PREDICTION OF DRAPE COEFFICIENT BY ARTIFICIAL NEURAL NETWORK

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Abstract:

An artificial neural network (ANN) model was developed to predict the drape coefficient (DC). Hanging weight, Sample diameter and the bending rigidities in warp, weft and skew directions are selected as inputs of the ANN model. The ANN developed is a multilayer perceptron using a back-propagation algorithm with one hidden layer. The drape coefficient is measured by a Cusick drape meter. Bending rigidities in different directions were calculated according to the Cantilever method. The DC obtained results show a good correlation between the experimental and the estimated ANN values. The results prove a significant relationship between the ANN inputs and the drape coefficient. The algorithm developed can easily predict the drape coefficient of fabrics at different diameters.

Keywords:

Bending rigidity, drape coefficient, neural networks, back-propagation

1. Introduction

Drape is the term used to describe the way a fabric hangs down under its own proper weight in folds. It gives an idea on how good a garment looks in use. Moreover, drape indicates the conformity of garments to body contours. When a fabric is draped, various configurations are found and different forms are obtained.

The study of the textile fabrics 'drapability' is related to the deformation capacities and thus their harmonised aptitude with the bodies in contact. When selecting fabrics for garments, several problems due to nonconformity between the style of the draped model are found. So, drape is a significant textile property which must be taken into account for garment selection.

Drape has been widely studied in the literature review. The fabric drape has been measured by the F.R.L. Drapemeter according to Chu et al. [5]. They defined a dimensionless value called the drape coefficient (DC). Their work was revised by Cusick [10] who modified the experimental method and used a parallel light source reflecting a circular specimen drape shadow from a hanging disc onto a paper ring. The drape coefficient calculation is based at this stage in terms of paper tracing and weighing method. It is defined as the ratio between the draped shadow paper weight and the full specimen paper weight. The drape coefficient varies from 0 to 1. It is high on stiff fabrics and low on floppy fabrics. But, the hanging area of the samples modifies significantly the value of the drape coefficient (DC).

Collier et al. [7] presented a digital drape meter to evaluate drape coefficient. The method is based on the photovoltaic cells

light absorbance, placed in the bottom surface of the Cusick drape meter, to determine the amount of light blocked by a fabric specimen draped on a platform. In fact, the absorbed light amount by the photovoltaic cells is in accordance with the drape amount. So, the drape coefficient is calculated and displayed digitally.

In recent years, the drape coefficient determination is based on numerical considerations given by scanned images obtained from a camera mounted on Cusick drapemeter [1,6,9,11-13].

The drape is a complex deformation, closely related to the fabrics bending properties.

The bending of woven fabrics has been widely investigated in the literature. Actually, Abbott et al. [1], Jeong [18] and Hu et al. [16] analysed the bending behaviour of plain-weave fabrics. It has been proved that the bending rigidity and bending hysteresis are high correlated. Pierce [23] developed a relationship to calculate the stiffness of a fabric in any direction in terms of stiffness in the warp and weft directions. Cooper [8] used Cantilever methods to study the stiffness of fabrics in various directions. Jedda H. et al. [17] proposed an artificial neural network (ANN) to predict the fabric drape using FAST parameters. Behre [3], Grosberg [14], Lindbergh et al. [19] and Oloffson [22] found that the most significant parameters which are correlated well with drape are the bending length and the bending rigidity.

Other Authors had developed ANN techniques to evaluate drape coefficient. We can cite Antony Lam et al. [2], they used a multilayer neural network with a back propagation (BP) technique and a Radial Basis Function (RBF) to predict the drape coefficient. In their paper, they consider as input

parameters: the fabric weight, the fabric thickness, the bending rigidity, the shear rigidity, the hysteresis of shear force at 0.5 degrees, the linearity of load-extension curve and the weave structure. The BP method was more effective than the RBF method but they found that the RBF method was faster when it came to training.

In this paper we present an ANN approach to predict the drape coefficient. The proposed model estimates the drape coefficient as function of bending rigidities, fabric specimen diameter and hanging weight. The originality of this approach is to consider a very limited input data which are obtained easily with basic equipment. There is no need to carry out complex tests as shear apparatus or to use specific and expensive machines to identify input characteristics presented in like other works.

To develop the ANN model, several configurations were evaluated. An optimal neural network was selected with one hidden layer and four hidden neurons. The ANN was trained with a training data set and tested with another untrained data set. The drape coefficient values obtained from the ANN were compared to experimental data obtained from Cusick drape meter.

