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Modelling of Needle-Punched Nonwoven Fabric Properties Using Artificial Neural Network

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1. Introduction

Needle-punched nonwoven is an industrial fabric used in wide range of applications areas. The physical structure of needle-punched nonwoven is very complex in nature and therefore engineering the fabric according the required properties is difficult. Because of this, the basic mathematical modeling is not very successful for predicting various important properties of the fabrics.

In recent days, artificial neural networks (ANN) have shown a great assurance for modeling non-linear processes. Rajamanickam et al., 1997 and Ramesh et al., 1995 used ANN to model the tensile properties of air jet yarn. The ANN model had also been used to model to assess the set marks and also the relaxation curve of yarn after dynamic loading (Vangheluwe et al., 1993 and 1996). Luo & David, 1995 used the HVI experimental test results to train the neural nets and predict the yarn strength. Researchers also made an attempt to build models for predicting ring or rotor yarn hairiness using a back propagation ANN model by Zhu & Ethridge, 1997. Fan & Hunter, 1998 developed ANN for predicting the fabric properties based on fibre, yarn and fabric constructional parameters and suggested the suitable computer programming for development of neural network model using back-propagation simulator. Wen et al., 1998 used back-propagation neural network model for classification of textile faults. Postle, 1997 enlighten on measurement and fabric categorisation and quality evaluation by neural networks. Park et al., 2000 also enlightened the use of fuzzy logic and neural network method for hand evaluation of outerwear knitted fabrics. Gong & Chen, 1999 found that the use of neural network is very effective for predicting problems in clothing manufacturing. Xu et al., 1999 used three clustering analysis technique viz. sum of squares, fuzzy and neural network for cotton trash classification. They found neural network clustering yields the highest accuracy, but it needs more computational time for network training. Vangheluwe et al., 1993 found Neural nets showed good results assessing the visibility set marks in fabrics. The review of literature shows that the ANN model is a powerful and accurate tool for predicting a nonlinear relationship between input and output variables.

Jute, polypropylene, jute-polypropylene blended and polyester needle punched nonwoven fabrics have been prepared using series of textile machinery normally used in needle-punching process for preparation of the fabric samples. Textile materials are compressive in nature. It has been reported by various authors that the effect of compression behaviour of jute-polypropylene (Debnath & Madhusoothanan, 2007) and polyester (Midha et al., 2004) is largely influenced by fibre linear density, blend ratios of fibres, fabric weight, web laying type, needling density and depth of needle penetration. Kothari & Das, 1992 and 1993 explained that the compression behaviour of needle-punched nonwoven fabrics is dependent on fibre fineness, proportion of finer fibre present in different layers of nonwoven fabrics, and fabric weight for polyester and polypropylene fibres. In the present study, some of these important factors, viz. fabric weight, blend proportion, three different types of fibres and needling density, have been taken into consideration for modeling of the compression behaviour. Jute, polypropylene and polyester fibres have been used in this study. Woollenisation of jute has been done to develop crimp in the fibre. This study also elaborates the effect of number of hidden layers and simulation cycles for jute-polypropylene blended and polyester needle-punched nonwoven fabrics. Different fabric properties like fabric weight, needling density, blend composition of the fibres are the basic variables selected as input variables. The output variables are selected as air permeability, tensile, and compression properties.

Under tensile properties, tenacity and initial modulus of jute-polypropylene blended needle punched nonwoven fabric both in machine (lengthwise) and transverse (width wise) directions have been predicted accurately using artificial neural network. Empirical models have also been developed for the tensile properties and found that artificial neural network models are more accurate than empirical models. Prediction of tensile properties by ANN model shows considerably lower error than empirical model when the inputs are beyond the range of inputs, which were used for developing the model. Thus the prediction by artificial neural network model shows better results than that by empirical model even for the extrapolated input variables.

The jute-polypropylene blended needle-punched nonwoven fabric samples were produced as per a statistical factorial design for prediction of air permeability. The efficiency of prediction of two models has been experimentally verified wherein some of the input variables were beyond the range over which the models were developed. The predicted air permeability values from both the models have been compared statistically. An attempt has also been made to study the effect of number of hidden layer in neural network model. The highest correlation has been found in artificial neural network with three hidden layers. The neural network model with three hidden layer shows less prediction error followed by two hidden layers, empirical model and artificial neural network with one hidden layer. Artificial neural network model with three hidden layers predicts the value of air permeability with minimum error when inputs are beyond the range of inputs used for developing the model.

Initial thickness, percentage compression, thickness loss and percentage compression resilience are the compression properties predicted using artificial neural network model of needle-punched nonwoven fabrics produced from polyester and jute-polypropylene blended fibres varying fabric weight, needling density, blend ratio of jute and polypropylene, and polyester fibre. A very good correlation (R^2 values) with minimum error between the experimental and the predicted values of compression properties have been obtained by artificial neural network model with two and three hidden layers. An attempt has also been made for experimental verification of the predicted values for the input variables not used during the training phase. The prediction of compression properties by artificial neural network model in some particular sample is less accurate due to lack of learning during training phase. The three hidden layered artificial neural network models take more time for computation during training phase but the predicted results are more accurate with less variations in the absolute error in the verification phase. This study will be useful to the industry for designing the needle-punched nonwoven fabric made out of jute-polypropylene blended or polyester fibres for desired fabric properties. The cost for design and development of desired needle-punched fabric property of the said nonwovens can also be minimised.

2. Materials and methods

2.1 Materials

Polypropylene fibre of 0.44 tex fineness, 80 mm length; jute fibres of Tossa-4 grade and polyester fibre of 51 mm length and 0.33 tex fineness fibre of were used to prepare the fabric samples. Some important properties of fibres are presented in Table 1. Sodium hydroxide and acetic acid were used for woollenisation of the jute.

Property	Jute	Polypropylene	Polyester
Fibre fineness (tex)	2.08	0.44	0.33
Density (g/cm^3)	1.45	0.91	1.38
Tensile strength (cN/tex)	30.1	34.5	34.83
Breaking elongation (%)	1.55	54.13	51.00
Moisture regain (%) at 65% RH	12.5	0.05	0.40

Table 1. Properties of jute, polypropylene and polyester fibres

2.2 Methods

2.2.1 Preparation of jute, jute-polypropylene blended and polyester fabrics

The raw jute fibres do not produce good quality fabric because there is no crimp in these fibres. To develop crimp before the fabric production, the jute fibres were treated with 18% (w/v) sodium hydroxide solution at 30°C using the liquor-to-material ratio of 10:1, as suggested by Sao & Jain, 1995. After 45 min of soaking, the jute fibres were taken out, washed thoroughly in running water and treated with 1% acetic acid. The treated fibres were washed again and then dried in air for 24 h. This process apart from introducing about 2 crimps/cm also results in weight loss of ~ 9.5%.

The jute reeds were opened in a roller and clearer card, which produces almost mesh-free stapled fibre. The woollenised jute and polypropylene fibres were opened by hand separately and blended in different blend proportions (Table 2). The blended materials were thoroughly opened by passing through one carding passage.

The blended fibres were fed to the lattice of the roller and clearer card at a uniform and predetermined rate so that a web of 50 g/m^2 can be achieved. The fibrous web coming out from the card was fed to feed lattice of cross-lapper and cross-laid webs were produced with cross-lapping angle of 20°. The web was then fed to the needling zone. The required needling density was obtained by adjusting the throughput speed.

