results. The average error −0.88% confirms the validation of the ANN model.

For the elongation at break (MD) prediction, with referring to Table V the five inputs selected are the fiber count, basis weight uniformity, fiber volume density, total pore volume and thickness of nonwovens. Table VIII gives the experimental values, predicted values and errors for the elongation at break (MD). The predicted values are the average of 18 results. The average error is −0.84%, which indicates that the ANN model has a fine performance.

It can be seen from Tables VI–VIII that some of the errors between the experimental value and predicted value are a little larger (the absolute value is nearly 10%) although the average error is small (the absolute value is less than 1%). The possible reasons may be as follows.

First, the number of samples for training is quite small. It is well known that more training samples will bring smaller prediction errors. However, just as mentioned above, to make this work closely linked with industrial applications, the samples used are all collected from a nonwoven manufacturer. It is impossible to obtain many samples made from different raw materials and different technologies from a

TABLE VII
Results of ANN Model: Strength at Break (MD)

Sample no.	Experimental value (N)	Predicted value (N)	Error (%)
1	39.30	35.85	−8.78
2	51.30	55.37	7.93
3	67.60	72.04	6.57
4	69.90	66.45	−4.94
5	97.20	104.64	7.65
6	133.00	124.02	−6.75
7	27.50	24.79	−9.85
8	41.70	37.98	−8.92
9	68.70	72.19	5.08
10	91.00	98.82	8.59
11	186.00	174.71	−6.07
12	220.00	203.26	−7.61
13	27.60	30.06	8.91
14	53.90	49.77	−7.66
15	99.10	93.16	−5.99
16	154.00	168.05	9.12
17	172.00	183.26	6.55
18	154.00	139.24	−9.58
Average error			−0.88

TABLE VI
Results of ANN Model: Air Permeability

Sample no.	Experimental value ($l/m^2/s$)	Predicted value ($l/m^2/s$)	Error (%)
1	1193.89	1079.78	−9.56
2	765.28	822.62	7.49
3	668.06	608.15	−8.97
4	488.61	442.18	−9.50
5	389.71	368.42	−5.46
6	364.72	336.18	−7.83
7	1698.00	1578.36	−7.05
8	1361.00	1493.41	9.73
9	930.00	969.49	4.25
10	715.00	679.42	−4.98
11	267.00	286.56	7.33
12	258.00	242.89	−5.86
13	756.00	825.37	9.18
14	722.00	767.87	6.35
15	360.00	324.87	−9.76
16	214.00	205.51	−3.97
17	187.50	204.74	9.19
18	131.00	137.96	5.31
Average error			−0.78

TABLE VIII
Results of ANN Model: Elongation at Break (MD)

Sample no.	Experimental value (%)	Predicted value (%)	Error (%)
1	8.70	9.19	5.63
2	8.60	8.13	−5.47
3	8.80	9.22	4.77
4	10.10	9.26	−8.32
5	9.80	8.97	−8.47
6	9.40	8.53	−9.26
7	21.30	23.15	8.69
8	24.20	22.16	−8.43
9	15.10	15.99	5.89
10	18.40	16.79	−8.75
11	15.60	16.82	7.82
12	18.20	17.53	−3.68
13	21.80	20.36	−6.61
14	33.20	35.28	6.27
15	34.90	32.18	−7.79
16	33.00	35.92	8.85
17	33.80	31.85	−5.77
18	24.20	26.48	9.42
Average error			−0.84

textile mill that is in stable production. In fact, it is exactly the aim of this research to establish a soft computing based prediction model with few samples but tolerable predicting error for textile applications.

Second, the structural parameters are selected and several parameters that are not very relevant to the properties investigated are excluded from the ANN model. This will cause information loss including loss of useful information, which will produce larger prediction errors. A small number of samples require small-scaled ANN models that have few input neurons. To decrease the prediction errors, solutions are applied to the established ANN model. For example, the Bayesian framework is employed in the training procedure to avoid overfitting. By comparison, it is found that the prediction errors can be much more reduced than the conventional back-propagation algorithm.

CONCLUSIONS

A soft computing approach to model the structure–property relations of nonwoven fabrics for filtration use is developed. The structural parameters are selected by using a two-part ranking method designed to deal with nonlinear relationships between input and output variables, and no large number of data is required to run it. The models of structure–property relations of nonowovens are established by using the artificial neural network technique. The results show that the ANN model yields accurate prediction, and a reasonably good ANN model can be achieved with relatively few data points by integrated with the input variable selecting method developed in this research. The results also show that there is great potential for this research in the field of computer-assisted design in nonwoven technology.

References

1. Ericson, C. W.; Baxter, J. F. Textile Res J 1973, 43, 371.
2. Troesch J.; Hoffmann, G. Tappi 1976, 59, 133.
3. Wyatt, N. E.; Goswami, B. C. J Coated Fabrics 1984, 14, 100.
4. Wei, K. Y.; Vigo, T. L.; Goswami, B. C. J Appl Polym Sci 1985, 30, 1523.
5. Nosov, M. P.; Dzhavakhishvili, D. S. Fibre Chem 1988, 19, 423.
6. Subramaniam, V.; Madhusoothanan, M.; Debnath, C. R. Textile Res J 1988, 58, 677.
7. Pan, Y.; Wang, S. H. J Donghua Univ Eng Ed 2001, 18, 79.
8. Genis A. V. Fibre Chem 2001, 33, 33.
9. Lin, J. H.; Xu, Z. H.; Lei, C. H.; Lou, C. W. Textile Res J 2003, 73, 917.
10. Rong, H.; Bhat, G. S. J Appl Polym Sci 2004, 19, 3148.
11. Castro, J. C.; Ríos, M. C.; Mount-Campbell, C. A. Modell Simul Mater Sci Eng 2004, 12, S121.
12. Ramesh, M. C.; Rajamanickam, R.; Jayaraman, S. J Textile Inst 1995, 86, 459.
13. Zhu, R.; Ethridge, M. D. Textile Res J 1997, 67, 694.
14. Fan, J.; Hunter, L. Textile Res J 1998, 68, 763.
15. Ertugrul, S.; Ucar, N. Textile Res J 2000, 70, 845.
16. Debnath, S.; Madhusoothanan, M.; Srinivasamoorthy, V. R. Indian J Fiber Textile Res 2000, 25, 251.
17. Guba, A.; Chattopadhyay, R.; Jayadeva. J Textile Inst. 2001, 92, 139.
18. Chen, Y.; Zhao, T.; Collier, B. J. J Textile Inst 2001, 92, 157.
19. Chen, T.; Li, L. Q.; Huang, X. B. Modell Simul Mater Sci Eng 2005, 13, 575.
20. Chen, T.; Wang J.; Huang, X. B. J Appl Polym Sci 2006, 99, 424.
21. Zeng, X.; Koehl L.; Sanoun, M.; Bueno, M. A.; Renner, M. Int J Gen Syst 2004, 33, 243.
22. Zeng, X.; Koehl, L. Int J Intell Syst 2003, 18, 355.
23. Hu, Y.; He, S. Overall Evaluation Method; Science Press: Beijing, 2000.
24. Wang, Y. China Soft Sci 1998, 13, 36.
25. MacKay, D. J. C. Neural Comput 1992, 4, 415.
26. Pourdeyhimi, B.; Koehl, L. Textile Res J 2002, 72, 1065.