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The Prediction of Elongation and Recovery of Woven Bi-Stretch Fabric Using Artificial Neural Network and Linear Regression Models

Abstract
Stretch woven fabrics are widely used because of their good elongation and recovery (residual extension) properties. Several parameters and test method are used to measure the properties of these fabrics. Each different set of test parameters means a different test application. Sometimes, repeating tests for different test involves wasting time and labour. In this study, the test results were used to try and predict elongation and recovery using neural network and linear regression models. Certain test parameters such as rate of extension, gauge length (jaw separation), and maximum load were selected as input variables. The accuracies of predictions of elongation in the direction of warp and weft by both models were found to be similar and satisfactory. The predictions for the recovery test showed differences as to fabric warp and weft direction. All the statistical results indicate that predicting the fabrics' test results from an unseen data set is very good for both models.

Key words: *woven fabric, elongation, recovery, artificial neural network, regression model.*

Introduction

In recent years, fabric manufacturing processes have become more and more rapid and automated; the consumer market has also become increasingly sophisticated. Elongation and recovery properties are very important for fabrics including elastane. In order to obtain good-quality products with high-efficiency production lines, clothing companies have established advanced laboratories to measure fabric properties by controlling production processes and fabric quality. Therefore, these laboratories have devoted their efforts to measuring and determining the different properties of their fabrics. For this purpose, many test methods are being developed and applied in the laboratories. Every test method has some test parameters which are determined according to the test aim and structure of fabric. In this case, every test must be repeated for each different test parameter values. This wastes time. However, with some statistical methods and models, the test results can be predicted with high accuracy before applying an actual test. For example, Witkowska & Frydrych (2004) studied a tear strength test for different kinds of protective fabric. They investigated the effect of different tear strength techniques on the results, and calculated the correlation coefficient between the results and test methods [1]. In another study about this subject, Lizak (2002) tried to find out the effect of gauge length (one of the test parameters) on yarn strength by using statistical methods [2].

Artificial neural networks (ANN) and regression models have been used in many engineering fields to predict material properties. Within the textile industry alone, numerous applications have been reported. For example, Kuo, Hsiao & Wu (2004) considered the extruder screw speed, gear pump, gear speed, and winder winding speed of a melt-spinning system as inputs, and the tensile strength and yarn count of as-spun fibres as outputs. They indicated their ANN model could predict the tensile strength and yarn count of as-spun fibres to provide a very good and reliable reference for as-spun fibre processing [3]. Strumillo et al. (2004) describes the design of a yarn spinning model based on the use of artificial neural networks, as well as measurements aimed at collecting the data necessary for this model. Feed-forward neural networks were used for modelling. In the study, the percentage content of flax and of the linear density of yarn was used as inputs, and some yarn quality parameters were used as outputs [4]. Majumdar & Majumdar (2004) used an ANN to predict the breaking elongation of ring spun cotton yarns and compared their predictions with statistical and mathematical models. They used cotton fibre properties and yarn count as inputs to these models. They found that prediction performance was the best for the ANN model, followed by the statistical and mathematical models [5]. Lewandowski & Stanczyk (2005) used an ANN technique for identification and classification of spliced wool combed yarn joints. They used the Adaline type of ANN. In the first part of the study, an ANN model was developed; in the other part, the network was tested [6, 7].

In recent years, ANN has been widely used to predict fabric properties. Ertugrul & Ucar (2000), Gong & Chen (1999), Kuo et al. (2003a), Kuo & Lee (2003b), Tilocca et al. (2002) have successfully used ANN models to predict various fabric properties. All these researchers have obtained high prediction accuracy of the ANN models, even for unseen data sets. Gong & Chen (1999) investigated the use of artificial neural networks to predicte fabric performance in garment manufacture and the appearance of the made-up garment [8 - 12].

In this paper, we attempt to predict elongation and recovery test results of woven stretch fabric for warp and weft direction using different test points with regression and ANN models, and to compare the prediction results with each other.

The artificial neural network and regression model

The artificial neural network and back-propagation algorithm

The most commonly used type of ANN is the multi-layered feed-forward back-propagation trained neural network [18]. Networks of this type are very general; they can approximate accurately complex mappings and possess the statistical property of consistency (learnability) for unknown regression functions.