Different web combinations, as per fabric weight (g/m^2) requirements were passed through the needling zone of the machine for a number of times depending upon the punch density required. A punch density of 50 punches/cm^2 was given on each passage of the web, changing the web face alternatively. The fabric samples were produced as per the variables presented in Table 2.

Fabric code	Fabric weight g/m²	Needling density punches/cm²	Woollenised jute %	Polypropylene fibre %	Polyester fibre %
1	250	150	40	60	-
2	250	350	40	60	-
3	450	150	40	60	-
4	450	350	40	60	-
5	250	250	60	40	-
6	250	250	20	80	-
7	450	250	60	40	-
8	450	250	20	80	-
9	350	150	60	40	-
10	350	150	20	80	-
11	350	350	60	40	-
12	350	350	20	80	-
13	350	250	40	60	-
14	350	250	40	60	-
15	350	250	40	60	-
16	393	150	0	100	-
17	440	150	0	100	-
18	410	250	0	100	-
19	392	350	0	100	-
20	241	150	100	0	-
21	310	250	100	0	-
22	303	350	100	0	-
23	300	150	80	20	-
24	276	250	80	20	-
25	205	350	80	20	-
26	415	300	-	-	100
27	515	300	-	-	100
28	680	300	-	-	100
29	815	300	-	-	100

Table 2. Experimental design of fabric samples

The polyester fabric samples were made from parallel-laid webs, which were obtained by feeding opened fibres in the TAIRO laboratory model with stationary flat card (2009a). The fine web emerging out from the card was built up into several layers in order to obtain desired level of fabric weight (Table 2). The needle punching of all parallel-laid polyester fabric samples was carried out in James Hunter Laboratory Fiber Locker [Model 26 (315 mm)] having a stroke frequency of 170 strokes/min. The machine speed and needling density were selected in such a way that in a single passage 50 punches/cm² of needling density could be obtained on the fabric. The web was passed through the machine for a number of times depending upon the needling density required, e.g. the web was passed 6 times through the machine to obtain fabric with 300 punches/cm². The needling was done alternatively on each side of the polyester fabric.

The needle dimension of 15 × 18 × 36 × R/SP 3½ × ¼ × 9 was used for all jute-polypropylene, jute and polyester samples. The depth of needle penetration was also kept constant at 11 mm in all the cases.
The actual fabric weights of the final needle-punched fabric samples were measured considering the average weight of randomly cut 1 m^2 sample at 5 different places from each sample.

2.2.2 Measurement of tenacity and initial modulus

The mechanical properties like tenacity and initial modulus were measured both in the machine and transverse directions (Debnath et al., 2000a) of the fabric using an Instron tensile tester (Model 4301). The size of sample and the rate of straining were chosen according to ATSM standard D1117-80 (sample size 7.6 cm x 2.5 cm, cross head transverse speed 300 mm/min). Breaking load verses elongation curves were plotted for all the tests. The tenacity was calculated by normalising the breaking load by fabric weight and width of the specimen as suggested by Hearle & Sultan, 1967. The initial modulus was calculated from the load elongation curves.

2.2.3 Measurement of air permeability

The air permeability measurements were done using the Shirley (SDL-21) air permeability tester (Debnath & Madhusoothanan, 2010b). The test area was 5.07 cm^2. The pressure range = 0.25 mm and flow range = 0.04 – 350 cc/sec. The airflow in cubic cm at 10 mm water head pressure was measured. The air permeability of fabric samples was calculated using the formula (1) given below (Sengupta et al., 1985 and Debnath et al., 2006).

$$AP = \frac{AF}{TA} \times 10^{-2} \tag{1}$$

Where, AP = air permeability of fabric in $m^3/m^2/sec$, AF = air flow through fabric in cm^3/sec at 10 mm water head pressure and TA = test specimen area in cm^2 for each sample.

2.2.4 Measurement of compression properties

The initial thickness (Debnath & Madhusoothanan, 2010a), compression, thickness loss and compression resilience were calculated from the compression and decompression curves. For measuring these properties, a thickness tester was used (Subramaniam et al., 1990). The pressure foot area was 5.067 cm^2 (diameter = ϕ2.54 cm). The dial gauge with a least count of 0.01 mm and maximum displacement of 10.5 mm was attached to the thickness tester. The compression properties were studied under a pressure range between 1.55 kPa and 51.89 kPa.
The initial thickness of the needle-punched fabrics was observed under the pressure of 1.55 kPa (Debnath & Madhusoothanan, 2007). The corresponding thickness values were observed from the dial gauge for each corresponding load of 1.962 N. A delay of 30 s was given between the previous and next load applied. Similarly, 30 s delay was also allowed during decompression cycle at every individual load of 1.962 N. This compression and recovery thickness values for corresponding pressure values are used to plot the compression-recovery curves.
The percentage compression (Debnath & Madhusoothanan, 2007), percentage thickness loss (Debnath & Madhusoothanan, 2009a and Debnath & Roy, 1999) and percentage

compression resilience (Debnath & Madhusoothanan, 2007, 2009a and 2009b), were estimated using the following relationships (2,3,4):

$$\text{Compression (\%)} = \frac{T_0 - T_1}{T_0} \times 100 \tag{2}$$

$$\text{Thickness loss (\%)} = \frac{T_0 - T_2}{T_0} \times 100 \tag{3}$$

$$\text{Compression resilience (\%)} = \frac{W_c'}{W_c} \times 100 \tag{4}$$

where T_0 is the initial thickness; T_1, the thickness at maximum pressure; T_2, the recovered thickness; W_c, the work done during compression; and W_c', the work done during recovery process.

The average of ten readings from different places for each sample was considered. The coefficient of variation was less than 6% in all the cases.

All these tests were carried out in the standard atmospheric condition of 65 ± 2% RH and 20 ± 2°C. The fabrics were conditioned for 24 h in the above mentioned atmospheric conditions before testing.

2.2.5 Empirical model

An empirical equation of second order polynomial (Box & Behnken, 1960) was derived to predict the mechanical properties (Debnath et al. 2000a) like tenacity and initial modulus, and physical property like air permeability (Debnath et al. 2000a) were predicted from the results obtained from the samples produced using Box and Behnken factorial design.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3 \tag{5}$$

Where, Y = predicted fabric property (tenacity or initial modulus or air permeability), X_1 = fabric weight, X_2 = needling density, X_3 = percentage of polypropylene, β_0 is the constant and β_i is the coefficient of the variable X_i. The predicted values of fabric properties were then compared with the actual values and error (6) was calculated.

$$E\ (\%) = \frac{A - P}{A} \times 100 \tag{6}$$

Where, E is error in percentage, A is the actual experimental values and P is the predicted values from models.

2.2.6 Artificial neural network model

The physiology of neurons present in biological neural system such as human nervous system was the fundamental idea behind developing the ANNs. This computational model was trained to capture nonlinear relationship between input and output variables with scientific and mathematical basis. In recent days, commonly used model is layered feed-forward neural network with multi layer perceptions and back propagation learning algorithms (Vangheluwe et al., 1993, Rajamanickam et al., 1997, Zhu & Ethridge, 1997 and Wen et al., 1998).

