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Study of the Hairiness of Polyester-Viscose Blended Yarns. Part III - Predicting Yarn Hairiness Using an Artificial Neural Network

Abstract
The hairiness of blended yarns is influenced by several parameters at the ring frame. For this reason, it is necessary to develop a model based on experimental evidence that includes all known processing factors. The generalised from of this model is a candidate for predicting yarn hairiness. In this paper, an artificial neural network and multiple linear regression were used for modelling and predicting the hairiness of polyester-viscose blended yarns based on various process parameters. The models developed were assessed by applying PF/3, the Mean Square Error (MSE), and the Correlation Coefficient (R-value) between the actual and predicted yarn hairiness. The results indicated that the artificial neural network has better performance (R = 0.967) in comparison with multiple linear regression (R = 0.878).

Key words: *polyester-viscose blended yarn, hairiness, artificial neural network, ring frame parameters.*

Introduction

Several authors have studied yarn hairiness and the effect of fibres and process parameters on it. Barella [1] stated that yarn hairiness is defined as the fibre ends and loops protruding from the main yarn body. Hairiness is one of the most important yarn characteristics, which affects weaving, knitting, dyeing and finishing processes in textiles [2]. The importance of yarn hairiness as a factor influencing the handle, appearance, thermal insulation, and pilling propensity of fabrics is well known. Hairiness is generally considered as a negative attribute of spun yarns. However, some hairiness is also required for specific yarns to produce good handle and comfort properties [3 - 5]. Beltran et al [6] studied the influence of the hairiness of worsted wool yarns on the pilling propensity of knitted wool fabrics. The results suggested that a relatively large reduction in yarn hairiness was needed to achieve a moderate improvement in fabric pilling, and that the nature of yarn hairiness was also a key factor in influencing fabric-pilling propensity. Canoglu and Tanir [7] studied the hairiness of polyester/cotton blended yarns with different blend ratios. They found that among the yarns produced, the best result was obtained from the blend yarn with a polyester/cotton ratio of 33/67. Altas and Kadoglu [8] investigated the effect of cotton fibre properties and linear density on yarn hairiness. They found that yarn hairiness increases with an increase in yarn linear density. According to Pillay [9], torsional rigidity, flexural rigidity and fibre length are the major cotton fibre properties for determining the level of yarn hairiness. Viswanathan et al. [10] demonstrated the relationship between fibre quality parameters and yarn hairiness. The effect of processing factors such as the drafting system, winding section factors, and yarn parameters have already been reported [11-12].

Some researches have attended to the prediction of yarn hairiness using an Artificial Neural Network (ANN) and multiple linear regression (MLR) models based on fibre characteristics, yarn properties and processing factors. Khan et al [13] evaluated the performance of multilayer perceptron (MLP) and MLR models for predicting the hairiness of worsted-spun wool yarns from various tops, yarns, and process parameters. Their results indicated that the MLP model predicted yarn hairiness more accurately than the MLR model. Jackowska-Strumillo et al [14] stated that the hairiness of cotton – polyester blended yarns could be predicted using an MLP artificial neural network based on the characteristics of feeding streams. Beltran et al. [15, 16] examined pattern recognition algorithms as a practical alternative to existing experimental techniques for the prediction of spinning performance, in which they successfully predicted worsted spinning performance with an ANN model and showed that the MLP approach was slightly better than the other approaches. Their results also indicated that the ANN method provided a more precise mill specific spinning performance than the traditional experimental technique.

Few researchers have studied the predicting of the hairiness of blended yarns on the basis of spinning parameters. Therefore, this paper presents a feed forward backpropagation model of an ANN and another MLR model for predicting the hairiness of polyester-viscose blended yarn at the ring frame based on significantly effective parameters of the spinning system.