A feed-forward network has a layered structure. Each layer consists of units which receive their input from a layer directly below, and send their output to units in a layer directly above the unit. There are no connections within the layer itself. In most applications, a feed-forward network with a single layer of hidden units is used with a sigmoid activation function for the units [19]. Therefore, we used a feed-forward network with a single layer of hidden units. In our work, jaw separation (mm), rate of extension (test speed-mm/min), and maximum load (N) were chosen as inputs to the neural networks. The output layer had two nodes; the output nodes produced warp & weft elongation and recovery values.

Training is an important feature of neural networks. The objective of the training process is to minimise the squared error between the network output and the desired output. This is done by adjusting the connection weights across the network. The error is computed by making a forward calculation through the hidden and output layers of the network. For weight adjustment, the network errors are propagated backward through the network by different learning algorithms. In our networks we used a back-propagation learning algorithm as learning, since the back-propagation (BP) algorithm is among the most popular learning algorithms for learning in a multi-layered feed-forward neural network [20].

The BP algorithm is processed in two distinct phases, the feed-forward phase and the error back-propagation. In the feed-forward phase, an input signal is propagated from the input layer to the output layer. The process starts with the random values for weights (w). The calculated output, o_k is then compared to the target output, t_k and the backward phase begins with the computation of least mean squares' (LMS) weight adjustment by minimising the error function, E:

$$E(w) = \tfrac{1}{2}\sum_{k=1}^{c}(t_k - o_k)^2 \qquad (1)$$

The usual BP algorithm updates the weights by using the gradient descent rule as:

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \qquad (2)$$

where η is the learning rate that controls the learning time of the network [21]. The forward and backward passes are iteratively repeated until the overall network error is less than a pre-defined threshold value, or when the maximum number of allowed iterations is reached.

Regression model

In general, the response variable y may be related to k regressor variables. The following model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \qquad (3)$$

is called a multiple linear regression model with k regressor variables. This model describes a hyperplane in k-dimensional space of the regressor variables x_j. The least-square method is typically used to estimate the regression coefficients (β_j) in a multiple linear regression model. The least-square method chooses the βs in Equation (4), so that the sum of the squares of the errors ε_i, are minimised.

The least-square function is

$$L = \sum_{i=1}^{n} \varepsilon_i \qquad (4)$$

The function L is to be minimised with respect to

$$\beta_0, \beta_1, \ldots, \beta_k.$$

The least-square estimators, say

$$b_0, b_1, \ldots, b_k,$$

must satisfy [22].

$$\left.\frac{\partial L}{\partial \beta_0}\right|_{b_0, b_1, \ldots b_k} = 0 \qquad (5)$$

Experimental design

Fabric structural properties

The fabric used for experimental study (Table 1) consists of blended fibres such as polyester/viscose/elastane (DuPont Lycra®). This fabric has elastane fibre in both warp and weft directions.

Two performance criteria of the fabric were investigated in this study, elongation and recovery. Elongation can be explained as the changing the form of material temporarily with the effects of out forces (pull, etc.). This deformation recovers when the effect of out forces disappear. Recovery can be explained as the ratio between the original dimension (length towards the effect) and the permanent deformation amount of material with the effect of the force applied to it over a definite time [18].

Elongation and recovery in percent:

$$\frac{\delta}{L} \times 100\% \qquad (7)$$

were: δ is the total elongation of the member (temporarily or permanently), and L is the original length of the member [19].

Experimental method and data collection

In the study, the elongation and recovery properties of stretch woven fabric are measured on the latest Titan Universal

Table 1. Some structural properties of test specimen.

Parameters	Specimen	
Yarn properties	Warp	Ne 20 (Tex 29,53) + 78 dtex Elastane (core-spun)
	Weft	Ne 20 (Tex 29,53) + 78 dtex Elastane (core-spun)
Raw material	48% Polyester / 48% Viscose / 4% Elastane (DuPont Lycra®)	
Warp direction density, ends/cm	33	
Weft direction density, picks/cm	25	
Weight, g/m2	238.12	
Weave	Twill 1/2 (S)	

Table 3. Some elongation and recovery values of fabric by ANN and regression.