The ANNs are computing systems composed of a number of highly interconnected layers of simple neuron like processing elements, which process information by their dynamic response to external inputs. The information passed through the complete network by linear connection with linear or nonlinear transformations. The weights were determined by training the neural nets. Once the ANN was trained, it was used for predicting new sets of inputs. Multi layer feed-forward neural network architecture (Figure 1) was used for predicting the tenacity, initial modulus, air permeability, initial thickness, percentage compression, thickness loss and compression resilience properties of fabrics (Debnath et al., 2000a, 2000b and Debnath & Madhusoothanan, 2008). The circle in Figure 3.5 represents the neurons arranged in five layers as one input, one output and three hidden layers. Three neurons in the input layer, three hidden layers, each layer consisting of three neurons and one neuron in the output layer. HL-1, HL-2 and HL-3 are 1st, 2nd and 3rd hidden layers respectively, whereas i and j are two different neurons in two different layers. The neuron (i) in one layer was connected with the neuron (j) in next layer with weights (W_{ij}) as presented in the Figure 1.

The data were scaled down between 0 and 1 by normalizing them with their respective values. The ANN was trained with known sets of input-output data pairs.

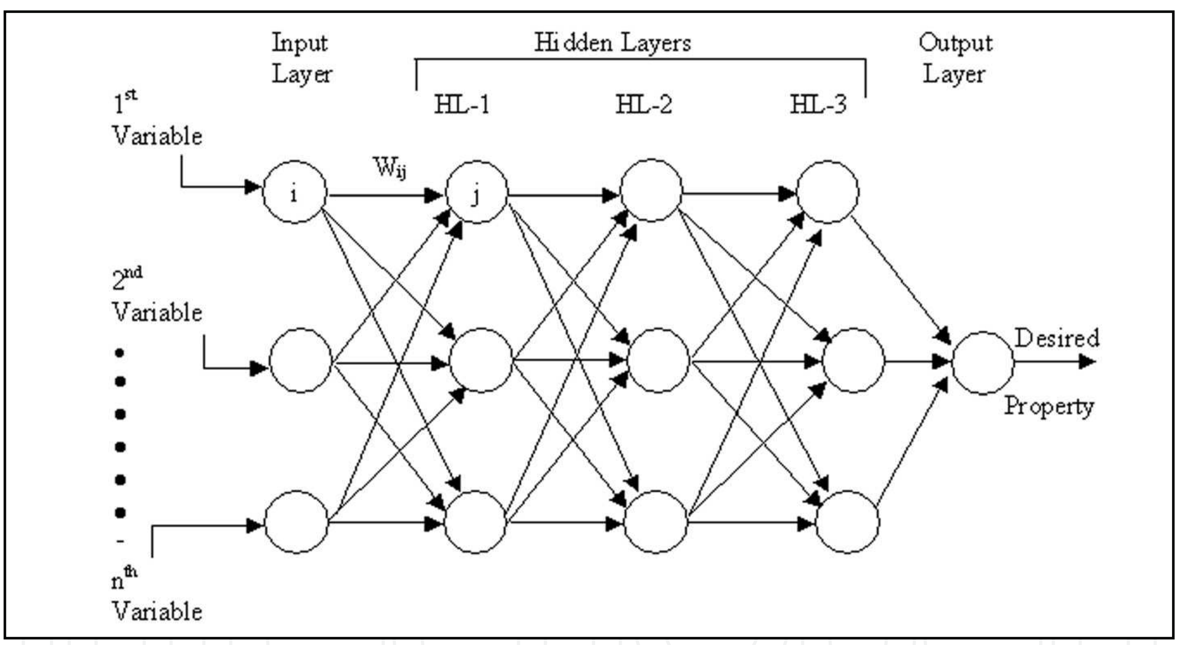

Fig. 1. Neural architecture of the fabric property

3. Results and discussion

3.1 Modelling of tenacity and initial modulus

The empirical and ANN models for tensile properties have been developed from the experimental values (Debnath et al., 2000a) of fifteen sets of selected fabric samples as shown in Table 3.

The constants and coefficients of the empirical model for the fifteen fabric sample sets (Table 3) were calculated with the help of multiple regression analysis, are given in Table 4.

The ANN was trained up to 64,000 cycles to obtain optimum weights for the same sample sets used to develop emperical model (Table 3). The weights of ANN for tenacity and initial

modulus on both machine and transverse direction were presented in Table 5. Tables 6 and 7 show the experimental, predicted values and their prediction error for tenacity and initial modulus respectively.
The Table 6 shows a very good correlation (R^2 values) between the experimental and predicted tenacity values by ANN than by empirical model in both the machine and transverse directions of the fabrics. Similar trend was also observed in the case of initial modulus (Table 7).
The ANN models of tenacity and initial modulus show much lower absolute percentage error and mean absolute percentage error than that of empirical model (Tables 6 and 7). The standard deviation of mean absolute percentage error also follows the similar trend. This

Fabric code	Fabric weight g/m^2	Needling density punches/cm^2	Woollenised jute %	Polypropylene fibre %
1	250	150	40	60
2	250	350	40	60
3	450	150	40	60
4	450	350	40	60
5	250	250	60	40
6	250	250	20	80
7	450	250	60	40
8	450	250	20	80
9	350	150	60	40
10	350	150	20	80
11	350	350	60	40
12	350	350	20	80
13	350	250	40	60
14	350	250	40	60
15	350	250	40	60

Table 3. Fabric samples for development of Emperical and ANN models

	Tenacity		Initial Modulus	
	Machine direction	Transverse direction	Machine direction	Transverse direction
β_0	-9.882	-9.157	-7.448E-01	-2.832E-01
β_1	1.484E-02	1.228E-02	1.925E-03	2.806E-03
β_2	3.129E-02	2.610E-02	6.544E-03	5.279E-03
β_3	1.362E-01	1.833E-01	-4.700E-03	-2.063E-02
β_{11}	-6.084E-06	-1.817E-06	-3.908E-06	-7.840E-06
β_{22}	-2.838E-05	-2.682E-05	-1.388E-05	-1.941E-05
β_{33}	-5.033E-04	-3.787E-04	-3.216E-05	6.992E-05
β_{12}	-3.068E-05	-2.155E-05	1.835E-06	1.147E-05
β_{13}	-5.0170E-05	-1.157E-04	1.817E-05	2.775E-05
β_{23}	-1.251E-04	-1.849E-04	2.242E-05	2.596E-05

Table 4. Coefficients and constants of empirical models of tenacity and initial modulus