Evaluation of the models

Artificial Neural Networks

The development and use of neural networks is part of an area multidisciplinary study that is commonly called neural computing but is also known as connectionism, parallel distributed processing and computational neuroscience. The ANN is a powerful data-modeling tool that is able to capture and represent each kind of input-output relationship [17]. In the field of textiles, artificial neural networks have been extensively studied during the last two decades. In the field of spinning, previous researches have concentrated on predicting yarn properties and spinning process performance using fibre properties or a combination of fibre properties and machine settings as the input of neural networks [18].

Multi-layer perceptron neural networks are responsible for approximately 80% of all practical application. A typical feed forward network with a single hidden layer is shown in ***Figure 1*** (see page 34). In the MPL, the units are arranged in distinct layers, with each unit receiving weighted input from each unit in the previous layer. A neural network is usually trained so that a particular input leads to a specific output. The process of training

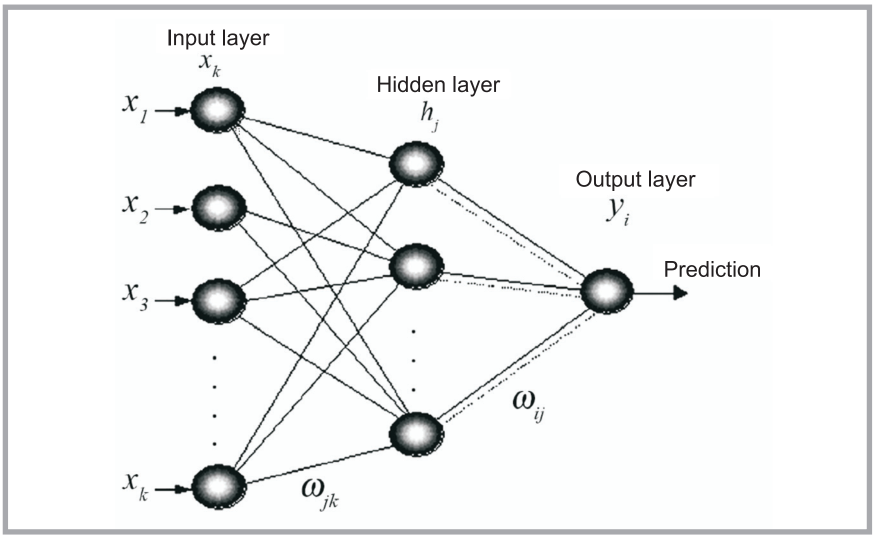


Figure 1. *Multi - layer feed forward network [17].*

is adjusting the weight and bias values to sliding down the error surface. Among the various kinds of algorithms for training neural networks, backpropagation is the one most widely used [17]. The supervised learning technique is the one most frequently used for ANN training. The backpropagation algorithm is based on the Widrow-Hoff delta-learning rule, in which weight adjustment is carried out through the mean square error of the output response to the sample input [18]. A set of these sample patterns is repeatedly presented to the network until the error value is minimised. The packpropagation algorithm uses the steepest decent method, which is essentially a first order method to determine a suitable direction of gradient movement. Patterson [19] and Schalkoff [20] detailed this algorithm. *Trainlm* is often the fastest backpropagation algorithm and is highly recommended as a first-choice supervised algorithm. *Trainlm* is a network training function that updates weight and bias values according to Levenberg-Marquardt optimisation [21]. The learning function BLF (Backpropagation weight/bias Learning Function) can be the backpropagation *Learngd* or *Learngdm* learning functions. *Learngd* and *learngdm* are the gradient descent weight and bias learning functions.

Multiple linear regression

Statistical regression is a model for analysing and modelling dependent variables as a function of one or more independent variables. The simplest form of regression is multiple linear regression (MLR). During the second half of the twentieth century, statistical regression, especially MLR, was one of the most popular methods of making predictive models in a wide range of textile related problems [22 - 24]; it is known as the conventional method [23]. Majumdar et al [25], Ethridge and Zhu [26] reported the good performance of MLR.

The general linear regression model (MLR) represents the relationship between a continuous response y and a continuous or categorical predictor x in the form [21]:

$$y = \beta_1 f_1(x) + \beta_2 f_2(x) + ... + \beta_p f_p(x) + \varepsilon \tag{1}$$

The response is modelled as a linear combination (not necessarily linear) of predictor functions, plus a random error ε. The expressions $f_j(x)$ $(j = 1, ..., p)$ are the terms of the model, and β_j $(j = 1, ..., p)$ are the coefficients. The error ε is assumed to be uncorrelated and distributed with mean zero and constant (but unknown) variance. Whether or not the predictor x is a vector of predictor variables, multivariate regression refers to the case where the response $y = (y_1, ..., y_M)$ is a vector of M response variables. Given n independent observations $(\mathbf{x}_1, y_1), ..., (\mathbf{x}_n, y_n)$ of the predictor x and response y, the linear regression model becomes an n-by-p system of equations [21]:

$$\underbrace{\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}}_{y} = \underbrace{\begin{pmatrix} f_1(\mathbf{x}_1) & \cdots & f_p(\mathbf{x}_1) \\ \vdots & \ddots & \vdots \\ f_1(\mathbf{x}_n) & \cdots & f_p(\mathbf{x}_n) \end{pmatrix}}_{X} \underbrace{\begin{pmatrix} \beta_1 \\ \vdots \\ \beta_p \end{pmatrix}}_{\beta} + \underbrace{\begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{pmatrix}}_{\varepsilon} \tag{2}$$

X is the design matrix of the system. The columns of X are the terms of the model evaluated at the predictors. To fit the model to the data, the system must be solved for the p coefficient values in $\beta = (\beta_1, ..., \beta_p)^T$.

Materials and methods

Fibre and roving properties, and preparation of a yarn sample

Experiments were carried out using polyester-viscose blended yarns (80:20). The characteristics of the fibre, roving and yarn sample and hairiness testing are given in the first part of our research [11]. Several yarns were produced with different machine settings, in which only one factor was changed at each stage, while the other factors were kept constant. Based on the ANOVA statistical test, some of the parameters that have a significant influence on yarn hairiness, such as the total draft, roving twist, yarn count, yarn twist, spindle speed, traveller weight, back zone setting, break draft, balloon control ring, front roller covering hardness, and drafting system angle were considered [11, 12]. The processing plan of these parameters is shown in ***Table 1***.

Neural network parameters

Before training, it is often useful to use preprocessing to normalise and scale the inputs and outputs so that they always fall within a specified range to eliminate the effect of different units of the input and output parameters, and remove any influence of quantitative effects on the training process. The function "mapminmax" scales inputs and outputs (v_i) so that they fall in the range [-1, 1] by using equation (3):

$$x_i = 2\left(\frac{v_i - v_{min}}{v_{max} - v_{min}}\right) - 1 \quad i=1, 2.......n \tag{3}$$

where x_i is the scaled value, and v_{max} & v_{min} are the respective maximum and minimum values of inputs (outputs).

To predict yarn hairiness, neural network models with one neuron in the output layer were planned. The networks designed had 11 input units and one unit output as a neuron.

Moreover, five cases of ANN (*N1, ...N5*) with different data sets, transfer, training, learning functions, number of neurons in hidden layers, and *MSE* performance function were used (see ***Table 2***). The *learning Rate* in the learning functions was 0.01, and the *Momentum Constant* was 0.9.

In the neural network, input data (training set) were divided randomly in three groups so that 60% of the samples were assigned to the training, 20% to the validation set, and 20% to the test set. The first subset is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The third subset is used to verify the network design, and provides an independent measure of how well the network could be expected to perform for data not used in its training.

For evaluating the performance of the ANN, the five–fold cross-validation technique was used. Therefore, the data set of 57 samples was divided randomly into 5 subsets, in accordance with other works [27]. The subsets were combined together, and five sets of train and final test data were designed. Each time, four subsets were used for the training set and one subset for the final testing set (the training set and final test set contained 46 and 11 samples, respectively). Consequently, each network designed was trained and tested five times, for the purpose of which MATLAB (R2008b) software was used.

Statistical regression

In this study, the MLR model was used for developing a model of yarn hairiness on polyester-viscose blended yarns, for which the same five sets of data used for evaluation of the ANN model, were undertaken in the MLR algorithm. Then the resulting five models were applied to the testing data sets. The independent variables were the total draft, roving twist, yarn count, yarn twist, spindle speed, traveller weight, back zone setting, break draft, balloon control ring, front roller covering hardness, and drafting system angle.

For instance, by using the first set of data, ***Equation 4*** was derived with an MLR algorithm.

$$\begin{aligned}\text{Average of hairs/m} = \\ -\ 8.424 - 0.736\ (\text{T.D.}) + 0.085\ (\text{R.T.F.}) + \\ -\ 0.118\ (\text{B.Z.S.}) + 0.2\ (\text{D.S.A.}) + \\ -\ 0.163\ (\text{F.R.C.H.}) + 0.001\ (\text{S.S.}) + \\ -\ 0.242\ (\text{L.B.C.R.}) - 0.766\ (\text{Y.T.F.}) + \\ +\ 0.970\ (\text{Y.C.}) + 0.002\ (\text{T.C.}) + \\ +\ 7.805\ (\text{B.D})\end{aligned} \qquad (4)$$

Table 1. *Experimental values measured in different process settings; T.D. - Total Draft, R.T.F. - Roving Twist Factor, B.Z.S. - Back Zone Setting, D.S.A. - Drafting System Angle, F.R.C.H. - Front Roller Covering Hardness, S.S. - Spindle Speed, L.B.C.R. - Location of Balloon Control Ring, Y.T.F. - Yarn Twist Factor, Y.C. - Yarn Count, T.C. - Traveller Count, B.D. - Break Draft.*

Sample	T.D.	R.T.F., $\propto_{tex}$	B.Z.S., mm	D.S.A., degree	F.R.C.H., shore	S.S., r.p.m.	L.B.C.R., mm	T.C., mg/piece	Y.C., tex	Y.T.F., $\propto_{tex}$	B.D.	Average of hairs/m
1	26.5											20.75
2	32.0	912										18.78
3	37.5											18.68
4	43.0											19.77
5		776	56									18.76
6		814										18.81
7		862		49								18.77
8		891										19.05
9		948										20.40
10			50		70							30.41
11			52.5			13000						30.60
12			55									28.83
13			57.5									29.76
14			60				116					30.81
15				35								23.03
16				47				40				22.49
17				59								26.90
18				71								31.92
19				83								34.48
20					75				20			27.11
21					85							25.60
22					90					3400		25.33
23						5000						23.50
24						8000						19.71
25						11000						20.92
26						14000					1.3	29.88
27						17000						31.33
28						20000						30.78
29							100					32.87
30							108					30.33
31	27.2						124					27.53
32							132					27.66
33		912						18				45.22
34								20				44.23
35								23.6				41.49
36			56					30				37.39
37								35.5				33.12
38				49				45				30.23
39								50				27.42
40					70				9.9			19.99
41									11.3			18.97
42									13.1			21.52
43						13000			15.8			23.32
44									19.7			28.94
45							116			2300		39.67
46										2680		36.57
47										3060		29.41
48								40		3400		29.39
49										3820		31.33
50										4200		34.21
51									20	4580		35.76
52											1.1	27.81
53											1.18	28.94
54										3400	1.26	28.11
55											1.34	29.75
56											1.42	30.95
57											1.5	29.74

Table 2. *Different network architectures.*

Code	Network architectures	Training function	Learning function	Performance function	Transfer function		
					Input layer	Hidden layer	Output layer
N1	11-8-6-1					Tansig	Tansig
N2	11-8-6-1		Learn GD			Logsig	Purelin
N3	11-6-4-1	Traianlm		MSE	Tansig	Tansig	Tansig
N4	11-6-4-1					Logsig	Purelin
N5	11-8-6-1		Learn GDM			Tansig	Tansig

Table 3. Performance of N1, N2, N3, N4 and N5 for training and test data sets.

Code	Data set	Training			Testing		
		R- value	PF/3	MSE	R- value	PF/3	MSE
N1	1	0.957	7.200	3.890	0.983	5.297	2.824
	2	0.975	5.720	2.033	0.965	8.461	5.160
	3	0.926	9.853	6.714	0.965	7.662	4.655
	4	0.934	8.752	5.226	0.950	8.049	7.260
	5	0.955	7.504	3.560	0.975	5.826	3.003
	Average	0.949	7.806	4.285	0.967	7.059	4.580
N2	1	0.962	6.447	3.064	0.937	9.461	8.364
	2	0.926	9.685	5.772	0.931	10.133	12.582
	3	0.922	9.237	5.916	0.768	18.649	26.970
	4	0.987	13.099	9.115	0.937	9.691	7.920
	5	0.947	7.753	3.927	0.820	14.97	13.130
	Average	0.948	9.244	5.558	0.878	12.581	13.793
N3	1	0.912	9.722	6.485	0.915	10.746	12.695
	2	0.974	5.468	2.035	0.848	15.398	18.52
	3	0.925	8.851	5.947	0.861	17.575	16.344
	4	0.922	9.287	6.663	0.824	16.585	13.304
	5	0.960	6.134	2.876	0.857	18.212	17.035
	Average	0.939	7.892	4.801	0.861	15.703	15.580
N4	1	0.949	7.637	3.970	0.964	7.4506	4.194
	2	0.812	14.362	13.642	0.854	15.046	15.970
	3	0.921	9.842	6.841	0.753	20.525	26.600
	4	0.815	15.107	13.725	0.820	15.585	19.102
	5	0.942	8.562	4.806	0.823	14.290	18.105
	Average	0.888	11.102	8.597	0.843	14.579	16.794
N5	1	0.948	7.690	4.135	0.938	9.129	6.615
	2	0.923	9.696	5.697	0.897	13.089	12.028
	3	0.914	9.450	6.827	0.819	15.696	19.826
	4	0.929	9.059	6.143	0.924	8.959	9.551
	5	0.812	13.192	13.714	0.763	20.125	26.015
	Average	0.905	9.817	7.303	0.868	13.400	14.807

Table 4. Performance of multiple linear regression for training and test data sets.

Data set	Training			Testing		
	R- value	PF/3	MSE	R- value	PF/3	MSE
1	0.853	24.062	10.510	0.863	20.825	12.960
2	0.833	21.398	10.909	0.891	19.063	12.742
3	0.835	15.364	11.127	0.874	17.942	16.801
4	0.826	25.241	13.005	0.873	21.510	18.434
5	0.853	11.995	9.001	0.833	25.101	22.85
average	0.840	19.612	10.910	0.867	20.888	16.757

The abbreviations have been explained in section **Fibre and roving properties, and preparation of a yarn sample** (***Table 1***).

Result and discussion

The prediction capability of ANN models configured as described previously were compared with the MLR model. For each network model, the R-value between the predicted and measured hairiness was considered along with the MSE (***Equation 5***). In addition, to verify the models, ***Equation 6*** was used, because it is more sensitive to the difference between experimental and predicted outputs, showing better results than the correlation coefficient.

$$MSE = \frac{\sum_{i=0}^{n}(t_i - y_i)^2}{n} \quad (5)$$

where *MSE* is the mean square error between experimental and predicted values, t_i: predicting value, y_i: experimental value, and *n* is the number of patterns

$$PF/3 = 100(\gamma - 1 + V_{AB} + CV/100)/3 \quad (6)$$

where

$$\gamma = 10^{((\sum_{i=1}^{n}(\log Y_i - \log(F_1 \times X_i))^2)/n)^{0.5}} \quad (7)$$

$$V_{AB} = (\sum_{i=1}^{n}((Y_i - FX_i)^2 / FX_iY_i) \Big/ n)^{0.5} \quad (8)$$

$$CV = [100n(\sum_{i=1}^{n}(Y_i + - bX_i - a)^2/(n-1))^{0.5}] \Big/ \sum_{i=1}^{n} Y_i \quad (9)$$

$$[b, a, r_1] = postreg(Y, X) \quad (10)$$

where *X, Y* and *n* are measured outputs, predicted outputs and number of outputs, respectively.

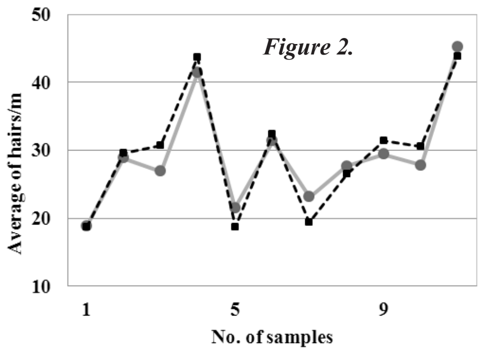
$$F_1 = [\sum_{i=1}^{n} Y_i / X_i] \Big/ n \quad (11)$$

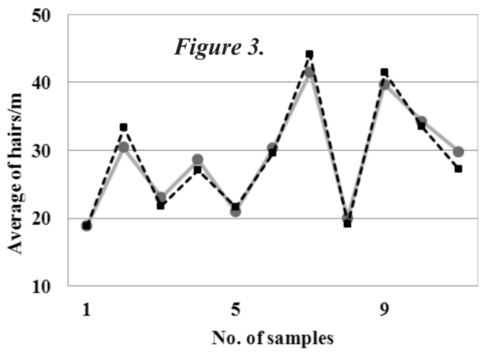
$$F = (\sum_{i=1}^{n} Y_i / X_i \Big/ \sum_{i=1}^{n} X_i / Y_i)^{0.5} \quad (12)$$

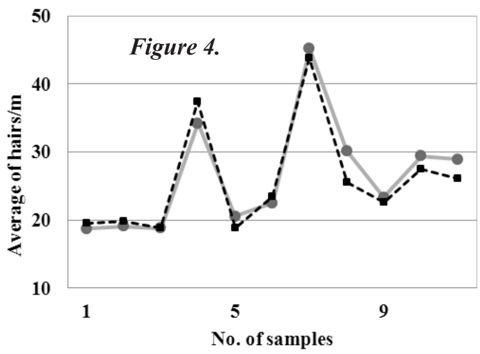
In order to test the performance and validate the prediction of the regression models and ANN models, the testing data sets were used as previously explained. The results of ANN and MLR models for predicting yarn hairiness are given in ***Tables 3*** and ***4***, showing the difference between the correlation coefficient of these models: MSE and PF/3. The results of the ANN obtained indicated that the performance of network *N1* for the training and test data sets is better than the other networks. These results show that the planning of networks is very important for achieving the best prediction of values. For instance, network *N1* is compared with the MLR model. For the testing sets, the average of the R-value in network N1 is higher than that in the MLR model (0.967 > 0.867), and the average of PF/3 and MSE are less than those in the MLR model - (7.059 < 20.888) and (4.580 < 16.757), respectively. The values of PF/3 show the prediction accuracy of the ANN - in network *N1* it is 93% and in the MLR models it is 79%. In general, the performance of the ANN is better than the MLR model. ***Figures 2 - 6*** show the relationship between experimental and predicted hairiness for testing data sets in network *N1* that verify the capability of the ANN to predict yarn hairiness. The poor performance of the MLR in predicting yarn hairiness implies that the relationship between spinning parameters and the hairiness of polyester-viscose blended yarns is nonlinear, since the MLR is based on first order equations. Therefore it can be stated that the ANN model with two hidden layers is useful for nonlinear relationships.

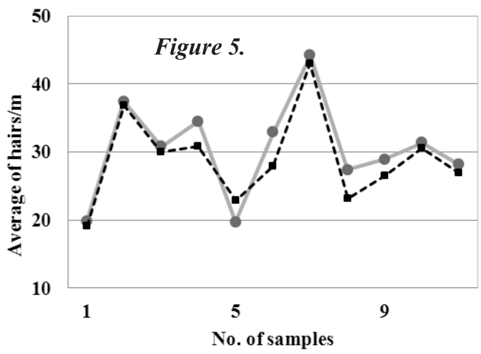
Conclusion

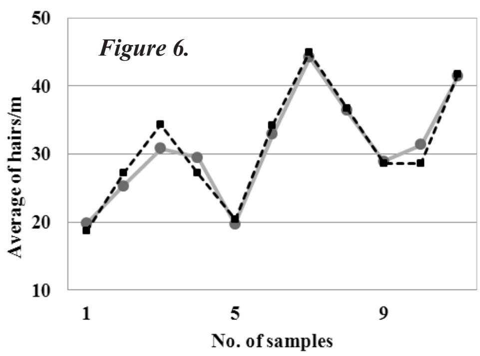
According to the results, it can be concluded that the ANN model was more exact than the MLR, and that the values of PF/3 and MSE for the ANN are accept-











- experimental, - predicted

Figure 2. *Testing performance of N1 for test data set 1.*
Figure 3. *Testing performance of N1 for test data set 2.*
Figure 4. *Testing performance of N1 for test data set 3.*
Figure 5. *Testing performance of N1 for test data set 4.*
Figure 6. *Testing performance of N1 for test data set 5.*

able. The prediction of yarn hairiness by the ANN model indicated a considerably lower error than that of the MLR.

The results showed that nonlinearity existed in the relationship between yarn hairiness and process parameters. This study also exhibited that yarn hairiness could be predicted with high accuracy from the yarn and ring spinning factors. The use of an ANN model can help spinning factories to produce yarns of high quality by presenting appropriate settings and improving the processing parameters using the prediction results of the model.

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LABORATORY OF BIODEGRADATION

The Laboratory of Biodegradation operates within the structure of the Institute of Biopolymers and Chemical Fibres. It is a modern laboratory with a certificate of accreditation according to Standard PN-EN/ISO/IEC-17025: 2005 (a quality system) bestowed by the Polish Accreditation Centre (PCA). The laboratory works at a global level and can cooperate with many institutions that produce, process and investigate polymeric materials. Thanks to its modern equipment, the Laboratory of Biodegradation can maintain cooperation with Polish and foreign research centers as well as manufacturers and be helpful in assessing the biodegradability of polymeric materials and textiles.

The Laboratory of Biodegradation assesses the susceptibility of polymeric and textile materials to biological degradation caused by microorganisms occurring in the natural environment (soil, compost and water medium). The testing of biodegradation is carried out in oxygen using innovative methods like respirometric testing with the continuous reading of the CO_2 delivered. The laboratory's modern MICRO-OXYMAX RESPIROMETER is used for carrying out tests in accordance with International Standards.

The methodology of biodegradability testing has been prepared on the basis of the following standards:

- **testing in aqueous medium:** 'Determination of the ultimate aerobic biodegrability of plastic materials and textiles in an aqueous medium. A method of analysing the carbon dioxide evolved' (PN-EN ISO 14 852: 2007, and PN-EN ISO 8192: 2007)
- **testing in compost medium:** 'Determination of the degree of disintergation of plastic materials and textiles under simulated composting conditions in a laboratory-scale test. A method of determining the weight loss' (PN-EN ISO 20 200: 2007, PN-EN ISO 14 045: 2005, and PN-EN ISO 14 806: 2010)
- **testing in soil medium:** 'