Predicting the Properties of Needlepunched Nonwovens Using Artificial Neural Network

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ABSTRACT: Needlepunching is a well-known nonwoven process of converting fibrous webs into self-locking or coherent structures using barbed needles. In this study, Artificial Neural Network (ANN) modeling technique has been used to predict the bulk density and tensile properties of needlepunched nonwoven structures by relating them with the main process parameters, namely, web area density, punch density, and depth of needle penetration. The simultaneous effect of more than one parameter on bulk density and tensile properties of needlepunched nonwoven structures have been investigated based upon the results of trained ANN models. A comparison is also made between the experimental and predicted values of fabric bulk density and tensile strength in the machine and crossmachine directions in unseen or test data sets. It has been inferred that the ANN models have achieved good level of generalization that is further ascertained by the acceptable level of mean absolute error obtained between predicted and experimental results. © 2009 Wiley Periodicals, Inc. J Appl Polym Sci 112: 3575–3581, 2009

Key words: artificial neural network; bulk density; modeling; needlepunched nonwoven; tensile strength

INTRODUCTION

Nonwoven structures consist of sheets or webs of randomly or directionally oriented fibers consolidated by thermal, chemical, or mechanical bonding techniques. Mechanical bonding is generally carried out by means of needlepunching or hydroentanglement (fibrous webs are bonded using high pressure water jets). Needlepunching is a well-known nonwoven process of converting fibrous webs into self-locking or coherent structures using barbed needles. The barbed needles pull the fibers from the surface of web and reorientate them in the thickness direction leading to a complex three-dimensional (3D) structure. The structural coherence of a needlepunched fabric depends upon the frictional characteristics and interaction of constituent fibers.[1–4] Hearle and Sultan[5–10] have extensively investigated the effect of fiber, web and machine parameters including type and area density of the web, amount of needling, depth of needle penetration, type of needle and number of passes on the fabric physical (mass per unit area, thickness, bulk density), and mechanical (tenacity, breaking extension, initial modulus) properties. However, the simultaneous effect of more than one parameter was not been analyzed. More recently, the effect of more than one parameter has been studied based on empirical models developed between process parameters and properties of needlepunched nonwoven structures.[11,12] These models were developed based upon statistical regression techniques but artificial neural network (ANN) techniques are useful in handling the noisy data and modeling nonlinear problems along with the small number of experiments.[13] Our literature review reveals that only a few articles have been published in the scientific literature which focuses on the modeling of nonwoven processes and structures by ANN technique.[13–17]

Therefore, the objective of the study is to predict the bulk density and tensile properties of needlepunched nonwoven structure from main process parameters including web area density, depth of needle penetration, and punch density by using ANN modeling technique. The ANN models of needlepunched nonwoven properties have also been tested under a given set of process parameters.

EXPERIMENTAL

Previous work[12] has described the production of needlepunched nonwoven structures, where preneedled cross-laid webs were produced using

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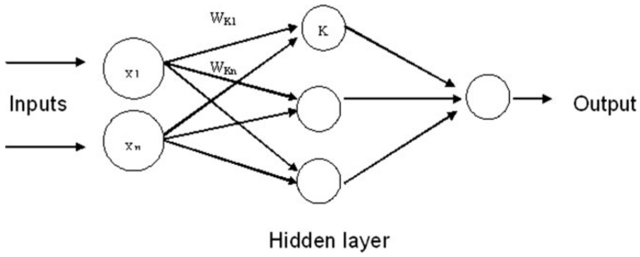

Figure 1 An example of single output neural network model.

polypropylene fibers (10 dtex and 100 mm) at the collaborating company, i.e., Geofabrics (Liversedge, UK). Twenty-seven samples were produced using statistical design consisting of three design factors namely web area density (WAD), punch density (PD), and depth of needle penetration (NP) at three levels. Subsequently, the standard tests were performed on the needlepunched nonwoven structures to determine fabric area density (EN 965, 1995; EN stands for EUROPAISCHE NORM), thickness (EN 964-1, 1995) and tensile strengths in the machine and crossmachine directions (EN-ISO 10319, 1996).

Artificial neural network modeling

ANN, a branch of artificial intelligence, is a very potent modeling and classification tool that can emulate the functioning of biological neurons. ANN model, when trained properly, can precisely map the existing functional relationship between inputs and outputs using experimental data. In ANN, one or more hidden layers are positioned between one input layer and one output layer. Each layer is composed of a number of nodes or processing elements which perform all the mathematical computations. Each node receives a signal from the nodes of the previous layer and each of these signals is multiplied by a separate weight known as synaptic weight, as shown in Figure 1. The weighted inputs are then summed up and passed through a transfer function, usually a sigmoid, which converts the output to a fixed range of values. The output of the transfer function is then transmitted to the nodes of next layer. Finally, the output is produced at the nodes of the output layer. Optimum training of ANN is of utmost importance to obtain good prediction performances from the developed model. Backpropagation, a supervised learning algorithm, is the most popular algorithm amongst the existing ANN training algorithms. According to this algorithm, training occurs in two phases, namely forward pass and backward pass. In the forward pass, a set of experimental data is presented to the network as an input and a set of outputs is produced and the error vector is calculated according to the following equation.

$$E = \sum_{j=1}^{P} E_j \tag{1}$$

where $E_j = 1/2 \sum_{k=1}^{S} (T_k - O_k)^2$.

E is the error vector, E_j is the error associated with the jth pattern and P is the total number of training patterns, T_k and O_k are the target output and predicted outputs at output node k and S is the total number of output nodes.

In the backward pass, the error signal is propagated backwards to the network and the synaptic weights are adjusted in such a manner that the error signal decreases in each iteration process. The corrections necessary in the synaptic weights between output and hidden layers are carried out by a delta rule,[14] as shown below.

$$\begin{aligned}\Delta W_{jk} &= -\eta\left[\partial E/\partial W_{jk}\right] \\ &= \eta[(T_k - O_k)O_k(1 - O_k)]O_j = \eta\delta_k O_j\end{aligned} \tag{2}$$

where W_{jk} is the weight connecting the neurons j of hidden layer and neuron k of the output layer, ΔW_{jk} is the correction applied to W_{jk} at a particular iteration, η is the learning rate and O_j is the output of neuron j.

Optimization of ANN parameters

Construction of a proper network structure and optimization of learning parameters largely influence the prediction performance of ANN model. The important structural parameters to be determined are the number of hidden layers and the number of nodes in each hidden layer. Only one hidden layer was used in this investigation, as it is capable of handling most of the situations. Transfer function[14] in the hidden and output layers was log-sigmoid as shown below.

$$f(Z) = \frac{1}{(1 + e^{-Z})} \tag{3}$$

where, Z is the weighted sum of inputs to a neuron and *f(Z)* is the transformed output from that neuron.

In this work, the fabric bulk density and tensile strengths in the machine direction and crossmachine direction were modeled by using web area density, punch density, and depth of needle penetration as inputs. Two different ANN models were developed, one for predicting fabric bulk density and another for predicting the tensile strength in the machine and crossmachine directions. The fundamental difference between the two models is that the number of nodes in the outer layer is one and two for

TABLE I
Properties of Needlepunched Nonwoven Structures

	Parameters			Property				
Sample ID	WAD	NP	PD	FAD	FBT	FBD	TMD	TXMD
NP1	400	08	150	523	6.48	80.71	22.66	55.41
NP2	400	10	150	502	5.43	92.45	25.20	50.08
NP3	400	12	150	526	4.58	114.85	24.50	56.26
NP4	400	08	225	540	6.12	88.24	26.65	50.76
NP5	400	10	225	535	4.79	111.69	29.82	50.07
NP6	400	12	225	561	4.00	140.25	29.61	50.90
NP7	400	08	375	480	5.38	89.22	24.51	39.87
NP8	400	10	375	568	4.22	134.60	30.09	43.58
NP9	400	12	375	605	4.17	145.08	40.04	54.10
NP10	800	08	150	1056	11.15	94.71	43.75	81.67
NP11	800	10	150	1085	8.55	126.90	46.98	95.49
NP12	800	12	150	1030	6.96	147.99	56.07	107.58
NP13	800	08	225	1198	9.24	129.65	57.97	81.23
NP14	800	10	225	1215	7.70	157.79	55.61	98.11
NP15	800	12	225	1289	6.68	192.96	65.83	97.22
NP16	800	08	375	1158	8.36	138.52	42.65	60.01
NP17	800	10	375	1145	6.26	182.91	58.10	75.39
NP18	800	12	375	1285	6.21	206.92	55.22	78.90
NP19	1200	08	150	1446	11.33	127.63	67.05	100.28
NP20	1200	10	150	1677	10.71	156.58	81.39	144.64
NP21	1200	12	150	1739	9.74	178.54	76.37	148.57
NP22	1200	08	225	1768	11.16	158.42	68.59	90.25
NP23	1200	10	225	1875	9.95	188.44	88.22	126.53
NP24	1200	12	225	1884	9.22	204.34	79.43	145.82
NP25	1200	08	375	1772	10.22	173.39	45.22	59.73
NP26	1200	10	375	1869	8.30	225.18	67.11	92.16
NP27	1200	12	375	1895	7.58	250.00	74.68	123.52

