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Optimization and prediction of the pilling performance of weft knitted fabrics produced from wool/acrylic blended yarns

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Effects of fibre, yarn and fabric parameters on the pilling performance of weft knitted fabrics produced from wool/acrylic blended yarns have been investigated. In order to optimize the process conditions and estimate the individual effects of each controllable factor on a particular response, Taguchi's experimental design is used. The controllable factors considered in this study are blend ratio, yarn twist multiple and count, number of feeding yarns, fabric structure and knit density. According to the signal-to-noise ratio analysis, it is observed that the used materials type and the number of feeding yarns have the largest and smallest effect on the pilling performance, respectively. Knit density is the second factor affecting the pilling performance of knitted structures and it is followed by factors knit structure, yarn twist and yarn count. The optimum condition to achieve the least pilling is determined. The prediction of fabric pilling is made using neural network. The maximum and minimum errors of prediction are found to be 4.18% and 0.21% respectively. The average of predicted error of the number of pills for weft knitted fabrics is 1.92%. The results show the good capability and predictive power of artificial neural network algorithm to predict the pilling performance of weft knitted fabric.

Keywords: Artificial neural networks, Pilling, Taguchi method, Wool/acrylic blend yarns, Weft knitted fabrics

Pilling performance is one of the most important characteristics of fabrics. When different parts of garments are rubbed together through some mechanical actions, the fibres present on fabric surface get entangled and form pills. It considerably affects the appearance and handle of fabric which is undesirable for consumers. Previous investigations[1-14] have identified many factors that contribute to fabric pilling. These factors constitute every stage of the fibre to fabric processing chain and include fibre properties (type, diameter, tensile strength, fatigue, bending rigidity, and initial modulus), yarn properties (type, twist factor, blend ratio) and fabric structures. However, fabrics pilling problems have not yet been solved[2].

Weft knitted fabrics find wider use in time since they can be produced more easily at a lower cost, and they are more flexible. Since the weft knitted fabrics have open structures, are produced with low twist yarns and are less stable than woven fabrics; for this reason, knitted fabrics are rarely objected to the pilling phenomenon. Furthermore, knitted constructions are composed of a series of loops; a greater yarn surface area is exposed, making such fabrics more susceptible to abrasive wear[3].

Campos and Bechtold[15] presented a mathematical model for estimating fibre–fibre friction. Using this model, an indication of the pilling properties of man-made cellulosic knitted fabrics was obtained. Cooke and Arthur[9] reported that the pilling process occurs in three stages including fuzz formation, entanglement into pills, and pill wear-off. Li *et al.*[16] investigated the effect of cashmere yarn properties on the pilling of cashmere knitted fabric using the optimal scaling regression analysis method. Buceline *et al.*[17] investigated the influence of fibrous composition and chemical softeners on the propensity of fuzzing and pilling of plain and plated jersey pattern knitted fabrics.

Although the problem of pilling has attracted extensive research attentions, the modeling and predicting this phenomenon is still elusive. Present work was therefore undertaken to study the effects of fibre, yarn and fabric parameters on the pilling performance of weft knitted fabrics produced from wool/acrylic blended yarns. In order to estimate the optimum process conditions and examine the individual effects of each of the controllable factors on a particular response, Taguchi's experimental design was used. The controllable factors considered in this study are blend ratio, yarn twist, yarn count, the number of feeding yarns, fabric structure and knit density. Finally, fabric pilling was predicted using artificial neural network methodology which is known as one of the most popular algorithms used in textile disciplines[18-28].