No	Inputs			Elongation						Recovery					
	JS, mm	ROE, mm/min	ML, N	Actual		Predicted regression		Predicted ANN		Actual		Predicted regression		Predicted ANN	
				Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft	Warp	Weft
1	100	500	125	29.14	31.41	29.66	32.70	29.37	32.61	15.00	19.75	16.69	20.12	16.96	21.20
2	100	500	500	15.23	16.02	15.76	17.56	15.61	16.96	2.00	5.00	0.73	4.47	2.21	4.23
3	120	500	500	28.40	31.47	29.47	32.96	29.18	32.39	13.25	19.00	12.43	19.18	12.46	16.03
4	170	500	250	18.78	21.90	20.15	22.43	20.24	22.22	4.44	9.00	4.59	9.79	4.81	7.22
5	170	250	125	29.39	31.90	29.21	32.29	28.97	32.15	13.25	17.16	14.71	20.54	15.31	19.29
6	100	500	250	19.61	21.86	20.33	22.70	20.46	22.48	5.00	11.00	4.63	9.37	4.41	7.09

Test Equipment with different rates of extension (ROE), jaw separation (JS-gauge length) and maximum load (ML) with a jaw method based on BS 4952 [20]. The application of BS 4952, standard measurement of fabric elongation and recovery is executed on a JL of 100 mm and an ROE of 500 mm/min. The Titan test equipment allows users to measure different performance criteria of woven or knitted fabric and yarn, such as strength properties (tensile and tearing strength etc.). During the experimental application in jaw methods, the fabric specimen is placed between the bottom stable jaw of the machine and its upper active jaw. Then, the experiment is started according to the test parameter loaded into the test machine's memory at the beginning. All tests are carried out under standard laboratory conditions (humidity 65%, temperature 20 °C), and the samples were conditioned at these environmental parameters for 24 hours.

In order to examine elongation performance, the ROE and ML experiment parameters were applied with 3 levels, but the JS was applied with 5 levels. In total, 45 different experiment points were formed. At each point, the experiment was replicated five times. Therefore, 225 experiments for elongation were carried out. For rate of extension 50-250-500 mm/min test speeds were used; for jaw separation 100-120-150-170-200 mm specimen length, and for maximum load 125-250-500 N. However, for recovery, all the input parameters were accepted at 3 levels, i.e. rate of extension (50-250-500 mm/min), jaw separation (100-150-200 mm) and maximum load (125-250-500 N). In total, 27 different experiment points were formed. Similarly, the experiment was replicated five times at each point. Therefore, 135 experiments for elongation were carried out.

From the experimental study results; 45 and 27 sets of input-output data sets were available for elongation and recovery respectively. 27 and 16 data sets were used for the training of elongation and recovery models. While training, 5 and 3 data sets were used for cross-validating for elongation and recovery. The remaining data sets were used to evaluate the prediction performance of the ANN and regression models. While forming the regression model, the training and validation data sets used in the ANN were combined.

Neural network parameters

In this study, we used four different network structures with only one hidden layer. The number of nodes in the hidden layer varied from 3, 12, 30 and 50. The learning rate and momentum were optimised at 0.1 and 0.0 respectively. We found that the neural network model with 12 nodes in the hidden layer gives the best prediction results in the test.

Regression model parameters

This statistical model is used to predict the properties of the woven fabric. The model was developed with a linear multiple regression algorithm. The models used for prediction are as follows:

$$\text{Fabric elongation-warp} = 11.78 + - (0.0370\times JS) - (0.00043\times ROE) + + (0.0365\times ML)$$

$$\text{Fabric elongation-weft} = 12.67 + - (0.0532\times JS) + (0.000584\times ROE) + + (0.0411\times ML)$$

$$\text{Fabric recovery-warp} = 1.65 + - (0.00834\times JS) - (0.00946\times ROE) + + (0.0312\times ML)$$

$$\text{Fabric recovery-weft} = -0.23 + + (0.0839\times JS) - (0.00208\times ROE) + + (0.0393\times ML)$$

As seen from the regression models above, JS affected the elongation and recovery properties negatively, apart from recovery-weft. The ROE's effect on these properties is negative too, apart from elongation-weft. However, the ML has a positive effect on all responses.

