Predicting the Pilling Propensity of Fabrics through Artificial Neural Network Modeling

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ABSTRACT

Fabric pilling is affected by many interacting factors. This study uses artificial neural networks to model the multi-linear relationships between fiber, yarn and fabric properties and their effect on the pilling propensity of pure wool knitted fabrics. This tool shall enable the user to gauge the expected pilling performance of a fabric from a number of given inputs. It will also provide a means of improving current products by offering alternative material specification and/or selection. In addition to having the capability to predict pilling performance, the model will allow for clarification of major fiber, yarn and fabric attributes affecting fabric pilling.

Pilling may be defined as a surface fabric fault comprising of circular accumulations of entangled fibers that cling to the fabric surface thereby affecting the appearance and handle of the fabric. The pilling of fabrics is a serious problem for the apparel industry and in particular wool knitwear fabrics [13]. It is realized that the problem of pilling is one of the biggest quality issues for the wool industry, however the problem remains.

The formation of pills occurs as a consequence of mechanical action during washing or wear. Under the influence of mechanical action, loose fibers that protrude from the fabric surface entangle. Subjected to further mechanical action the entanglements develop into roughly spherical accumulation of fibers (pills) that are distinct from the fabric surface. Wear-off of pills occurs under continued abrasion from laundering, drying, etc., and during wear. For a given fabric, the degree to which pills form and wear-off is determined by the physical properties of the fiber, yarn and fabric constituents [20]. Many researchers have investigated the influence of these properties and have identified numerous factors that contribute to the pilling of wool fabrics. At the fiber level, fiber tenacity [12], diameter [6, 21], length [10, 19], and curvature [9, 11] have been proven to impact on the rate of fuzz formation, extent of entanglement and the degree of wear off. Of the yarn parameters to affect pilling, yarn type [2] along with the degree of singles twist and/or fold twist [16] are most influential parameters. Yarn hairiness [3, 10] and yarn linear density [5] have also been shown to contribute significantly in fabric pilling. Fabric construction also plays a role in the pilling process, the tightness of the knitted construction (cover factor) impacts on the development of fuzz and pills along with the tendency for pill wear-off [11, 16].

Although the problem of pilling has attracted extensive research over the decades, due to the nature of pilling, the accurate modeling or prediction of the process is still elusive. Much research has gone into understanding the key factors and mechanisms responsible for pilling but failed to move beyond assessing the problem at a single particular stage of the manufacturing process. Without considering the complex interactions of the various factors at the different processing stages, the weight of each factor and their synergistic effect on the propensity of a fabric to pill cannot be fully understood.

With the advent of artificial neural networks, the opportunity to predict the pilling propensity of fabrics exists. Neural networks have been used extensively in various textile disciplines ranging from the classification of wool/mohair fibers [18] to the prediction of human psychological perception of clothing comfort [22]. Recently Beltran *et al*. [4] employed neural networks in the prediction of worsted spinning performance. The advantage of neural networks lies in their ability to represent both linear and non-linear relationships and to learn these relationships directly from the data being modeled [15]. As neural networks can capture many kinds of relationships it enables modeling of phenomena which otherwise may have been very difficult or impossible to explain otherwise.

Artificial neural networks are information processing paradigms that are inspired by the way biological nervous systems, such as the brain, process information [8]. Neural networks consist of many neurons, each receiving connections from other neurons. The signals flowing on connections are scaled by adjustable parameters called weights. The neuron sums all of these contributions and multiplies this value with a transfer function to produce an output that is a nonlinear (static) function of the sum according to equation (1) [1].

$$u_j = (\sum_{i=0}^{n} w_{ji} y_i) + b$$

where y_i is the functional signal of signal y in layer i according to

$$y_i = \frac{1}{1 + e^{(-u_i)}}$$

The outputs are either transferred to other neurons from layer to layer or become the system outputs.

Neural network training is achieved by adjusting the values of the connection weights, through the repeated application of the error backpropagation algorithm [17]. Network weights are adapted iteratively until some appropriate stopping criteria is met and the best weight vector that corresponds to the best generalization is achieved. One such method is to terminate training using the cross-validation error [14].

Key fiber, yarn, and fabric properties identified from the literature were used as inputs along with their corresponding pilling intensities in an artificial neural network designed to predict the pilling performance of knitted wool fabrics.