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Experimental

In the present study, the number of pills was considered as 'smaller the better' type of quality characteristic since the goal was to minimize it. The controllable factors considered were material type, yarn count and twist, knit structure, knit density and the number of feeding yarns. Table 1 represents the layout of the experimental design, which has been obtained by assigning the selected factors and their levels to appropriate columns of L_{36} orthogonal array. An orthogonal array L_{36} was chosen because it required only 36 runs for combination of six controllable factors. Four factors (knit density, number of feeding yarns, yarn count and yarn twist multiple) were varied at two levels and the remaining two factors (material type, knit structure) at three levels. While conducting the experiments, the test runs were randomly made in order to avoid the unidentified noise sources, which were not considered but could have an adverse impact on the response characteristic. Number of pills formed on samples surfaces in revolution of 2000 have been reported as the response of each experiment.

The blended yarns were spun using a commercial long staple spinning system. Wool fibres (fineness 3.15 den, mean length 84 mm) and acrylic fibres (fineness 8.15 den, mean length 85 mm) were used in this investigation.

Fabrics were knitted in three different structures using a flat knitting machine (E10). The structures of fabrics are depicted in Fig. 1. To prepare the wet-and-dry relaxed samples, the fabrics were washed in a

Table 1— Taguchi array L36

Run	Yarn count Nm	The number of feeding yarns	Knit density loop/cm^2	Twist multiple α_m	Material Wool/acrylic	Knit structure	Specifications	
							Weight g/m^2	Thickness mm
1	10	Single	High	80	25/75	Plain	0.66	209.42
2	10	Single	High	80	50/50	Rib	0.66	209.42
3	10	Single	High	80	75/25	Full-milano	0.76	245.27
4	10	Single	High	80	25/75	Rib	0.85	272.16
5	10	Single	High	80	50/50	Plain	1.12	312.91
6	10	Single	High	80	75/25	Full-milano	1.14	332.46
7	10	Single	Low	90	25/75	Plain	1.43	470.18
8	10	Single	Low	90	50/50	Rib	1.51	428.62
9	10	Single	Low	90	75/25	Full-milano	2.01	669.82
10	10	Double	High	90	25/75	Plain	1.91	609.52
11	10	Double	High	90	50/50	Rib	1.99	704.04
12	10	Double	High	90	75/25	Full-milano	1.94	655.96
13	10	Double	Low	80	25/75	Rib	1.13	299.87
14	10	Double	Low	80	50/50	Full-milano	1.13	299.87
15	10	Double	Low	80	75/25	Plain	1.18	316.17
16	10	Double	Low	90	25/75	Rib	1.33	374.84
17	10	Double	Low	90	50/50	Full-milano	1.63	450.62
18	10	Double	Low	90	75/25	Plain	1.78	491.36
19	15	Single	Low	90	25/75	Rib	2.19	620.11
20	15	Single	Low	90	50/50	Full-milano	2.08	616.85
21	15	Single	Low	90	75/25	Plain	1.16	361.80
22	15	Single	Low	80	25/75	Rib	1.19	453.88
23	15	Single	Low	80	50/50	Full-milano	1.30	387.06
24	15	Single	Low	80	75/25	Plain	1.18	366.69
25	15	Single	High	90	25/75	Full-milano	1.71	443.29
26	15	Single	High	90	50/50	Plain	1.71	443.29
27	15	Single	High	90	75/25	Rib	1.63	365.06
28	15	Double	Low	80	25/75	Full-milano	1.85	432.69
29	15	Double	Low	80	50/50	Plain	0.98	254.24
30	15	Double	Low	80	75/25	Full-milano	1.07	257.50
31	15	Double	High	90	25/75	Rib	1.17	338.98
32	15	Double	High	90	50/50	Plain	1.05	273.79
33	15	Double	High	90	75/25	Rib	1.86	499.51
34	15	Double	High	80	25/75	Full-milano	1.86	506.84
35	15	Double	High	80	50/50	Plain	1.76	484.84
36	15	Double	High	80	75/25	Rib	1.95	559.00

domestic washer at 40°C for 30 min with commercial detergent and tumble dried at 70°C for 15 min in an electrically heated dryer after they had been dry relaxed. This procedure was repeated three times. Before measurements taking, the samples were conditioned for 24 h in a standard atmosphere. Weight and thickness of fabrics were measured. The specifications of the fabric samples are reported in Table 1.