Weights between the layers number		Tenacity		Initial modulus	
		Machine direction	Transverse direction	Machine direction	Transverse direction
1st and 2nd	W_{11}	-4.053	1.185	0.379	-6.844
	W_{12}	1.363	-2.341	11.313	1.539
	W_{13}	2.035	5.420	2.564	-2.829
	W_{21}	-4.530	-0.496	0.919	16.684
	W_{22}	3.401	-0.667	-16.856	4.141
	W_{23}	7.707	5.064	-9.534	-0.370
	W_{31}	5.997	3.669	-4.380	-1.518
	W_{32}	-6.298	0.890	2.876	-7.049
	W_{33}	-7.736	-9.883	4.257	1.298
2nd and 3rd	W_{11}	1.207	3.113	-2.472	-0.752
	W_{12}	1.689	-6.265	10.783	3.987
	W_{13}	-3.273	0.630	-3.429	-2.242
	W_{21}	-17.135	-8.309	1.478	2.702
	W_{22}	5.736	3.556	-2.926	-0.151
	W_{23}	10.765	2.652	0.811	6.455
	W_{31}	3.907	-12.208	-5.815	-8.148
	W_{32}	-6.176	5.439	3.362	-3.522
	W_{33}	4.880	-5.658	0.882	9.483
3rd and 4th	W_{11}	-12.307	3.779	1.784	-1.669
	W_{12}	3.732	-5.345	6.455	4.879
	W_{13}	-11.562	6.306	-5.127	-4.866
	W_{21}	10.984	-2.423	-0.415	2.262
	W_{22}	0.739	1.605	-9.454	2.647
	W_{23}	6.466	-1.513	0.686	-2.908
	W_{31}	2.598	-2.440	-0.643	-0.846
	W_{32}	-13.977	3.412	4.862	-7.376
	W_{33}	-1.486	-4.109	0.810	7.533
4th and 5th	W_{10}	1.979	4.550	2.702	5.054
	W_{20}	12.652	-7.022	11.945	8.722
	W_{30}	-9.348	7.491	-3.734	-4.757

Table 5. Weights of ANN model for tenacity and initial modulus

Fabric code	Tenacity in the machine direction					Tenacity in the transverse direction				
	Exp tenacity (cN/Tex)	Predicted tenacity (cN/Tex)		Absolute error (%)		Exp tenacity (cN/Tex)	Predicted tenacity (cN/Tex)		Absolute error (%)	
		Emp	ANN	Emp	ANN		Emp	ANN	Emp	ANN
1	0.513	0.827	0.514	61.65	00.04	2.220	2.540	2.222	14.43	00.09
2	1.357	1.214	1.355	10.57	00.20	2.000	1.775	1.961	11.23	01.97
3	1.279	1.423	1.277	11.22	00.20	2.484	2.708	2.462	09.05	00.89
4	0.896	0.579	0.901	35.32	00.55	1.402	1.081	1.402	22.86	00.04
5	0.544	0.466	0.545	14.39	00.22	0.827	1.020	0.845	23.36	02.13
6	1.837	1.743	1.838	05.15	00.01	3.819	3.530	3.818	07.56	00.02
7	0.551	0.646	0.544	17.17	01.23	0.931	1.220	0.922	31.02	00.95
8	1.443	1.521	1.444	05.43	00.07	2.998	2.805	2.994	06.44	00.33
9	0.435	0.197	0.433	54.71	00.51	1.611	1.098	1.603	31.88	00.50
10	1.996	1.774	1.996	11.12	00.01	3.916	3.885	3.914	00.81	00.07
11	0.247	0.468	0.248	90.00	00.69	0.610	0.641	0.601	05.18	01.35
12	0.806	1.044	1.001	29.55	24.22	1.435	1.949	1.425	35.79	00.71
13	1.345	1.356	1.348	00.84	00.22	2.296	2.313	2.315	00.75	00.80
14	1.391	1.356	1.348	02.51	03.11	2.609	2.313	2.315	11.33	11.28
15	1.332	1.356	1.348	01.78	01.15	2.035	2.313	2.315	13.68	13.75
'R^2' values		0.879	0.990				0.911	0.994		
Mean absolute percentage error				23.43	02.16				15.03	02.33
SD of absolute percentage error				26.34	06.15				11.34	04.21
Exp – Experimental; Emp – Empirical model and ANN – Artificial Neural Network Model										

Table 6. Experimental and predicted tenacity values by empirical and ANN models

indicates that the prediction by ANN model is closer to the experimental values and variations of error among the samples were also lower than the prediction by empirical model. This could be due to the fact that the prediction by empirical model is not very accurate when the relationship between the inputs and outputs is nonlinear (Debnath et al. 2000a).

3.1.1 Verification of tenacity and initial modulus models

An attempt was made to predict the tenacity and initial modulus in machine direction and in transverse direction to understand the accuracy of the models. The ANNs and empirical models were then presented to three sets of inputs, which have not appeared during the modeling phase as shown in Table 8. The input variables were selected in such a way that one input variable is beyond the range with which the ANN was trained or empirical model was developed. The Table 8 indicates that the prediction errors of ANNs were lower in both the directions of the fabric for tenacity and initial modulus in comparison with that of empirical model (Debnath et al., 2000a).

In Table 8 the predicted tenacity and initial modulus values by ANN gives higher absolute percentage error than the predicted values in Tables 6 and 7. This may be due to the fact that the selected input variables (Table 8) were beyond the range over which the empirical or ANN models were developed (Debnath et al., 2000a). However, in most of the cases of prediction ANNs give lesser absolute percentage error than the empirical model.

Fabric code	Initial modulus in the machine direction					Initial Modulus in the transverse direction				
	Exp (cN/Tex)	Predicted initial modulus (cN/Tex)		Absolute error (%)		Exp (cN/Tex)	Predicted initial modulus (cN/Tex)		Absolute error (%)	
		Emp	ANN	Emp	ANN		Emp	ANN	Emp	ANN
1	0.396	0.307	0.394	22.44	00.38	0.550	0.377	0.556	31.42	01.11
2	0.736	0.589	0.736	19.96	00.08	0.451	0.377	0.433	16.46	04.12
3	0.271	0.418	0.270	54.19	00.30	0.444	0.518	0.445	16.75	00.36
4	0.685	0.773	0.685	12.97	00.00	0.804	0.976	0.805	21.51	00.19
5	0.494	0.542	0.495	09.76	00.12	0.400	0.578	0.422	43.77	05.40
6	0.418	0.606	0.420	44.85	00.36	0.551	0.623	0.552	13.05	00.20
7	0.805	0.617	0.804	23.30	00.06	0.906	0.834	0.908	07.93	00.18
8	0.874	0.826	0.874	05.51	00.02	1.279	1.104	1.278	13.70	00.06
9	0.325	0.365	0.326	12.50	00.34	0.529	0.527	0.520	00.45	01.74
10	0.511	0.412	0.511	19.33	00.02	0.480	0.581	0.479	21.01	00.27
11	0.496	0.594	0.496	19.89	00.00	0.753	0.652	0.752	13.40	00.12
12	0.861	0.820	0.860	04.72	00.09	0.912	0.914	0.908	00.25	00.43
13	0.644	0.700	0.718	02.34	04.94	0.836	0.835	0.847	00.13	01.40
14	0.688	0.700	0.718	01.64	04.23	0.815	0.835	0.847	02.47	04.04
15	0.727	0.700	0.718	03.73	01.23	0.854	0.835	0.847	02.21	07.71
'R^2' values		0.703	0.997				0.803	0.997		
Mean absolute percentage error				17.14	00.81				13.63	01.36
SD of absolute percentage error				15.23	01.57				12.48	01.73
Exp – Experimental; Emp – Empirical model and ANN – Artificial Neural Network Model										

Table 7. Experimental and predicted initial modulus values by empirical and ANN models

3.2 Modelling of Air permeability

The emperical and ANN models were developed from selected fifteen sets of fabric samples as shown in Table 3. The empirical model (7) derived using Box and Behnken factorial design for predicting the air permeability is given below.

$$AP = -8.54E\text{-}3X_1 + 2.695E\text{-}3X_2 - 4.58E\text{-}2X_3 + 3.05E\text{-}6X_1^2 + 9.925E\text{-}6X_2^2 + 3.578E\text{-}4X_3^2 - 1.79E\text{-}5X_1X_2 + 5.076E\text{-}5X_1X_3 - 3.846E\text{-}5X_2X_3 + 5.401 \quad (7)$$

Where, AP= air permeability ($m^3/m^2/s$) X_1 = fabric weight (g/m^2), X_2 = needling density (punches/cm^2) and X_3 = percentage polypropylene content in the blend ratio of polypropylene and woollenised jute. Since the coefficient of determination (R^2 = 0.97) value is very high, we can conclude that the empirical model fits the data very well.