According to the experimental design, the middle value of punch density should correspond to 262.5 cm^{-2}. However, we have encountered problems in producing the fabrics experimentally on the needlepunching line. Therefore, the nearest value of punch density was found to be 225 cm^{-2}. In addition, these values were matched with the industrial data sets.

WAD, Web area density ($g\ m^{-2}$); NP, Depth of needle penetration (mm); PD, Punch density (cm^{-2}); FAD, Fabric area density ($g\ m^{-2}$); FBT, Fabric thickness (mm); FBD, Fabric bulk density ($kg\ m^{-3}$); TMD, Tensile strength in machine direction ($kN\ m^{-1}$); TXMD, Tensile strength in cross machine direction ($kN\ m^{-1}$).

predicting the fabric bulk density and tensile strengths, respectively. Training of ANN was done using standard back-propagation algorithm using Easy NN plus software (Version 1.08). The number of nodes in the hidden layer and learning parameters, i.e., learning rate and momentum was optimized at 8, 0.6, and 0.8, respectively. Training was ceased when the error in the unseen or testing data sets approached at the minimum level. Out of 27 available data sets, 21 sets were randomly chosen for the training of ANN and remaining six sets were used for the testing purpose.

RESULTS AND DISCUSSION

Table I shows the bulk density and tensile properties of needlepunched nonwoven structures produced, tested, and fully analyzed using the experimental matrix.

TABLE II
Prediction and Performance of ANN Models

	Bulk density		TMD		TXMD	
Statistical parameter	Training	Testing	Training	Testing	Training	Testing
Coefficient of correlation (*R*)	0.986	0.907	0.997	0.986	0.997	0.982
Mean absolute error (%)	5.40	6.70	3.17	9.21	3.69	6.71

TABLE III
Comparison Between Tested and Predicted Properties of Needlepunched Nonwoven Structures

Sample ID	Bulk density ($kg\ m^{-3}$)			TXMD ($kN\ m^{-1}$)			TMD ($kN\ m^{-1}$)		
	Measured	Predicted	Absolute error (%)	Measured	Predicted	Absolute error (%)	Measured	Predicted	Absolute error (%)
NP6	140.25	125.70	10.37	50.90	53.61	5.32	29.61	30.94	4.49
NP9	145.08	165.11	13.81	54.10	50.82	6.06	40.04	34.07	14.91
NP15	192.96	177.85	7.83	97.22	90.07	7.35	65.83	57.3	12.96
NP17	182.90	178.96	2.15	75.39	82.98	10.07	58.10	55.64	4.23
NP23	188.44	190.76	1.23	126.53	133.5	5.51	88.22	76.3	13.51
NP26	225.18	214.34	4.81	92.16	97.66	5.97	67.11	63.64	5.17

Evaluation and validation of ANN model

In this study, 27 samples were produced out of which 21 data sets were randomly chosen for training the ANN model and remaining six sets (sample ID: NP6, NP9, NP15, NP17, NP23, NP26) were used for the validating or testing the model. Table II shows the summary of prediction performance of ANN models in training and testing data sets. Correlation coefficients between the experimental and predicted values are found to be excellent except in the case of testing data set of bulk density. Therefore, it has been inferred that the ANN models have achieved good level of generalization. This has been further ascertained by the acceptable level of mean absolute error obtained between experimental and predicted results, even in the testing or unseen data sets. Furthermore, the experimental and predicted values for testing data sets are reasonably close, as shown in Table III. The differences between the two sets of results are mainly due to a fewer number of samples used for training the ANN model. However, training of ANN with comparatively larger data set can lead to better generalization of the model and therefore can enhance the prediction accuracy.

