



Modeling of bending length based on concentrated loading method

Parisa Heydarian, Morteza Vadood^a &
Ali Asghar Alamdar Yazdi

Department of Textile Engineering, Faculty of Engineering,
Yazd University, Yazd, Iran

*Received 18 September 2018; revised received and accepted
1 April 2019*

Presented study is aimed at designing a model for bending length based on the concentrated loading method using 10 parameters extracted from the modified tensile test. After that, a new database has been reproduced by using principal component analysis and the modeling is conducted by regression and artificial neural network (ANN) based on the trial and error method. The obtained R-squared of 0.97 between ANN outputs and corresponding real bending lengths proves that the proposed method has a great potential for evaluating the mechanical properties of fabrics.

Keywords: Artificial neural network, Bending length, Concentrated loading method, Polypropylene, Principal component analysis

One of the most important mechanical properties is the bending which affects the draping, wrinkling, buckling, deformation ability and fabric handle. Peirce¹ studied the fabric bending based on the cantilever theory and introduced the bending length and rigidity as the bending properties. After that, some researchers worked on the fabric bending behavior and tried to find its reasonable explanation²⁻⁹. Alamdar Yazdi¹⁰ investigated the ability of concentrated loading to measure the bending properties for heavy weight woven fabrics. Du and Yu¹¹ evaluated the fabric bending properties based on a quasi-three-point bending model using the theoretical modeling. Du and Zhou¹² developed a comprehensive handle evaluation system (CHES) to measure the fabric bending properties based on the pulling-out test. Moghassem¹³ suggested a new method based on the Peirce's structural model for plain woven fabric to determine bending properties before fabric production according to yarn count and density. Fridrichová¹⁴ presented a device called TH-7 which measures the bending rigidity. Kim and Inui¹⁵ predicted bending rigidity of

laminated weft knitted fabric based on the theoretical methods. Plaut¹⁶ presented formulas to compute the bending rigidity and length based on the results from nine simple tests. Wang and Liu¹⁷ tried to relate the bending properties, such as bending rigidity, with crease recovery through the viscoelasticity modeling. Sun and Chen¹⁸ built weaving-structure models of woven fabrics and simulated the three-point bending test based on the finite element analysis.

When a fabric is stretched at two points, a closer look reveals that there is a bending form across the stretching direction. This is the key idea to relate the concentrated tensile test to the bending properties. As mentioned above, up to now many researchers worked on the measuring or predicting bending properties but to the best of the author's knowledge, hardly any trace of scientific work that encompasses the scope of bending properties of spun bonding nonwovens based on concentrated loading is available. Therefore, in this study, the relation between bending length and variables extracted from the concentrated tensile test has been investigated and a model is designed.

Methodology

So far, numerous articles on the use of ANNs in the various textile areas have been published¹⁹⁻²⁹. As a matter of fact, ANN is a data processor made up of three layers, namely, input, hidden and output layer. Each layer contains some neurons and they are connected to the neurons in the next layer by associated weights. The input parameters are received in output layer through hidden layer or layers³⁰.

Principal component analysis (PCA) is a powerful method to change raw data to the new ones, so that each new variable or component is a linear combination of the original variables. The first component does explain most of what is happening in the original data and the second component explains less than first component and so on³¹.

Experimental Details

Seventeen (17) polypropylene melt spun fabrics (spunbonded) were selected by the weight of 40-200 g. From each fabric, three ribbons (size 25×5 cm), according to Alamdar Yazdi³², were cut in the three directions [Fig. 1(a)]. After that, to have a more uniform sample, the ribbons were folded and punched [Fig. 1(b)].

^aCorresponding author.
E-mail: mortezavadood@yazd.ac.ir

Altogether 51 samples were prepared and the tensile test was performed at the speed of 10 mm/min with two hooks attached at the punches to the sample. The loading was stopped when the force is reached to 500 gf and then the unloading step was begun. The results of the tests were analyzed and 10 parameters were determined (Fig. 2). Moreover, the bending length was measured for all fabrics in three directions according to BS-3356.