2. Materials and methods

Fifty one samples, made up of two kinds of weave (plain and twill), were tested for this study. We began by calculating the drape coefficient using the cut and weight method with a Cusick Drape meter according to ISO 9073-9. This method

consists on the preparation of circular fabric samples which are draped over a horizontal circular disk with a constant and fixed diameter (18 cm). The samples, which have bigger diameters than the circular disk, fold under their proper weights. After fifteen minutes of stabilisation we draw the shadows of the draped samples projected on a paper and finally we cut and weigh the obtained forms of paper. The sample diameters used in this study are 24, 30 and 36 cm.

To calculate the drape coefficient we use equation 1.

$$DC = \frac{\text{Paper shaded area mass(g)}}{\text{Paper total mass(g)}} \quad (1)$$

For each sample, we calculate the drape coefficient (DC) for the three diameters. The variation of the DC values is presented in Table1.

We note that higher the sample diameter, lower is the drape coefficient. When the sample area increases, the hanging mass is more important and the mean diameter of the drape shadow is smaller.

Figure 2 presents the variation of the drape coefficient (DC) with samples diameters.

For each sample, we note that the drape coefficient varies with the hanging diameter. There is a strong relationship between the drape coefficient and the diameter of the used specimen. We note also that when the used diameter is higher the value of the drape coefficient decreases.

Figure 1. The Cusick Drape meter

Table 1. The range of the DC parameter

	Sample Diameters		
	24 cm	30 cm	36 cm
Min	0,62	0,28	0,2
Max	0,98	0,87	0,6
Mean	0,868	0,55	0,348
Standard deviation	0,05946988	0,13271021	0,09193519

The area of the hanging disc is constant; the increase of the diameter of fabric samples gives a best fallen. The hanging weight in higher diameter samples is more significant, the shade is more compact due to the gravity and the drape coefficient decreases. So, we consider that the drape is influenced by the mass of fabrics in free suspension.

Also, the variation of the drape coefficient with the sample diameter is not linear, the structure of weaving and especially the bending rigidities of samples influence strongly the drape coefficient.

2.1. Measurement of the bending rigidities

The bending rigidities parameters were measured using the Cantilever test according to ASTM D1388. The cantilever test is an apparatus developed by Pierce [23] and performed later. The test consists on allowing a rectangular strip of fabric to bend under its proper weight to a fixed angle equal to $41,5^\circ$. It permits the measure of fabric bending rigidities in weft, warp and in any direction [15]. When the tip of the strip reaches the inclined plan, the overhanging length is measured and noted L. The bending rigidity is calculated according to the following equation:

$$B_{(\mu N.m)} = W_{\left(\frac{g}{m^2}\right)} \times (L/2)^2_{(cm^2)} \times 10^{-2} \quad (2)$$

Where: L is the overhanging length, W the fabric surface mass, B the bending rigidity.

2.2. Measurement of the hanging weight

The hanging weight is calculated by the following equation:

$$M_{(g)} = W_{(g/m^2)} \times (S_{(m^2)} - S_{0(m^2)}) \quad (3)$$

Where M is the hanging weight, W the fabric surface mass, S the surface of the circular specimen of the fabric sample (diameter equal to 24, 30 & 36 cm), S_0 the surface of Cusick platform drape meter (diameter equal to 18 cm).

In Table 2 we present the 51 samples characteristics used in this paper for the neural network model. We also present in the same table the drape coefficient of each fabric calculated at different diameters.

The first 38 samples were used for training the ANN model and the last 13 samples for the test.

2.3. Artificial Neural Network model

A neural network is a mathematical model inspired by biological brains [20][21]. It consists of an interconnected group of artificial neurons or nodes. Neural networks are used to model complex relationships between inputs and outputs parameters. The most widely used ANN is known as multilayer feed forward neural network. This neural approach models the relationship between input parameters (X) and output parameters (Y) in the form presented by equation 4.

$$Y = g\left[\sum_{j=1}^M w_{kj} f\left(\sum_{i=1}^P w_{ij} X_i\right)\right] \quad (4)$$

Where X_i is the input parameters vector of dimension M, Y the output parameters vector of dimension D, $g(x)$ and $f(x)$ the functions of activation, w_{kj} the weights between neurons of input and hidden layer, w_{ij} the weights between neurons of hidden and output layers.