During training the ANN models for air permeability, the minimum prediction error for all ANN models was obtained within 40,000 cycles (Debnath et al., 2000b). Table 9 depicts the interconnecting weights used for calculating the air permeability of ANN model with three hidden layers, where, W_{mn} – Interconnecting weights between the neuron (m) in one layer and neuron (n) in next layer.

Fabric code	D	Tenacity (cN/Tex)					Initial Modulus (cN/Tex)				
		Exp	Prediction		AE (%)		Exp	Prediction		AE (%)	
			Emp	ANN	Emp	ANN		Emp	ANN	Emp	ANN
16	MD	1.6730	1.9886	1.9960	18.86	19.31	0.4968	0.4445	0.4750	10.53	04.38
	CD	3.7860	4.6575	3.9150	23.02	03.41	0.3123	0.7559	0.2366	142.0	24.24
18	MD	2.2947	1.4784	1.9958	35.57	13.02	0.8467	0.8582	0.8401	01.36	00.77
	CD	4.3700	3.3917	3.9157	22.38	10.40	1.2551	1.2542	1.2434	00.07	00.93
21	MD	0.0240	-2.2031	0.0221	-	07.91	0.3194	0.3875	0.2968	21.32	7.08
	CD	0.0850	-2.3606	0.0975	-	14.71	0.9759	0.8271	1.0112	15.24	3.62
D – Test direction of sample; MD - Machine direction; CD – Cross direction, Exp – Experimental; Emp – Empirical model and ANN – Artificial Neural Network model, AE – Absolute error											

Table 8. Experimental verification of predicted results (tenacity and initial modulus)

Weights between the layers		1st and 2nd	2nd and 3rd	3rd and 4th
	W_{11}	6.110	-21.555	-2.205
	W_{12}	1.811	11.242	-0.073
	W_{13}	-9.048	0.859	-2.135
	W_{21}	-14.213	-2.992	-0.163
	W_{22}	8.363	0.675	-23.549
	W_{23}	-3.274	4.588	-25.085
	W_{31}	-11.762	-10.013	16.168
	W_{32}	1.202	-13.005	-4.871
	W_{33}	-11.006	-2.470	-11.349
Weights between 4th and 5th layers	W_{10}	W_{20}	W_{30}	
	10.465	-8.925	5.433	

Table 9. Weights of ANN model with three hidden layers for air permeability

The Table 10 shows the correlation between experimental and predicted values of air permeability. It is clear that the 'R^2' values for ANN of three hidden layers were maximum followed by empirical model, two layers and single hidden layer ANN respectively. From the Table 10 it can also be observed that the average absolute error was found minimum while using ANN with three hidden layers, followed by ANN with two hidden layers, empirical model and ANN by single hidden layer respectively. The standard deviation of absolute error also follows the same trend. The ANN model with single hidden layer has low correlation between the experimental and predicted values (Debnath et al., 2000b). This may be because the ANN with one hidden layer has only two neurons. Both the number of neurons and the hidden layers are responsible for the accuracy in the predicted model. The ANN with three hidden layers shows the best, predicted results. The empirical model is not as good as ANN of three hidden layers. Though, the correlation between the experimental and predicted values of empirical model is higher than ANN model with two hidden layers, but the mean percentage absolute error is quite high in the case of empirical model than ANN with two or three hidden layers. This is probably due to the fact that the empirical model may require a larger sample size when the relationship between input and output variables is nonlinear (Fan & Hunter, 1998).

Fabric code	Exp AP	Empirical Model		Artificial neural network models					
		Pre AP	AE, %	1 HL Pre AP	AE, %	2 HL Pre AP	AE, %	3 HL Pre AP	AE, %
1	2.285	2.368	03.36	2.426	06.71	2.516	10.10	2.311	01.15
2	2.659	2.543	04.39	2.629	01.27	2.672	00.47	2.671	00.42
3	1.308	1.585	11.40	1.467	12.19	1.506	15.13	1.334	01.98
4	0.966	0.617	36.10	1.425	47.45	0.887	08.21	0.962	00.49
5	2.663	2.495	06.30	2.244	15.72	2.580	03.10	2.665	00.07
6	2.682	2.503	06.67	2.620	02.31	2.612	02.61	2.670	00.47
7	0.786	0.725	07.74	1.379	75.38	0.901	14.66	0.796	01.22
8	1.262	1.391	10.19	1.519	20.31	1.366	08.19	1.395	10.54
9	1.856	1.693	08.75	1.534	17.35	1.639	11.67	1.898	02.26
10	2.361	2.058	12.81	2.197	06.96	2.216	06.15	2.382	00.89
11	1.627	1.664	02.25	1.732	06.45	1.684	03.45	1.701	04.54
12	1.824	1.722	05.63	2.015	10.46	1.867	02.31	1.826	00.09
13	1.675	1.542	07.93	1.676	00.05	1.674	00.70	1.677	00.14
14	1.677	1.542	08.02	1.676	00.05	1.674	00.17	1.677	00.04
15	1.672	1.542	07.79	1.676	00.20	1.674	00.07	1.677	00.29
'R^2'		00.97		00.82		00.96		00.99	
Mean Absolute Error (%)			09.28		14.85		05.79		01.58
SDER			07.94		20.67		05.23		02.73
Exp – Experimental; Emp – Empirical model ; Pre – Predicted; HL – Hidden layer; AE – Absolute error; AP - Air permeability in $m^3/m^2/s$ and SDER – Standard deviation of percentage absolute error									

Table 10. Experimental and predicted air permeability values by empirical and ANN models – absolute error and correlation

3.2.1 Verification of air permeability models

The trained ANN with three hidden layers (3HL) and the empirical models were then used to predict the air permeabilityproperty of six different sets of input pairs. The input variables are selected in such a way that one or two input variables are beyond the range, with which the ANN was trained and empirical model was developed (Table 11).

It can be observed that, the percentage absolute error with ANN, ranges between 00.60 and 14.62. However, the percentage absolute error is between 04.32 and 30.00, while predicting with empirical model. The prediction of air permeability was more accurate with ANN, compared to empirical model even when the inputs are beyond the range of modeling (Debnath et al., 2000b).

3.3 Modelling of compression properties

The ANN models for initial thickness (IT), percentage compression (C), percentage thickness loss (TL) and percentage compression resilience (CR) have been developed from the selected twenty-five sets of fabric samples and corresponding experimental values of compression properties shown in (Table 12).