Results and Discussion

At first, it is needed that all obtained data are analyzed statistically. To this aim, the correlation

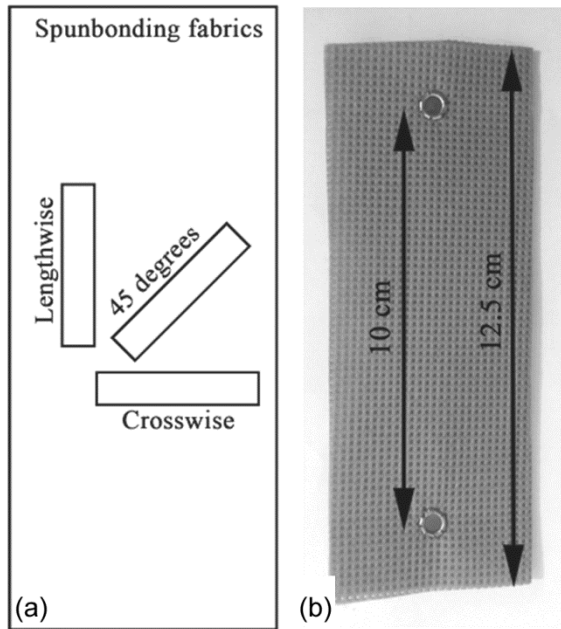


Fig. 1 — (a) schematic of cut directions and (b) a punched sample

coefficient matrix for all parameters is calculated as shown in Table 1. It is observed that high values of correlation exist between the parameters, which makes it difficult to interpret the data. Therefore, to remove these correlations, principal component analysis (PCA) has been implemented and a new database is reproduced in such a way that the correlation between two parameters remains zero. The new database contains 10 components and 51 datasets. Figure 3 indicates the explained variance by each component. As can be seen, components 1-6 can together represent more than 90% of the variance of original data.

Now, the relation between independent components and bending length as the depended variable can be investigated. To this aim, the stepwise regression method is considered at 95% confidence interval and the obtained result is presented in Table 2 with R-squared of 0.64 which proves that the relation between components and bending length is nonlinear and a more power tool such as ANN model is needed for modeling.

In this step, all data are divided into three groups, namely training, validation and testing sets. The first set is used to adjust the ANN weights and biases, the second set is used to avoid overfitting error and the last one is used to test ANN ability to predict³⁰. About 60%, 20% and 20% of data were selected randomly for training, validation and test sets respectively. Two of the important parameters in ANN are the number of hidden layers and neurons in each hidden layer. In this study, the ANN model with two hidden layers is considered by 1-10 neurons in each hidden layer,

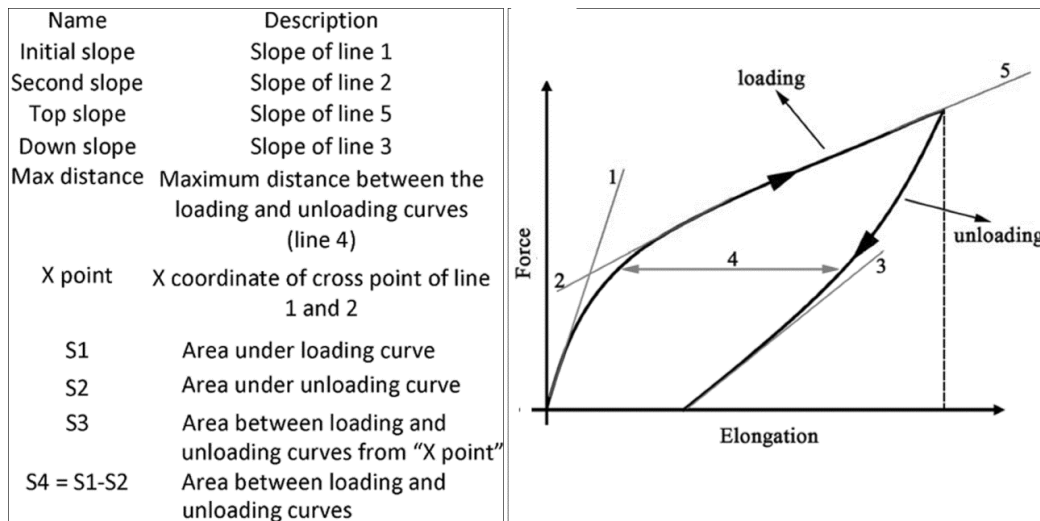


Fig. 2 — List of parameters extracted from the concentrated tensile test and the schematic of loading and unloading curves

Table 1 — Correlation coefficient matrix

Parameter	Initial slope	Second slope	Top slope	Down slope	Max distance	X point	S1	S2	S3	S4=S1-S2	Bending length
Initial slope	1.00	-	-	-	-	-	-	-	-	-	-
Second slope	0.39	1.00	-	-	-	-	-	-	-	-	-
Top slope	0.58	0.24	1.00	-	-	-	-	-	-	-	-
Down slope	0.63	0.43	0.61	1.00	-	-	-	-	-	-	-
Max distance	-0.58	-0.15	-0.67	-0.36	1.00	-	-	-	-	-	-
X point	0.41	0.29	0.27	0.25	-0.17	1.00	-	-	-	-	-
S1	-0.65	-0.17	-0.73	-0.40	0.97	-0.26	1.00	-	-	-	-
S2	-0.70	-0.19	-0.74	-0.41	0.89	-0.26	0.91	1.00	-	-	-
S3	-0.54	-0.15	-0.66	-0.35	0.94	-0.23	0.95	0.79	1.00	-	-
S4=S1-S2	-0.53	-0.14	-0.65	-0.35	0.95	-0.12	0.95	0.79	0.99	1.00	-
S1-S2											
Bending length	0.55	0.21	0.66	0.25	-0.72	0.11	-0.76	-0.71	-0.71	-0.72	1.00