Back-propagation training algorithm was used. The training was realised with both inputs and outputs. In fact, input parameters propagate through the network layer by layer producing in the end a response which was the output of the network. The output was then compared with the target response and generates

Figure 2. Drape Coefficient at different diameters

Table 2. Structural properties of fabric samples

N	Fabric Id.	Bending Rigidities			W (g/m ²)	Experimental drape coefficient		
		B _{skew}	B _{warp}	B _{weft}		24cm	30cm	36cm
1	Twill 01	0,0806	0,2502	0,1996	105	0,73	0,31	0,2
2	Twill 02	0,8719	0,7902	0,9591	187,33	0,81	0,36	0,24
3	Twill 03	0,5919	0,6799	0,3345	231,2	0,75	0,32	0,21
4	Twill 04	0,6023	0,8173	0,916	175,6	0,94	0,56	0,3
5	Twill 05	0,7138	0,9009	0,6397	238,4	0,83	0,44	0,24
6	Twill 06	1,7936	1,3475	0,774	263,2	0,93	0,6	0,35
7	Twill 07	0,7202	2,0959	1,162	151,2	0,92	0,74	0,27
8	Twill 08	0,6704	0,7477	0,8136	218	0,87	0,51	0,26
9	Twill 09	0,4138	0,3778	0,3607	137,6	0,9	0,54	0,39
10	Twill 10	4,6499	5,0372	4,107	340	0,94	0,72	0,3
11	Twill 11	0,7456	1,2754	0,942	184	0,86	0,48	0,33
12	Twill 12	1,281	0,8758	6,1885	110,66	0,94	0,72	0,53
13	Twill 13	0,3983	0,5397	1,4345	175,5	0,84	0,5	0,44
14	Twill 14	1,0331	0,4279	0,996	184	0,84	0,47	0,31
15	Plain 01	0,6961	0,6961	1,1549	221,4	0,82	0,43	0,23
16	Plain 02	0,142	0,1861	0,3788	95,4	0,86	0,45	0,2
17	Plain 03	0,15	0,1901	0,3882	95,8	0,87	0,44	0,26
18	Plain 04	0,4997	1,1395	0,5034	97,6	0,95	0,7	0,39
19	Plain 05	0,688	2,1086	0,3787	258,8	0,81	0,42	0,25
20	Plain 06	0,6164	0,834	0,4866	214,4	0,85	0,45	0,24
21	Plain 07	0,643	0,978	0,5089	125,6	0,91	0,6	0,3
22	Plain 08	0,566	0,8543	0,5638	121,6	0,9	0,5	0,33
23	Plain 09	0,5616	0,8534	0,562	122,4	0,91	0,51	0,32
24	Plain 10	0,57	0,8624	0,5551	123	0,9	0,52	0,3
25	Plain 11	0,566	0,8001	0,5622	122,4	0,91	0,51	0,34
26	Plain 12	0,7371	2,2356	0,9457	166,6	0,92	0,59	0,33
27	Plain 13	0,6154	0,4049	1,6084	66,4	0,95	0,72	0,51
28	Plain 14	0,6052	0,412	1,6103	66,8	0,96	0,73	0,52
29	Plain 15	0,4244	0,4624	0,4822	129,2	0,84	0,59	0,43
30	Plain 16	1,4247	3,2751	1,7728	224	0,93	0,53	0,36
31	Plain 17	1,2424	1,1078	1,7689	242,66	0,9	0,55	0,37
32	Plain 18	1,5927	0,8856	2,2182	166,66	0,94	0,63	0,48
33	Plain 19	2,1056	6,5107	6,5107	220,33	0,92	0,68	0,49
34	Plain 20	0,9267	1,3422	0,7909	138,33	0,93	0,65	0,34
35	Plain 21	0,8859	1,5049	0,5594	130	0,94	0,72	0,4
36	Plain 22	0,2828	0,7634	0,0877	103	0,8	0,45	0,31
37	Plain 23	0,2885	0,492	0,2885	160	0,83	0,44	0,33
38	Plain 24	0,3417	0,5906	0,3417	140	0,86	0,46	0,32
39	Plain 25	2,8741	2,5821	0,3607	194	0,92	0,81	0,5
40	Plain 26	0,0983	0,2332	6,1885	68	0,62	0,28	0,26
41	Plain 27	1,0718	1,0328	1,4345	198	0,95	0,67	0,41
42	Plain 28	0,1588	0,0409	0,996	95,5	0,86	0,5	0,34
43	Plain 29	0,6176	0,3773	0,3784	110	0,9	0,51	0,35
44	Plain 30	0,1437	0,0901	0,0004	70	0,84	0,41	0,33
45	Twill 15	0,3716	0,3025	0,3784	65	84,4	0,45	0,34
46	Twill 16	4,2584	8,3607	2,4387	280	88	0,78	0,47
47	Twill 17	0,9483	0,8346	1,1664	162	81	0,58	0,32
48	Twill 18	0,2499	0,48601	0,419	85	98	0,47	0,37
49	Twill 19	4,7123	2,8645	2,2093	266	84	0,87	0,6
50	Twill 20	0,3998	0,2602	0,4555	130	86	0,63	0,38
51	Twill 21	0,6767	0,5251	1,3217	167	0,95	0,55	0,36