Fabric code	Fabric weight (g/m²)	Needling density (punches/cm²)	Blend ratio (Polypropylene:Jute)	Air permeability (m³/m²/s)				
				Exp	Predicted values		Absolute error, (%)	
					ANN	Emp	ANN	Emp
20	241	150	00 :100	2.6923	2.6760	3.5000	00.60	30.00
21	310	250	00 :100	2.5641	2.6692	2.9528	04.10	15.15
22	303	350	00 :100	2.8679	2.6728	3.3924	06.80	18.28
23	300	150	20 : 80	2.4576	2.6292	2.3512	06.98	04.32
24	276	250	20 : 80	2.4951	2.6523	2.6497	06.30	06.19
25	205	350	20 : 80	3.1381	2.6791	3.8188	14.62	21.69
Exp – Experimental; Emp – Empirical model and ANN – Artificial Neural Network Model								

Table 11. Experimental verification of predicted results of air permeability values

Fabric code	Fabric weight g/m²	Needling density punches/cm²	Woollenised jute %	Polypropylene fibre %	Polyester fibre %	IT mm	C %	TL %	CR %
1	250	150	40	60	-	3.54	53.64	25.46	32.67
2	250	350	40	60	-	3.02	46.73	25.98	32.29
3	450	150	40	60	-	4.41	44.8	20.68	32.92
4	450	350	40	60	-	3.8	36.47	17.68	33.87
5	250	250	60	40	-	3.02	52.48	30.69	29.48
6	250	250	20	80	-	4.27	54.88	27.82	32.27
7	450	250	60	40	-	4.39	37.24	20.69	30.99
8	450	250	20	80	-	3.88	37.8	18.63	31.28
9	350	150	60	40	-	3.45	50.24	25.16	32.77
10	350	150	20	80	-	4.48	50.06	24.49	31.52
11	350	350	60	40	-	3.12	44.91	25.51	31.73
12	350	350	20	80	-	3.38	43.75	23.25	30.99
13	350	250	40	60	-	3.29	45.16	22.06	33.25
14	350	250	40	60	-	3.94	42.45	21.84	33.15
15	350	250	40	60	-	3.66	44.09	21.68	33.33
16	393	150	0	100	-	5.87	54.92	25.05	28.56
17	440	150	0	100	-	5.77	54.97	25.15	28.2
18	392	350	0	100	-	4.08	37.51	17.4	35.05
19	241	150	100	0	-	2.51	41.18	20.61	30.29
20	303	350	100	0	-	2.84	41.85	22.23	30.43
21	300	150	80	20	-	3.18	39.98	18.47	35.32
22	205	350	80	20	-	2.47	47.42	25.22	28.98
23	415	300	-	-	100	3.54	42.93	9.89	54.33
24	515	300	-	-	100	4.14	37.00	8.36	56.69
25	815	300	-	-	100	5.62	23.78	6.65	53.85

Table 12. Experimental design for compression properties

The ANN was trained separately up to certain number of cycles to obtain optimum weights for each compression properties. The number of cycles to achieve optimum weights for initial thickness, percentage compression, thickness loss (%) and percentage compression resilience are found between 320000 and 5120000 cycles as presented in Table 13. A very large number of simulation cycles was required because more number of input variables was used to develop the ANN model (Debnath & Madhusoothanan, 2008)..

Compression property	Number of cycle		
	One hidden layer	Two hidden layers	Three hidden layers
Initial thickness, mm	2560000	2560000	2560000
Percentage compression	1280000	2560000	5120000
Percentage thickness loss	320000	1280000	2560000
Compression resilience, %	640000	2560000	5120000

Table 13. Optimum number of cycles of one, two and three hidden layered ANN models for compression properties

The optimum weights of ANN for initial thickness, percentage compression, thickness loss (%) and percentage compression resilience are shown in Table 14.

Weights between the layers number	Initial thickness	Percentage compression	Percentage thickness loss	Percentage compression resilience
1st and 2nd				
W_{11}	-7.825	-9.697	-0.797	1.497
W_{12}	-3.144	6.650	1.176	-1.003
W_{13}	0.821	-1.560	1.221	-4.777
W_{14}	3.338	2.949	8.374	14.286
W_{21}	0.394	4.034	2.738	5.181
W_{22}	0.801	-11.441	-4.945	8.240
W_{23}	2.356	-12.284	-0.218	3.091
W_{24}	3.839	0.981	-7.399	-8.415
W_{31}	0.587	4.742	-0.658	-3.937
W_{32}	0.418	2.487	8.743	-2.320
W_{33}	5.436	9.689	-3.318	-2.272
W_{34}	-2.470	8.814	-0.340	0.617
W_{41}	4.336	-0.697	-1.058	2.704
W_{42}	1.140	6.674	-5.424	2.298
W_{43}	-2.877	-11.909	8.539	-3.649
W_{44}	-1.919	-2.500	1.827	4.803
W_{51}	2.555	3.046	0.206	0.552
W_{52}	0.428	-1.342	-1.456	4.349
W_{53}	-3.728	-0.608	-2.002	0.192
W_{54}	-0.958	1.000	1.431	0.350
2nd and 3rd				
W_{11}	-1.958	5.796	2.126	0.474

W_{12}	8.015	10.795	-5.784	-0.253
W_{13}	1.747	0.628	-3.575	6.556
W_{21}	6.622	2.771	0.908	3.378
W_{22}	-2.664	-5.510	4.585	13.901
W_{23}	-2.217	-2.485	0.170	0.471
W_{31}	-1.255	0.661	-1.004	-2.508
W_{32}	-4.467	-1.092	3.731	-8.715
W_{33}	-3.381	7.313	2.431	4.162
W_{41}	-1.670	-6.856	0.762	9.749
W_{42}	-4.480	-3.497	-8.304	-11.644
W_{43}	-1.602	0.590	3.243	-6.180
3rd and 4th				
W_{11}	1.780	-0.951	-1.025	7.269
W_{12}	-4.432	5.588	-6.411	–
W_{21}	-1.488	-0.675	0.401	-14.560
W_{22}	7.351	5.949	9.564	–
W_{31}	-1.375	0.999	3.754	7.599
W_{32}	1.381	-11.087	3.248	–
4th and 5th				
W_{10}	-1.442	-0.432	-1.923	–
W_{20}	13.259	8.769	12.222	–

Table 14. Weights of ANN model for compression properties

Tables 15 to 18 show the experimental and predicted values of initial thickness, compression (%), percentage thickness loss and percentage compression resilience respectively. These tables also indicate the effect of number of hidden layers on the percentage error, standard deviation and correlation between the experimental and predicted results for the corresponding compression properties.

Table 15 shows a very good correlation (R^2 values) between the experimental and the predicted initial thickness values by ANN. Among the results obtained, the ANN with three hidden layers presents comparatively highest R^2 value with lowest error. The standard deviation of percentage absolute error is also found to be less in the case of ANN model with three hidden layers. Similar trend has also been observed in case of percentage compression and percentage thickness loss as depicted in Tables 14 and 15 respectively. The ANN model with two hidden layers performs better in terms of percentage error and standard deviation of percentage error in the case of percentage compression resilience (Table 16). In the cases where average error for the ANN models with three different hidden layers shows more or less similar values, the priority is given to the standard deviation of errors (Debnath & Madhusoothanan, 2008). This study shows that in majority of the cases, the three hidden layered ANN models present better results for predicting compression properties of needle-punched fabrics. Though the three hidden layered ANN models take more time during training phase, the predicted results are more accurate in comparison to ANN models with one and two hidden layers, with less variations in the absolute error (Debnath et al., 2000a).