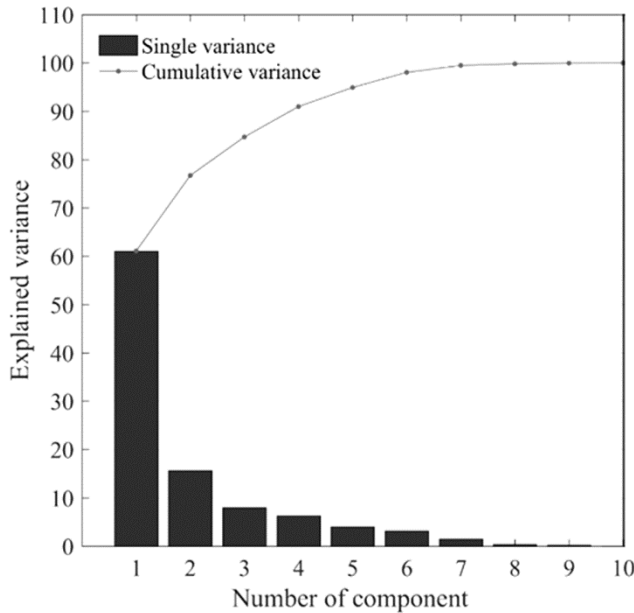


Fig. 3 — Cumulative and explained variance in original database by the components produced by PCA

which means a total of 100 ANN models. It should be mentioned that the activation function for all layers is hyperbolic tangent-sigmoid and for the last layer it is log-sigmoid, and the training algorithm is considered Levenberg-Marquardt back-propagation. Furthermore, to measure ANN accuracy in testing step, the mean absolute percentage error (MAPE) is calculated using the following equation:

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - t_i}{t_i} \right| \quad \dots (1)$$

where y and t are the ANN prediction and correspondence actual values respectively. The lower the MAPE, the more is accuracy in prediction.

Initially, the first component is considered as the only input to ANN and the best two hidden layer ANN is determined according to trial and error method. Then the first and second components are considered as inputs, and so on up to sixth component. Figure 4 indicates the lowest MAPE for the different number of components as the ANN inputs. As can be observed, use of first five components results in MAPE of 0.03 (R-squared=0.97) and the best ANN in this case contains 4 and 6 neurons in the first and second hidden layers respectively. Figure 5 illustrates the prediction of the best ANN and corresponding actual values for the testing group. It is proved that the prediction of bending length based on the results of concentrated tensile test is possible with high accuracy. Of course, this question may come to mind that when the bending length can be easily measured according to BS- 3356, what is the benefit of introducing such a complex method? As a matter of fact, the presented study as mentioned earlier actually indicates the potential of concentrated loading method to evaluate the mechanical properties of nonwoven fabrics and the good agreement between predictions and actual values proves its efficiency. Therefore, it can be considered as an appropriate approach to develop the measuring methods of mechanical properties and all it requires is only Instron apparatus which is commonly found in textile factories and labs.

In this study, it is found that the extracted parameters as the output of concentrated tensile test can be correlated strongly and implementing PCA reproduced a new database with independent components. Obtaining low accuracy in modeling bending length using regression based on the new database reveals that the relation between parameters are nonlinear. But the ANN model with two hidden

Table 2 — Result of regression for the new database (produced by PCA) with 10 components

Name	Coefficient	SE	Tstat	P-value
Intercept	5.78	0.17	34.61	0.00
Component 1	-0.58	0.07	-8.53	0.00
Component 6	-0.75	0.30	-2.50	0.02
Component 7	0.97	0.45	2.17	0.03