Relationship between process parameters and bulk density of needlepunched nonwoven structures

In the past, it has been demonstrated that the process parameters including amount of needling and depth of needle penetration have a significant effect on fabric area density and thickness.[6,18] Furthermore, we have also reported the simultaneous effect of more than one parameter on dimensional properties of needlepunched nonwoven structures.[12] However, it is interesting to analyze the effect of process parameters on the fabric bulk density which is a function of fabric mass per unit area and thickness. Nevertheless, to evaluate the combined effect of two process parameters on the dependent variable, one variable was kept constant at its middle value. The other two variables were then changed in steps from their respective minimum to maximum values and concomitant change in the dependent variable was noted. For example, while evaluating the effect of web area density (WAD) and depth of needle penetration (NP) on fabric bulk density (FBD), the third independent variable punch density (PD) was kept constant at 263 punches/cm^2. The WAD and NP were then changed in steps from 400 to 1200 g m^{-2} and from 8 to 12 mm, respectively. The corresponding change in the FBD was noted for each combination of WAD and NP and surface plot was created using MATLAB®.

Figure 2 shows the relationship between web area density (WAD) and depth of needle penetration (NP) on the fabric bulk density (FBD). It is expected that an increase in web area density effectively increases the number of fibers in a given volume and hence, fabric bulk density would increase accordingly. Increase in depth of needle penetration also increases the fabric density as more number of barbs are in contact with the surface fibers therefore, the number of fibers transferred from the surface to the thickness direction increases in addition to an increase in the transferred fiber length leading to a consolidated structure.[19] It is also observed that an increase in depth of needle penetration has

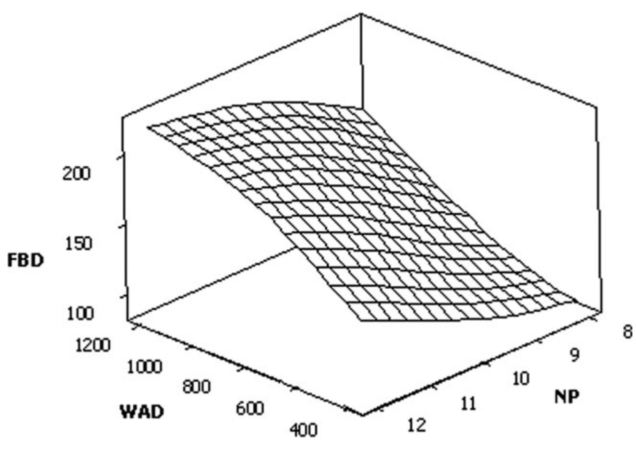

Figure 2 Effect of web area density (g m^{-2}) and depth of needle penetration (mm) on fabric bulk density (kg m^{-3}) at a punch density of 262.5 cm^{-2}.

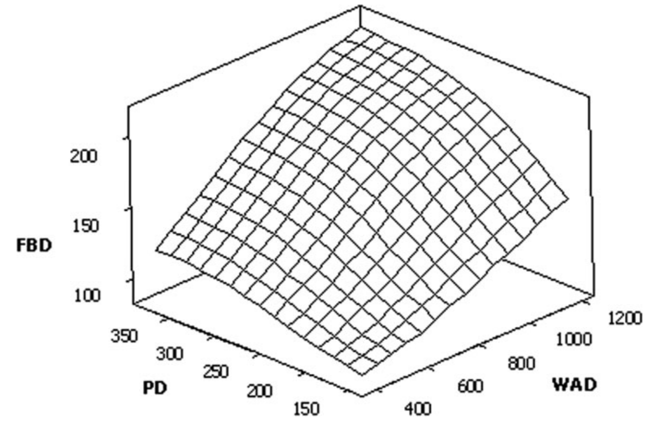

Figure 3 Effect of web area density (g m^{-2}) and punch density (cm^{-2}) on fabric bulk density (kg m^{-3}) at a depth of needle penetration of 10 mm.