Fabric code	Initial thickness, mm						
	Exp	ANN Predicted			Absolute error, %		
		1 HL	2 HL	3 HL	1 HL	2 HL	3 HL
1	3.54	3.531	3.539	3.546	0.259	0.034	0.171
2	3.02	3.046	3.019	3.036	0.868	0.030	0.520
3	4.41	4.369	4.398	4.351	0.932	0.266	1.349
4	3.8	3.785	3.780	3.783	0.399	0.524	0.443
5	3.02	3.012	3.012	2.995	0.272	0.261	0.821
6	4.27	4.287	4.267	4.272	0.399	0.071	0.041
7	4.39	4.398	4.383	4.407	0.187	0.149	0.384
8	3.88	3.930	3.878	3.916	1.298	0.053	0.939
9	3.45	3.601	3.538	3.580	4.379	2.564	3.771
10	4.48	4.456	4.482	4.472	0.540	0.043	0.181
11	3.12	3.133	3.166	3.139	0.432	1.479	0.598
12	3.38	3.364	3.389	3.359	0.484	0.256	0.634
13	3.29	3.627	3.648	3.630	10.229	10.870	10.343
14	3.94	3.627	3.648	3.630	7.956	7.421	7.861
15	3.66	3.627	3.648	3.630	0.915	0.338	0.812
16	5.87	5.867	5.870	5.869	0.053	0.002	0.025
17	5.77	5.777	5.771	5.773	0.117	0.017	0.056
18	4.08	4.074	4.087	4.083	0.159	0.168	0.061
19	2.51	2.578	2.614	2.558	2.724	4.124	1.904
20	2.84	2.847	2.857	2.831	0.262	0.603	0.333
21	3.18	3.038	3.030	3.062	4.469	4.708	3.712
22	2.47	2.460	2.440	2.478	0.415	1.200	0.332
23	3.54	3.540	3.540	3.540	0.000	0.003	0.010
24	4.14	4.140	4.140	4.140	0.001	0.006	0.005
25	5.62	5.620	5.620	5.621	0.000	0.004	0.016
R^2	–	0.9868	0.9872	0.9875	–	–	–
Mean of % absolute error		–	–	–	1.51	1.41	1.41
SD of % absolute error		–	–	–	2.6071	2.6932	2.55
Exp – Experimental; 1HL – One hidden layer; 2HL – Two hidden layers; 3HL – Three hidden layers; and SD – Standard deviation							

Table 15. Experimental and predicted values of initial thickness by ANN model

Fabric code	Percentage compression, %							
	Exp	ANN Predicted				Absolute error, %		
		1 HL	2 HL	3 HL		1 HL	2 HL	3 HL
1	53.64	54.126	53.638	53.648		0.906	0.003	0.015
2	46.73	48.817	46.729	46.727		4.467	0.003	0.006
3	44.8	44.536	44.807	44.789		0.589	0.016	0.025
4	36.47	36.223	36.473	36.453		0.677	0.007	0.047
5	52.48	50.449	52.638	52.486		3.869	0.301	0.011
6	54.88	54.333	54.883	54.872		0.997	0.006	0.015
7	37.24	37.576	38.740	37.240		0.902	4.028	0.001
8	37.8	38.590	38.159	37.800		2.089	0.951	0.001
9	50.24	48.230	50.358	50.224		4.001	0.234	0.031
10	50.06	50.703	50.411	50.078		1.285	0.701	0.037
11	44.91	45.650	44.035	44.912		1.648	1.949	0.004
12	43.75	43.949	43.581	43.756		0.454	0.386	0.013
13	45.16	44.244	43.780	43.863		2.028	3.056	2.871
14	42.45	44.244	43.780	43.863		4.227	3.133	3.329
15	44.09	44.244	43.780	43.863		0.350	0.704	0.514
16	54.92	54.807	54.930	54.951		0.205	0.019	0.056
17	54.97	54.896	54.954	54.943		0.135	0.029	0.050
18	37.51	36.873	37.269	37.515		1.699	0.641	0.012
19	41.18	41.666	40.616	41.178		1.181	1.369	0.005
20	41.85	42.787	41.536	41.842		2.240	0.751	0.019
21	39.98	40.793	39.785	39.984		2.033	0.489	0.009
22	47.42	47.242	47.570	47.423		0.376	0.316	0.007
23	42.93	42.933	42.928	42.927		0.007	0.004	0.007
24	37	36.997	37.002	37.003		0.007	0.005	0.007
25	23.78	23.780	23.780	23.791		0.001	0.001	0.047
R^2	–	0.9839	0.9941	0.9971		–	–	–
Mean of % absolute error		–	–	–		1.453	0.764	0.285
SD of % absolute error		–	–	–		1.386	1.117	0.856
Exp – Experimental; 1HL – One hidden layer; 2HL – Two hidden layers; 3HL – Three hidden layers; and SD – Standard deviation								

Table 16. Experimental and predicted values of percentage compression by ANN model

Fabric code	Thickness loss, %							
	Exp	ANN Predicted				Absolute error, %		
		1 HL	2 HL	3 HL		1 HL	2 HL	3 HL
1	25.46	25.547	26.448	25.462		0.341	3.881	0.007
2	25.98	27.399	26.468	25.976		5.462	1.879	0.017
3	20.68	20.574	21.035	20.676		0.515	1.717	0.018
4	17.68	17.147	17.720	17.662		3.013	0.225	0.100
5	30.69	30.660	30.689	30.688		0.096	0.003	0.007
6	27.82	26.361	26.453	27.813		5.244	4.913	0.025
7	20.69	20.634	20.739	20.686		0.271	0.235	0.019
8	18.63	18.564	18.189	18.621		0.357	2.369	0.047
9	25.16	25.200	25.057	25.157		0.159	0.410	0.011
10	24.49	24.554	24.250	24.508		0.261	0.981	0.073
11	25.51	25.488	25.465	25.509		0.087	0.176	0.002
12	23.25	23.236	23.087	23.264		0.060	0.702	0.060
13	22.06	22.064	21.843	21.851		0.017	0.982	0.946
14	21.84	22.064	21.843	21.851		1.024	0.015	0.052
15	21.68	22.064	21.843	21.851		1.770	0.753	0.790
16	25.05	24.994	25.279	25.016		0.225	0.914	0.134
17	25.15	24.733	25.035	25.169		1.657	0.456	0.075
18	17.4	17.817	17.708	17.401		2.396	1.772	0.008
19	20.61	21.149	20.642	20.611		2.614	0.154	0.005
20	22.23	21.340	22.208	22.229		4.002	0.100	0.003
21	18.47	18.334	18.472	18.469		0.734	0.011	0.004
22	25.22	25.207	25.219	25.220		0.053	0.005	0.002
23	9.89	9.876	9.881	9.892		0.144	0.091	0.020
24	8.36	8.368	8.358	8.357		0.096	0.027	0.036
25	6.65	6.652	6.652	6.657		0.037	0.025	0.101
R^2	–	0.9926	0.9954	0.9999		–	–	–
Mean of % absolute error		–	–	–		1.225	0.912	0.102
SD of % absolute error		–	–	–		1.655	1.259	0.234
Exp – Experimental; 1HL – One hidden layer; 2HL – Two hidden layers; 3HL – Three hidden layers; and SD – Standard deviation								

Table 17. Experimental and predicted values of percentage thickness loss by ANN model