Results and discussion

The ANN and regression model are in accordance with the experimental data of three inputs and two outputs, part of which (for elongation and recovery) are listed in Table 2.

After the completion of model development and training, the ANN and regression prediction models are verified by the unseen test data for elongation and recovery shown in Table 3.

Statistical parameters such as the correlation coefficient between the actual and predicted elongation and the recovery test results of woven stretch fabric in the direction of warp and weft, mean square error and mean absolute error were used to assess the predictive power of the two models. The results are shown in Table 4 and Table 5, for elongation and recovery respectively.

Table 4 indicates that the predictive power of the ANN and linear regression models are almostidentical. The correlation coefficient (R) between the actual and predicted elongation test results of warp and weft directions are also satisfactory for both the ANN and regression models. The R values in the warp direction are 0.985 and 0.986 for the ANN and regression models respectively. Also, in the weft direction the R values are 0.992 and 0.989 for ANN and regression respectively. In addition, the MAPE values for two models are less than 5%, so there is no significant difference. According to these results, both models could be used to predict the elongation values of the warp and weft direction of stretch fabric.

In Table 5, a comparison of the prediction performance of both models can be seen. With respect to the warp direc-

Table 2. Some data used for ANN and regression model for elongation and recovery test.

No	Inputs			Actual outputs			
				Elongation		Recovery	
	JS, mm	ROE, mm/min	ML, N	Warp	Weft	Warp	Weft
1	100	50	125	14.88	15.71	14.25	5.00
2	150	500	125	14.48	16.02	4.22	9.33
3	150	500	500	27.61	31.60	12.17	18.84
4	150	50	250	20.48	22.77	6.17	9.66
5	200	50	125	15.60	16.33	4.50	5.00
6	200	250	250	19.99	22.48	5.00	11.25

Table 4. Comparison of prediction performance of various models for elongation.

Statistical parameters	Warp direction		Weft direction	
	ANN	Regression	ANN	Regression
Correlation coefficient. R	0.985	0.986	0.992	0.989
Mean squared error (MSE)	1.234	1.065	0.564	0.896
Mean absolute percent error (MAPE)	4.0	3.8	2.7	3.4
Cases with more than 10% error	0	0	0	0

Table 5.Comparison of prediction performance of various models for recovery.

Statistical parameters	Warp direction		Weft direction	
	ANN	Regression	ANN	Regression
Correlation coefficient. R	0.983	0.975	0.948	0.976
Mean squared error (MSE)	1.474	1.723	5.925	1.930
Mean absolute percent error (MAPE)	12.2	20.5	18.6	7.8
Cases with more than 10% error	4	3	7	3

tion's results, when the R value for the ANN was compared with the regression model, no difference was seen. But when the MAPE values were computed, the value for ANN was found to be more satisfactory (the R value of ANN = 0.983, the R value of Reg. = 0.975, and the MAPE of ANN = 12.2%, the MAPE of Reg. = 20.5%). In contrast to the warp direction's results in the weft direction, the MAPE value for regression is more satisfactory (the R value of ANN = 0,948, the R value of Reg. = 0.976 and the MAPE of ANN = 18.6%, the MAPE of Reg. = 7.8%).

Conclusions

In this study, we predicted the elongation and recovery test results of the polyester/viscose/elastane blended bi-stretch woven fabric shown in Table 1 using different input variables (JS, ROE, and ML) with both ANN and linear regression models. On the basis of the results obtained, with the help of both ANN and regression analysis, we can predict the fabric's properties easily and accurately. When predicting the elongation values of the fabric, either one of two models could be used. However, for recovery, the prediction power of two models shows difference according to fabric direction such as warp and weft. In the warp direction, the performance of ANN seems to be better that of the regression model; in contrast, this is reversed in the weft direction. As a result, when comparing the prediction of elongation and recovery properties, it was determined that elongation properties were predicted more accurately using both models than that of recovery.

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Received 04.07.2005 Reviewed 06.12.2006