pronounced effect on fabric densities specifically at lower web area densities. Since, the fabric thickness decreases by increasing depth of needle penetration at lower web area densities.[12] Similar effects can be seen for punch density, i.e., amount of needling and web area density on fabric density, as shown in Figure 3. An increase in the punch density would increase the number of fibers in the thickness direction and yields higher resistance to drafting and spreading leading to an improved coherence in the structure. It has been found that fabric bulk density increases sharply at higher web area and punch densities. Higher punch density increases the fiber transfer from the surface to the thickness direction but its fiber transfer efficiency decreases as fewer fibers are transported in subsequent needling action due to the consolidation of structure during initial needling.[19] Therefore, higher punch density is relatively more effective in consolidating the higher web area density leading to sharp increase in fabric density. In general, an increase in punch density and/or depth

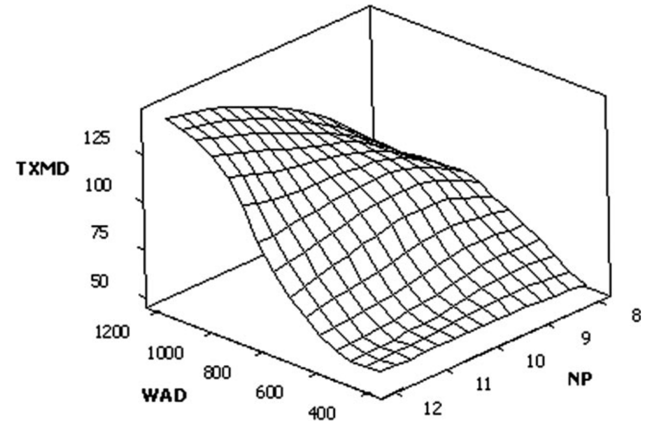

Figure 5 Effect of web area density (g m^{-2}) and depth of needle penetration (mm) on tensile strength in the crossmachine direction (kN m^{-1}) at a punch density of 262.5 cm^{-2}.

of needle penetration increases fabric bulk density as illustrated in Figure 4.

Relationship between process parameters and tensile properties of needlepunched nonwoven structures

In the past, the tensile properties of the needlepunched nonwoven structures have been related to the fabric dimensional properties and process parameters including depth of needle penetrations, number of barbs, etc.[6,10] The tensile properties of needlepunched structures are primarily dictated by the fibers oriented in *X*-*Y* plane and also controlled by the fibers in *Z* or thickness direction but the ratio of fibers in the *Z*-direction is a small fraction of the total number of fibers.[20] In this study, the fibers are predominantly oriented in the crossmachine direction during the production of needlepunched structures and therefore, it is expected that the tensile

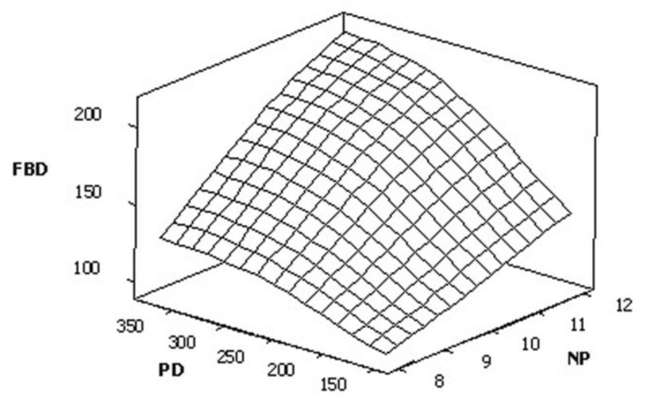

Figure 4 Effect of punch density (cm^{-2}) and depth of needle penetration (mm) on fabric bulk density (kg m^{-3}) at a web area density of 800 g m^{-2}.