Pilling was determined as the number of pills formed in a certain area of fabric surface at 2000 cycles using Martindale abrasion tester according to ASTM (D4970). A higher number means a higher abrasion resistance, whereas a lower number means a higher pilling performance.

The surfaces of samples were captured by an optical scanner (HP Scanjet G2410) with resolution 200 dpi. To analyze the images, a program was developed by Matlab software. To determine the boundary between pill and the fabric surface, a linear filter was used on the images. The image captured from the fabric which has no pill was selected as reference image. Each of these images was divided into small windows. Brightness histogram was computed for each of the windows and the data resulted from the reference image was compared with these brightness histogram. The correlation coefficient between the histograms of two windows was calculated. If the difference was significant, a number is reported as the number of pills.

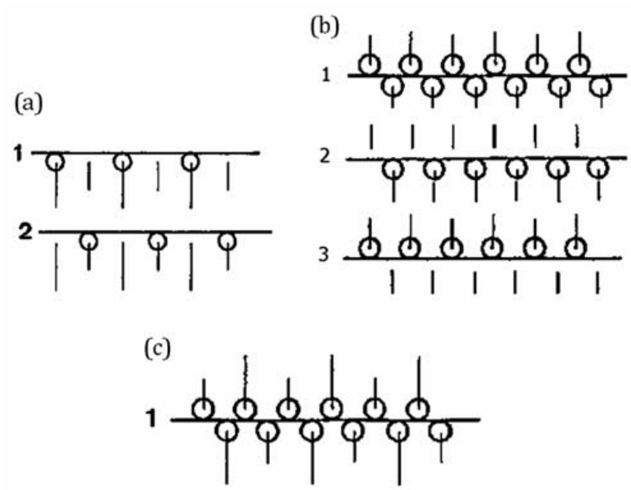

Fig. 1— Structures of knitted fabrics (a) plain, (b) Full-milano and (c) rib

In this study back propagation learning algorithm based on gradient descent with momentum and adaptive learning rate was used. Choosing a large learning rate value accelerates the training process but causes big errors at the output or destabilizes the training cycles, while a small value provides convergence with smaller errors and prolongs training time[19]. Therefore, using an adaptive learning rate enhances the training performance. For predicting the pilling performance of weft knitted fabrics, a feed forward multilayer neural network models with one neuron as output and six input unit in input layer was designed. The input parameters were yarn count (Nm), fabric structure, knit density, yarn twist (TPM), number of feeding yarns, and percentage of wool fibre. The levels chosen for qualitative input parameters (fabric structure and knit density) are coded as 1, 2 and 3 according to following cases:

- Fabric structure: Plain (1), Rib (2), Full-milano (3)
- Knit density: high density (1), low density (3)

In this study, due to the availability of only a small sample data, memorization or over fitting of networks was prevented using weight decay technique. This involves modifying the performance function. Therefore, mean square error regularization (MSEREG) performance function was used instead of common mean square error (MSE) function[23].

Samples were divided randomly in training and testing sets. For training the neural network models, thirty one sets of data were selected and also five sets of data used for testing the predictive power of developed models. In Table 2 parameters of testing data were presented. To eliminate the effect of different units of input and output parameters, data

Table 2—Parameters and the number of pills of testing data

Sample No.	Yarn count Nm	Number of fed yarn	Fabric density	Yarn twist TPM	Structure	Blending ratio		Number of pills after 2000 abrasion cycles
						Wool	Acrylic	
5	15.08	1	1	313.8	2	50	50	56
6	15.10	1	1	312.4	3	25	75	22
12	29.04	2	1	492.8	3	25	75	26
18	29.04	2	2	492.8	1	75	25	42
32	29.00	2	1	404.4	1	75	25	45

normalizing was carried out in such a way that they got zero mean and unit standard deviation[14].