error signals. These errors propagate in a backward direction through the network. In this phase, the weights of the network are adjusted to minimise the value of the quadratic error average (MSE) between the ANN response and the experimental values. The MSE calculation is given by equation 5.

$$MSE = 1/2 \sum_i^n (t_i - y_i)^2$$

(5) Number of hidden layers

Where t_i is the i^{th} desired output (target), y_i the i^{th} output.

To build correctly a neural network, several parameters must be optimised such as the number of hidden layers, the number of neurons in the hidden layer, the rate of training and the numbers of iterations during the training. The general architecture of the ANN is given by Figure 3.

2.4. Optimisation of the ANN model

The first decision in connection with the parameters of the neural network is to find out the number of hidden layers. The

use of more than one hidden layer allows having good results. But, Chattopadhyay and Guha [4] show in their study that the increase of the hidden layers number is able to produce a considerable improvement of performances of the network if only all the other parameters of the network are optimised.

The number of hidden layers (N_{hidden}) must be selected according to the correlation coefficient (R) existing between the experimental and the estimated values given by the network. The number of hidden layers giving the highest value of R must be selected (Figure 5). In this study, best results are obtained with only one hidden layer of neurons (Figure 4).

Number of hidden neurons

The number of hidden neuron is a very significant factor in the neural networks system. In this study, we found that the value of hidden neurons equal to 4 is the best value. It gives

Figure 3. The Artificial Neural Network Structure

Figure 4. Effect of the number of hidden layers variation on MSE

a minimal quadratic error (MSE) and a maximum efficiency of the model (R much closer to 1) as presented in Figure 6 and Figure 7.

Iteration count

The iteration count to be considered must give the smallest MSE. In this paper the cycle's number equal to 500 gives best results as presented by Figures 8 and 9.

In Figure 5, we can note that when the iteration count increases, the correlation coefficient is higher. But an accurate analysis must be developed to determine the influence of the iteration count on the quadratic error of the ANN and on the correlation coefficient R . The results are presented by Figures 8 and 9.

The iteration count 500 gives the highest correlation coefficient and the lowest MSE.

3. Results and discussion

The structure of the ANN was made with one hidden layer, 4 hidden neurons, 5 inputs and the drupe coefficient as output. The activation function used was the sigmoid function and the iteration count was equal to 500.

13 samples were used to test the neural network model developed. The pace of the average quadratic error obtained after 500 iterations was presented in Figure 10. It shows a good convergence of the algorithm.

We calculated the correlation coefficient of the samples and we noted that there was a good correlation between the drupe coefficients measured experimentally and those calculated by the neural network's method for the used diameters (24, 30 and 36) (Figure 11). The correlation coefficient obtained (0.916) explains a good quality of the forecast given by the training algorithm.

Figure 5. Effect of the number of hidden layers variation on the correlation coefficient R

Figure 6. Effect of the number of hidden neurons variation on MSE

Figure 7. Effect of the number of hidden neurons variation on the correlation coefficient R

Figure 8. Effect of the iteration count variation on MSE

Figure 9. Effect of the iteration count variation on Correlation Coefficient R

4. CONCLUSIONS

In this paper an ANN was developed and optimised to predict the drape coefficient for different fabric diameters. We simplified the forecast of the drape coefficient by simple, basic and fast physical testing fabric properties which give a good correlation between the experimental and the predicted values of the drape coefficient.

This method gives efficient results of the drape coefficient and can replace the cut and weight method which needs to draw the shadow of the folds of the fabric. The proposed model has been found efficient for proving correlation between the bending rigidities, the hanging weight and the drape.

The results obtained can be used to predict the drape coefficient at different diameters; they can help textile designers in the choice of the fabric structure to be used in garments.

Figure 10. Curve of training

Figure 11. the relation between predicted and measured DC

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