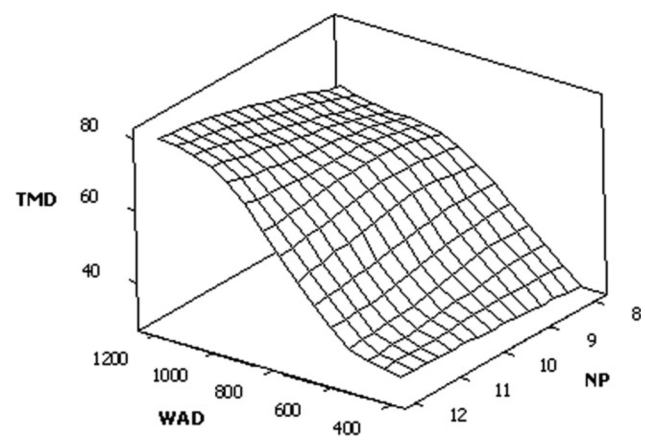

Figure 6 Effect of web area density (g m^{-2}) and depth of needle penetration (mm) on tensile strength in the machine direction (kN m^{-1}) at a punch density of 262.5 cm^{-2}.

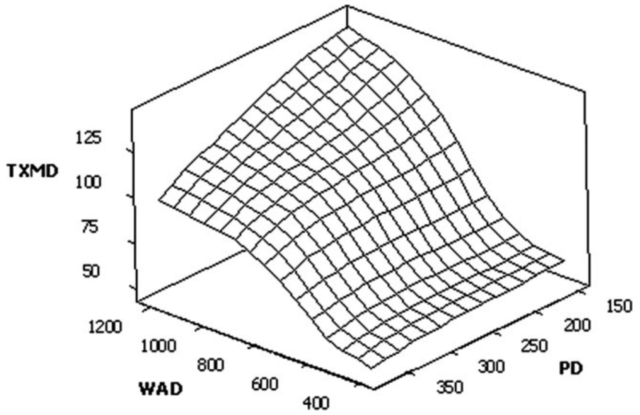

Figure 7 Effect of web area density (g m^{-2}) and punch density (cm^{-2}) on tensile strength in the crossmachine direction (kN m^{-1}) at a depth of needle penetration of 10 mm.

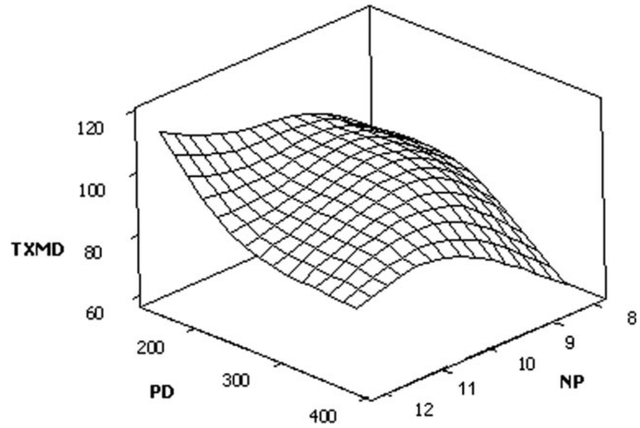

Figure 9 Effect of punch density (cm^{-2}) and depth of needle penetration (mm) on the tensile strength in the crossmachine direction at a web area density of 800 g m^{-2}.

strength is correspondingly higher in the crossmachine direction.

Figure 5 shows the combined effect of web area density and depth of needle penetration on tensile strength in the crossmachine direction. In general, the tensile strength increases with the web area density and depth of needle penetration but it decreases at higher web area density and lower depth of needle penetration. Since, the fibers are not effectively entangled as the distance traveled by the barb may not have been sufficient to form a loop at the bottom surface of the fabric. This results in poor locking of fibers in *X-Y* plane by the fibers present in the *Z*-direction. In addition, some of the fibers are reorientated in the machine direction at higher depth of needle penetration.[11] Figure 6 illustrates the relationship between the tensile strength in the machine direction, web area density and depth of needle penetration. It can be seen that tensile strength in the machine direction increases with web area density but becomes constant at lower depth of needle penetration due to loosely held fibers in the *Z*-direction. On the other hand, the tensile strengths in the machine and crossmachine directions decrease at higher punch densities. This is attributed to the fact that the significant amount of fiber damage occurs at higher punch densities and its fiber transfer efficiency from surface to the thickness or *z*-direction is also reduced. Figures 7 and 8 show the combined effect of web area density and punch density on tensile strengths in crossmachine and machine directions, respectively. To optimize the process parameters for a given web area density, it was found that maximum tensile strength in the crossmachine direction can be achieved at higher depth of needle penetration (10–12 mm) and lower punch density (specifically lower than 200 cm^{-2}). Since, the effective degree of fiber entanglement can take place at higher depth of needle penetration along with the minimum fiber damage or breakage at lower punch density. Figure 9 shows the combined effect of

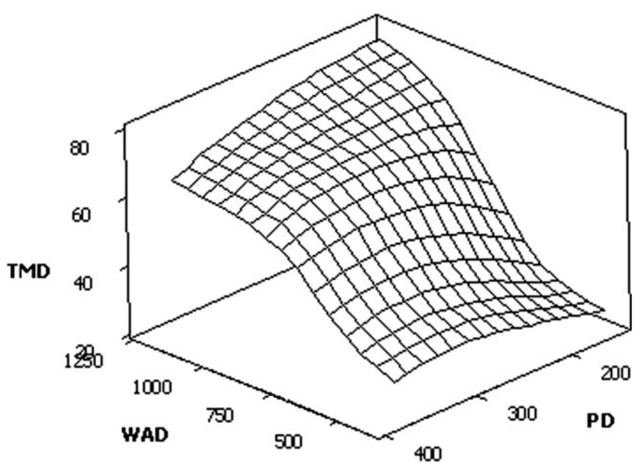

Figure 8 Effect of web area density (g m^{-2}) and punch density (cm^{-2}) on tensile strength in the machine direction (kN m^{-1}) at a depth of needle penetration of 10 mm.

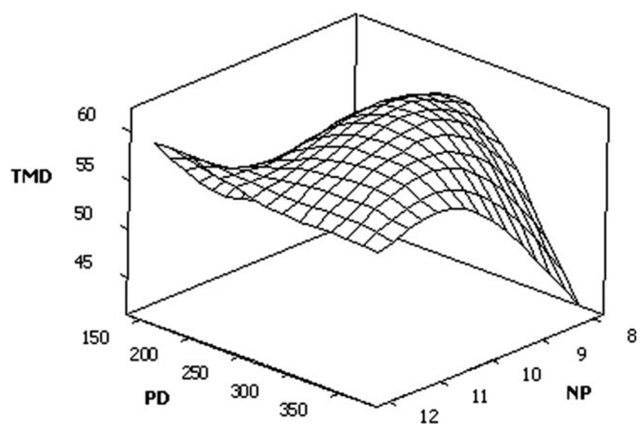

Figure 10 Effect of punch density (cm^{-2}) and depth of needle penetration (mm) on the tensile strength in the machine direction at a web area density of 800 g m^{-2}.

punch density and depth of needle penetration on the tensile strength in the crossmachine direction. However, maximum tensile strength in the machine direction is obtained at medium to higher depth of needle penetration at a given punch density. This is caused by the change in the preferred orientation of fibers from crossmachine to machine direction at a higher depth of needle penetration.[11] Figure 10 shows the combined effect of punch density and depth of needle penetration on the tensile strength in the machine direction.

CONCLUSIONS

Artificial neural network modeling technique has been employed for predicting the bulk density and tensile properties of needlepunched nonwoven structures. These properties have been related to the process parameters including web area density, punch density and depth of needle penetration. The correlation coefficients between the experimental and predicted values of fabric bulk density and tensile properties obtained from ANN models are found to be good although limited number of samples were used for training purposes. The effect of more than one parameter has been studied on bulk density and tensile properties of needlepunched nonwoven structures. It was shown that fabric bulk density increases sharply at higher web area and punch densities. Similarly, an increase in the depth of needle penetration increases the fabric bulk density as a higher number of fibers are transferred from surface to the thickness direction leading to more effective entanglements between the fibers. Furthermore, the tensile properties are highly dependent upon the degree of entanglement between the fibers as it was found that a higher web area density and a lower depth of needle penetration decrease the tensile strength specifically in the machine direction. However, the tensile properties are reduced at higher punch densities due to poor fiber transfer efficiency at successive needling actions. For a given web area density, maximum tensile strength in the crossmachine direction can be achieved at higher depth of needle penetration (10–12 mm) and lower punch density (specifically lower than 200 cm^{-2}). Similarly, the tensile strength in the machine direction is found to be maximum in medium to higher depth of needle penetrations with given web area density and punch density.

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