After some trials 300 epochs was selected as number of training cycle according to Table 3. Tangent hyperbolic and linear transfer functions were used for hidden neurons and output neuron, respectively. Momentum rate was optimized at 0.9. The number of hidden neurons and the number of hidden layers are usually adjusted by trial-and-error method because these are problem-dependent parameters. It is known that neural networks with one hidden layer are suitable for majority of applications[22]. Therefore, seven topologies with one hidden layer and 6-12 neurons in it were tested. The mean square error of testing sets was considered getting the best topology and performance. In programming the network architecture, training and testing the models involve the neural network toolbox of MATLAB software [23].

Table 3—Effect of transfer function on performance of ANN models after 300 epochs

ANN structure	Transfer function		MSE of testing data
	Output layer	Hidden layer	
6-8-1	Linear	Sigmoid	29.86
6-9-1	Linear	Sigmoid	30.72
6-8-1	Linear	Tangent hyperbolic	6.11
6-9-1	Linear	Tangent hyperbolic	5.61

Table 4—Response table for signal-to- noise ratios of the fabrics

Level	Yarn count	Number of feed yarn	Density	Yarn twist	Material type	Knit structure
1	-31.93	-31.65	-30.09	-32.09	-31.77	-31.83
2	-30.71	-31.00	-32.21	-30.58	-33.88	-31.9
3	-	-	-	-	-28.44	-30.17
Delta	1.22	0.65	2.13	1.51	5.44	1.73
Rank	5	6	2	4	1	3

Results and Discussion

Based on the Taguchi method, the values of signal-to-noise ratio for the controllable factors was calculated. Analysis of variance of SN-ratios calculated for fabric samples show that all selected controllable factors have significant effect on pilling performance of knitted fabrics. The response for signal-to-noise ratios of the fabrics is given in Table 4. According to the SN-ratio analysis, material type and the number of feeding yarns show the largest and smallest effect on the number of pills respectively. Knit density is found to be the second factor and is followed by other factors knit structure, yarn twist multiple and yarn count.

The curves referring to the average values of SN-ratios of the controllable factors at each level are shown in Fig. 2, from which the levels corresponding to the highest SN-ratio values are chosen for each parameter, representing the optimum condition. Here, the optimum condition corresponds to the minimization of the number of pills. It is clear from Fig. 2 that the optimum levels are: acrylic/wool blend ratio (75/25), yarn twist multiple (α_m 90), knit density (high), fabric structure (Full-milano), yarn count (coarser yarn, 10 Nm), and number of feeding yarns (double feeding).

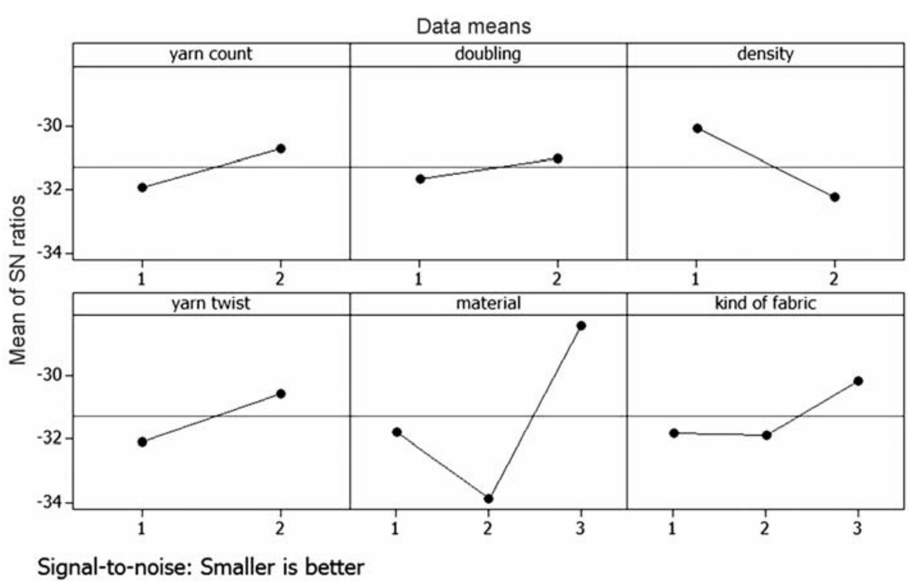

Fig. 2— Average values of S/N ratios of the controllable factors at each of the levels