Experimental

DATA PREPARATION

The focus of this research was constrained to pure wool knitted constructions. All yarns were ring spun, and top dyed sliver specimens were sampled at the third stage draw frame. The fabric samples were comprised of two different knitted structures, 1/1 rib and single jersey. Within each knitted structure, two variations in the cover factor exist, representing commercial extremes in knit
T1 ting tension for each gauge used (Table I).

TABLE I. Cover factors, knitting gauge and corresponding yarn counts.

		Cover factor (mmtex)	
Knitting gauge	Yarn count (tex)	1/1 rib	Single jersey
8	146–166	1.55–1.78	1.29–1.58
10	115–122	1.62–1.84	1.55–1.66
12	75–86	1.69–1.95	1.52–1.70
14	60–66	1.65–1.81	1.46–1.68
18	31–44	1.53–1.81	1.23–1.57

All tests were carried out according to standard test procedures in a standard atmosphere of 20 : 2°C and 65 : 2% relative humidity after a minimum period of 24 hours conditioning in an ISO9001 certified laboratory.

Mean fiber diameter, coefficient of variation of fiber diameter (CV_D), percentage of fiber greater than 30 (pm), and fiber curvature (deg/mm) were measured using OFDA 100® according to Australian Standard AS4492.5. Hauteur fiber length, coefficient of variation of fiber length (CV_H) and the percentage of short fibers (< 40 mm), were obtained using an Almeter Instrument, (IWTO-17). Bundle strength measurements were performed using a Sirolan Tensor® with a gauge length of 3.2 mm, extension rate of 20 mm/min and bundle weight of 500 : 100 tex.

Yarn linear density was measured according to Australian Standard AS2001.2.23. The determination of yarn evenness and imperfections was based on the ASTM standard D1425-89 using a testing speed of 400 m/min on a Uster 4®. The determination of yarn twist was carried out according to Australian Standard test method AS 2001.2.14 with a test length of 250 mm and a pretension of 0.5 cN/tex. Cover factor of the knitted structures was calculated according to the Woolmark® test method TM 169.

The ICI pill box was selected as the pilling test apparatus. New cork liners were run in for 200 hours (720 000 revolutions) prior to the commencement of pill testing. Testing was conducted in accordance with the requirements stipulated in the ISO standard-Determination of fabric propensity to surface fuzzing and to pilling 12945-1 : 2000 over a period of 4 hours (14 400 revolutions). Due to the subjective nature of pilling assessment, all ratings were made individually and independently by a panel of four experienced observers. Where one or more assessments varied greatly, that is, more than half a grade, the outlier rating was disregarded and the mean rounded off to the nearest half grade. Ordinarily this variation would not be considered of great consequence, however if this network is to accurately model the data then outputs differing merely on inconsistent assessments would reduce the performance of the neural network.