Fabric code	Compression resilience, %						
	Exp	ANN Predicted			Absolute error, %		
		1 HL	2 HL	3 HL	1 HL	2 HL	3 HL
1	32.67	32.864	32.568	32.684	0.594	0.312	0.044
2	32.29	32.041	32.253	31.838	0.772	0.115	1.401
3	32.92	30.169	32.805	32.923	8.356	0.350	0.009
4	33.87	33.917	33.640	33.624	0.139	0.679	0.725
5	29.48	29.334	29.375	29.514	0.495	0.357	0.115
6	32.27	32.324	31.931	31.832	0.169	1.051	1.358
7	30.99	31.959	30.700	30.997	3.126	0.935	0.022
8	31.28	30.803	30.890	31.256	1.523	1.248	0.076
9	32.77	33.355	32.304	32.802	1.784	1.422	0.097
10	31.52	30.943	31.071	31.445	1.830	1.425	0.237
11	31.73	31.471	31.735	31.374	0.817	0.016	1.122
12	30.99	31.581	31.029	32.012	1.907	0.127	3.297
13	33.25	33.123	33.162	33.307	0.383	0.266	0.172
14	33.15	33.123	33.162	33.307	0.083	0.035	0.474
15	33.33	33.123	33.162	33.307	0.622	0.505	0.069
16	28.56	29.678	28.624	28.577	3.915	0.223	0.058
17	28.2	29.141	28.083	28.212	3.337	0.414	0.041
18	35.05	34.855	35.006	35.083	0.557	0.125	0.094
19	30.29	30.234	30.215	30.319	0.183	0.249	0.096
20	30.43	30.477	30.399	29.597	0.154	0.103	2.736
21	35.32	35.221	35.130	35.283	0.281	0.537	0.105
22	28.98	29.010	28.998	30.004	0.105	0.064	3.533
23	54.33	54.335	54.340	54.330	0.008	0.018	0.001
24	56.69	56.684	56.687	56.689	0.010	0.005	0.001
25	53.85	53.851	53.837	53.850	0.002	0.025	0.001
R^2	–	0.9919	0.9996	0.9977	–	–	–
Mean of % absolute error		–	–	–	1.2461	0.424	0.635
SD of % absolute error		–	–	–	1.8555	0.450	1.055
Exp – Experimental; 1HL – One hidden layer; 2HL – Two hidden layers; 3HL – Three hidden layers; and SD – Standard deviation							

Table 18. Experimental and predicted values of compression resilience by ANN model

3.3.1 Verification of Models for compression properties

Further, attempts have been made to predict the compression properties to understand the perfection of the models. The ANNs models were then used to four sets of inputs, which have not been utilized during the modeling phase as shown in Table 19. Table 20 indicates the prediction of compression properties and respective absolute errors by ANNs models during verification phase.

Fabric code	Fabric weight g/m^2	Needling density $punches/cm^2$	Woollenised jute %	Polypropylene %	Polyester %
18	410	250	0	100	0
21	310	250	100	0	0
24	276	250	80	20	0
28	680	300	0	0	100

Table 19. Samples for experimental verification of ANN model for compression properties

Table 20 presents the predicted compression values of untrained fabric samples by ANN models, showing higher absolute percentage error than the predicted compression values of trained fabric samples as shown in Tables 15 to 18. Specifically, in case of sample code 28, all the properties predicted during verification are high. Two samples of this category (100% jute) have been used during the training phase (Table 10). This might be the reason for higher error in sample code 28 (Debnath & Madhusoothanan, 2008). Hence, the learning process by ANN itself is very poor compared to other samples, this ultimately increases the error during verification (Table 20).

Fabric code	Initial thickness with 3 hidden layer mm			Compression with 3 hidden layer %			Thickness loss with 3 hidden layer %			Compression resilience with 3 hidden layer %		
	E	P	A	E	P	A	E	P	A	E	P	A
18	5.07	5.25	3.53	38.07	54.88	44.17	17.87	19.17	7.26	34.12	30.73	9.95
21	2.47	3.17	28.47	43.96	29.20	33.59	22.38	27.85	24.46	32.89	17.41	47.05
24	3.00	2.91	3.09	41.53	48.57	16.95	21.59	30.68	42.12	30.71	27.80	9.48
28	5.13	5.26	2.54	22.35	23.95	7.15	6.19	6.76	9.24	54.21	56.62	4.44
E – Experimental; P – Predicted and A – Absolute error %												

Table 20. Experimental verification of predicted results on compression properties

4. Conclusions

From this study it is clear that the tensile and air permeability property of needle punched non-woven fabric can be predicted from two different methodologies– empirical and ANN models. The ANN model for prediction of tensile properties of needle punched non-woven is much more accurate compared to the empirical model. Prediction of tensile properties by ANN model shows considerably lower error than empirical model even when the inputs were beyond the range of inputs, which were used for developing the model.

It can also be concluded that ANNs can be used effectively even for predicting nonlinear relationship between the process parameters and fabric properties.
Both the methods can be implemented successfully as far as the air permeability of such needled fabric is concerned. The prediction accuracy of the ANN with three hidden layers is the best amongst all the predicting models used in this work. The ANN with three hidden layers is the best, which, gives highest correlation with lowest prediction error between actual and predicted values of air permeability of needle punched non-woven. The ANN with three hidden layers also shows lesser error when compared to an empirical model even when input variables are extrapolated over which the models were developed.
ANNs can be used effectively for predicting nonlinear relationship between the process parameters and the fabric compression properties.
The number of cycles to achieve optimum weights for initial thickness, percentage compression, thickness loss (%) and percentage compression resilience are found between 320000 and 5120000 cycles.
There is a very good correlation (R^2 values) with minimum error between the experimental and predicted initial thickness, percentage compression and thickness loss values by ANN with three hidden layers.
The standard deviation of percentage absolute error is also found to be less in the case of ANN model with three hidden layers for initial thickness, percentage compression and percentage thickness loss. The ANN model with two hidden layers performs better in terms of percentage error and standard deviation in the case of percentage compression resilience.
The three hidden layered ANN models take more time for computation during training phase but the predicted results are more accurate with less variations in the absolute error in the verification phase.
Based on the experiences the ANN model can be well used to model and predict other important properties of needle-punched nonwoven fabrics made of different fibre materials.

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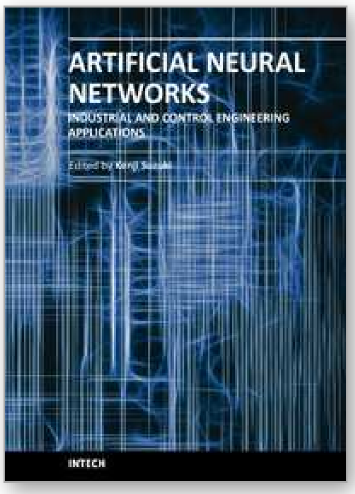

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Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications. The purpose of this book is to provide recent advances of artificial neural networks in industrial and control engineering applications. The book begins with a review of applications of artificial neural networks in textile industries. Particular applications in textile industries follow. Parts continue with applications in materials science and industry such as material identification, and estimation of material property and state, food industry such as meat, electric and power industry such as batteries and power systems, mechanical engineering such as engines and machines, and control and robotic engineering such as system control and identification, fault diagnosis systems, and robot manipulation. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in industrial and control engineering areas. The target audience includes professors and students in engineering schools, and researchers and engineers in industries.

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