Table 5— Performance of artificial neural network models

ANN topologies	Error percentage of prediction of testing data, %					MSE of prediction	
	32	18	12	6	5	Testing data	Training data
6-6-1	-6.13	-7.24	9.71	0.63	-2.58	28.28	4.62
6-7-1	9.75	-3.24	-3.11	1.35	-1.14	23.68	4.50
6-8-1	7.11	-2.17	-3.16	1.62	-0.89	14.24	4.47
6-9-1	0.14	1.96	5.18	2.93	-1.51	8.32	5.71
6-10-1	-2.73	4.18	-1.84	0.21	-0.64	5.57	3.21
6-11-1	-6.80	1.10	10.01	0.13	-1.27	29.89	4.94
6-12-1	-11.49	-7.31	-8.20	1.15	-0.88	50.98	2.72

In the acrylic-wool blend yarns, acrylic fibres are coarser and longer. In staple yarn fabric, the longer the staple, the less is the pilling in general; because there are fewer fibre ends protruding per unit area[5]. Furthermore, coarser fibres have fewer tendencies to pill because of their higher stiffness compared with finer fibres. Therefore, the blended yarn with higher ratio of acrylic fibres show the lower number of pills. Also, higher yarns twist causes the less pilling because of the compactness and lower number of protruding fibre on the yam surface. Doubled yarn gives less pilling than singles yam for the same reasons. In single yarns, the pilling tendency is lower with an increase in the twist multiple.

The results show that the knitted fabric produced with higher loop density represents the lower pilling rate. This might be attributed to the easier movements of yams owing to the greater instability of the loosely knitted fabrics, enabling the yarns to be secured more loosely in the body of the fabric.

The construction of a fabric is very important for determining its susceptibility to pilling. The results of this investigation show that the structure Full-milano shows lower pilling because of its tight or compact structure. Tight fabric structures lead to low pull-out and restricted pill growth. However, a loosely knitted structures such as plain or rib has more tendency to show such damage when continually worn.

Training results of seven selected topologies is presented in Table 5. Experimental results show that the number of neurons have a dominant effect on performance of proposed models. It is found that the model with one hidden layer and ten neurons into hidden layer gives the best performance and the least MSE on testing data for predicting the number of pills of weft knitted fabrics after 300 epochs. Obtained results show that the 6-10-1 topology i.e. ten neurons in first hidden layer, gives the best performance for predicting the number of pills of weft knitted fabrics. The mean square of prediction of testing data is 5.57 and that of training data is 3.21. According to Table 5, the maximum and minimum error of prediction for testing data is 4.18% and 0.21% respectively. The average of prediction error of the number of pills of weft knitted fabrics is 1.92%. The results confirm the good capability and predictive power of artificial neural network algorithm for predicting the pilling performance of weft knitted fabric.

According to the signal-to-noise ratio analysis, it is observed that material type and the number of feeding yarns have the largest and smallest effects on the number of pills respectively. Our findings reveal that the optimum levels of parameters are 75/25 acrylic/ wool, 90 αm, high knit density, Full-milano, coarser yarn and double feeding respectively.

The prediction of fabric pilling is carried out using back propagation artificial neural network algorithm based on gradient descent algorithm learning algorithm with adaptive learning rate and momentum. Obtained results showed that the topology with one hidden layer and ten hidden neuron yielded the best performance after 300 epochs. The mean square of prediction of testing data was 5.57 and ιaining data 3.21.

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