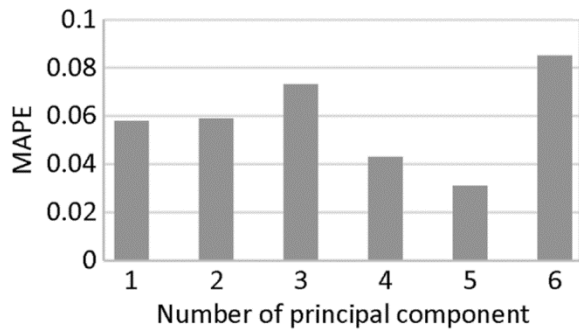


Fig. 4 — Accuracy index of ANN in prediction for different number of inputs

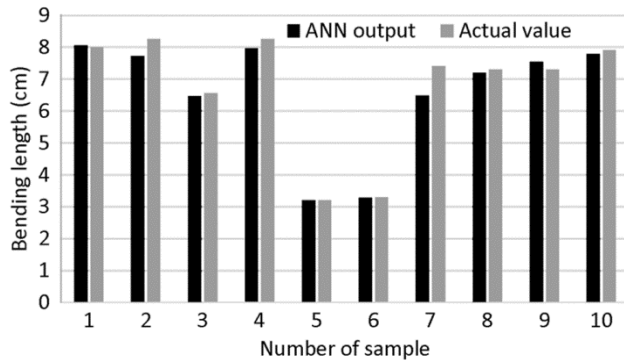


Fig. 5 — Output of the best ANN together with corresponding actual values for testing group

layers based on the new database can model bending length with R-squared of 0.97 which proves the ability of concentrated method for evaluating the mechanical properties of nonwovens.

References

- 1 Peirce F T, *J Text Inst Trans*, 21(9) (1930) T377.
- 2 Abbott N, Coplan M & Platt M, *J Text Inst*, 51(12) (1960) T1384.
- 3 Grosberg P, *Text Res J*, 36(3) (1966) 205.
- 4 Grosberg P & Swani N M, *Text Res J*, 36(4) (1966) 338.
- 5 Olofsson B, *J Text Inst*, 58(6) (1967) 221.
- 6 Abbott G M, Grosberg P & Leaf G A V, *Text Res J*, 41(4) (1971) 345.
- 7 Morton W E, Hearle J W S, *Physical Properties of Textile Fibres* (Textile Institute, Manchester), 1986.
- 8 Postle J R & Postle R, *Int J Cloth Sci Tech*, 4(5) (1992) 7.
- 9 Abbott G M, Grosberg P & Leaf G A V, *J Text Inst*, 64(6) (1973) 346.
- 10 Alamdar-Yazdi A, *Int J Cloth Sci Technol*, 15(1) (2003) 28.
- 11 Du Z & Yu W, *J Text Inst*, 96(6) (2005) 389.
- 12 Du Z Q, Zhou T, Yan N, Hua S & Yu W-D, *Fiber Polym*, 12(1) (2011) 104.
- 13 Moghassem A, *Fiber Polym*, 13(2) (2012) 237.
- 14 Fridrichová L, *Text Res J*, 83(9) (2013) 883.
- 15 Kim K, Inui S & Takatera M, *Text Res J*, 83(9) (2013) 937.
- 16 Plaut R H, *Text Res J*, 85(8) (2015) 884.
- 17 Wang L, Liu J, Pan R & Gao W, *J Text Inst*, 106(11) (2015) 1173.
- 18 Sun F, Chen C, Liu S, Jin H, He L, Du Z & Yu W, *Text Res J*, 87(16) (2017) 1977.
- 19 Ghorbani V, Vadood M & Johari M S, *Indian J Fibre Text Res*, 41(1) (2016) 19.
- 20 Moazeni N, Vadood M, Semnani D & Hasani H, *Mater Res Express*, (2018).
- 21 Soltani P, Vadood M & Johari M S, *Fiber Polym*, 13(9) (2012) 1190.
- 22 Malik S A, Gereke T, Farooq A, Aibibu D & Cherif C, *J Text Inst*, (2017) 1.
- 23 Babay A, Cheikhrouhou M, Vermeulen B, Rabenasolo B & Castelain J, *J Text Inst*, 96(3) (2005) 185.
- 24 Bhattacharjee D & Kothari V K, *Text Res J*, 77(1) (2007) 4.
- 25 Hu Z-H, Ding Y-S, Yu X-K, Zhang W-B & Yan Q, *Text Res J*, 79(14) (2009) 1319.
- 26 Jeon B S, Bae J H & Suh M W, *Text Res J*, 73(7) (2003) 645.
- 27 Özkan İ, Kuvvetli Y, Duru Baykal P & Erol R, *J Text Inst*, 105(11) (2014) 1203.
- 28 Debnath S, Madhusoothanan M & Srinivasamoorthy V, *Indian J Fibre Text Res*, 25(1) (2000) 31.
- 29 Debnath S, Madhusoothanan M & Srinivasamoorthy V, *Indian J Fibre Text Res*, 25(4) (2000) 251.
- 30 Vadood M, Semnani D & Morshed M, *J Appl Polym Sci*, 120(2) (2011) 735.
- 31 Bro R & Smilde A K, *Anal Methods-Uk*, 6(9) (2014) 2812.
- 32 Alamdar Yazdi A, *Indian J Fibre Text*, 29 (2004) 333.