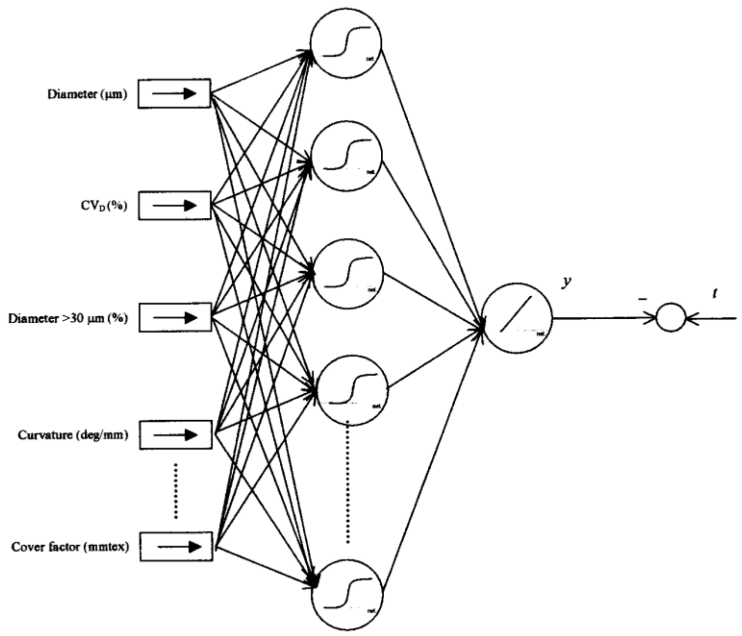
ARTIFICIAL NEURAL NETWORK TRAINING

Fiber properties, (diameter, CV_D, diameter > 30 pm, and curvature), top properties (Hauteur, CV_H, short fiber < 40 mm, bundle strength and strain), and yarn specifications (count, hairiness, thin and thick places, twist factor, folding twist ratio) along with fabric (cover factor) will serve as quantitative inputs to the neural network. To eliminate the influence caused by different quantitative level, the input data was normalized bounded within the prescribed range of 1 and O. Moreover input categories (111 rib, single jersey, shrink proof and fold twist) were also included. These inputs were encoded as 0 or 1, depending on the input class membership. For example, input patterns which had a shrink proof treatment, the shrink-proofed input channel was coded 1 and all non-shrink proof inputs patterns received a O. The corresponding mean pill rating which varied between 1 and 4-5, served as the target output (Figure 1). Table II shows the range of each input parameter. There were a total of 135 sets of data available. The first 105 sets of randomized data were assigned to training, 20 sets were assigned for cross-validation and the remaining 10 data sets selected for testing. The ten sets of data assigned for testing were independent from the training set, providing a means of assessing whether the model had memorized the training data or learned to model the underlying relationships. The network consisted of a single hidden layer multi-layer perception trained with the error backpropagation algorithm possessing hyperbolic tanh activation functions in both the hidden layer and output layer. The number of neurons in the hidden layer was set at nine. Step sizes were set at 0.95 in the synapse between the input and the hidden layer, and 0.1 in the synapse between the hidden and output layer. The momentum parameter was fixed at 0.7. Training was terminated after 50 epochs without improvement in the cross-validation error.

TABLE II. Quantitative input parameters and their range of values.

	Input parameters	Range of values Maximum	Minimum
Top	Diameter (/Lffi)	28.7	18.5
	CV_D (%)	26.3	21.4
	Diameter> 30 /Lm (%)	37.5	0.9
	Curvature (deglmm)	56.7	49.9
	Hauteur (mm)	92.3	68.6
	CV_H (%)	51.1	37.4
	Short fiber < 30 mm (%)	18.6	7.3
	Bundle strength (cN/tex)	9.60	11.59
Yam	Count (tex)	157.9	40.8
	Thick place (km)	78.8	O
	Thin place (km)	35	O
	Hairiness	24.11	5.73
	Twist factor (KJ	2960	2087
	Folding twist ratio	0.63	O
Fabric	Cover factor (mmtex)	1.98	1.23

FIGURE 1. Network model, a multilayer perceptron with a single hidden layer applying backpropagation learning rule with momentum term.



Results and Discussion

The training performance of the network has been summarized in Figure 2 by monitoring the evolution of the training and cross-validation errors over six training runs. Several independent trainings runs with different random initializations of the weights are important as it prevents the probability of converging at a less then optimal solution. The function of early stopping based on cross-validation error is also illustrated in Figure 2. Although the learning error continues to decrease to a minimum mean square error (MSE) of 0.008 after 150 epochs, the cross-validation error however reaches a minimum of 0.007 MSE after approximately 70 epochs beyond which the cross-validation error rises. Interpreting the curve in Figure 2, it can be deduced that this network has successfully modeled the current data. Although promising, a true unbiased indication of the network's performance can only be achieved with the testing of 'unseen' data sets independent from the training set.

The predicted outcomes of the model are presented in Table III. Here the neural network has been employed as an analytical tool, functioning in the forward propagation mode using the best weight vectors found during training. The resulting report contains a table of the target 'desired' output and actual network outputs. Furthermore, the sum of the squared errors (SSE) between the network and target outputs has been included.

When comparing the ratings made by the four observers (target) against the ANN outputs, it is evident that this model is able to make predictions based on the current inputs provided. After rounding off to the nearest half grade, the network manages to correctly classify eight out of the ten test data sets (Table III). This result is encouraging considering the number of data sets used to train the network and the fact that the two examples incorrectly classified were only half a grade incorrect. It is expected that the performance of the model will improve with an increase in the number of data sets available for training. Further improvements should also be found with network modification. Fine tuning of the network parameters was not undertaken due to the lack of data points.

To illustrate the applicability of the model for use as a prediction tool, five inputs (cover factor, fiber diameter, curvature, hairiness and twist factor) were varied while all other inputs were fixed. The variables were chosen based on their known contribution to pilling. The five inputs were perturbed in a manner so as to increase or reduce the pilling performance over the original dataset. With random increases in the normalized values of cover factor, fiber diameter, curvature, twist and a reduction in yarn hairiness there is up to one grade improvement in pilling performance (Table IV). These observations correspond to those found in previous studies. For example McGregor [11] found an increase in pilling resistance with increasing cover factor. In a study by Westenberg [21] it was concluded that the diameter distribution of fibers in the pills is appreciably finer than found in the bulk, indicating preferential migration of fine fibers due to their relatively low bending rigidity. Haigh and Robinson [9] observed that the higher crimp frequencies in wool better resisted pilling in knitted fabrics, while Greaves [7] and Richards [16] found that an increase in twist multiplier improved pilling resistance. The tendency to pilling is lower with reduced yarn hairiness [10].

When the network was presented with the opposite scenario, namely with the yarn hairiness normalized value increased and all other normalized input values reduced, the pilling propensity increased in all cases by half a grade (Table IV). Differences in output ratings can be contributed to the degree of significance that each of the inputs has on pilling. Future studies will be carried out to rank inputs on the basis of their influence on the resultant pilling propensity.

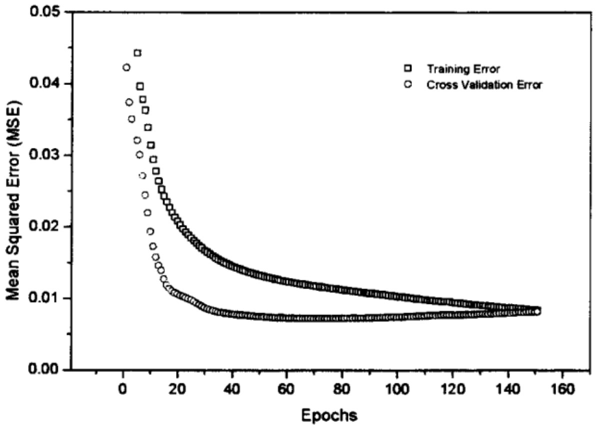


FIGURE 2. Simulation learning and cross-validation error curves obtained by executing 150 epochs over the training set. (Learning rate $\eta = 0.7$, momentum $\alpha = 0.9$).

TABLE III. Sum squared network error between the "target" pill rating and network predicted response.

Test dataset	Target	ANN Output	SSE
1	2.5	2.83 (3)	0.109
2	2	1.47 (1.5)	0.277
3	2.5	2.47 (2.5)	1.8E-04
4	2.5	2.54 (2.5)	1.5E-04
5	2.5	2.51 (2.5)	1.3E-04
6	1.5	1.35 (1.5)	0.021
7	2	1.93 (2)	0.005
8	3	2.98 (3)	2.3E-04
9	2	1.78 (2)	0.048
10	3.5	3.49 (3.5)	4.0E-05

TABLE IV. Sensitivity of the ANN model assessed through the variation of normalized input values.

Test dataset		Cover factor (cF)	Fiber diameter (μm)	Curvature (deg/mm)	Hairiness	Twist (k_t)	ANN Output	Target
Original Dataset	1	0.7521	0.3728	0.3922	0.3507	0.6136	2.40 (2.5)	2.5
	2	0.1624	0.4894	0.5799	0.7733	0.3458	1.33 (1.5)	1.5
	3	0.5214	0.5937	0.4358	0.1296	0.4599	3.04 (3)	3
Reduced pilling propensity	1	1.0000	0.7457	0.7839	0.1879	1.0000	3.29 (3.5)	–
	2	0.3333	0.8804	1.0000	0.5466	0.6915	2.71 (2.5)	–
	3	0.7350	1.0000	0.8346	0.0000	0.8233	3.24 (3)	–
Increased pilling propensity	1	0.4957	0.0000	0.0000	0.5135	0.2283	1.98 (2)	–
	2	0.0000	0.0993	0.1598	1.0000	0.0000	0.97 (1)	–
	3	0.2991	0.1874	0.0375	0.2592	0.0977	2.31 (2.5)	–

Conclusions

The findings from this study suggest that the accurate prediction of pilling propensity is achievable using an artificial neural network modeling technique. Considering the limited number of data sets used to train the network, additional data points would undoubtedly improve the performance of the model. Optimization of network parameter settings and pre-processing should also further improve the accuracy of the predictions. The capacity of the model to be utilized as a prediction tool has been demonstrated. By changing the value of various input parameters the network output values were altered according to the expected trends reported from previous observations on pilling. With the capacity to predict the propensity of a fabric to pill, the interactions between key parameters can be realized and therefore ultimately controlled.

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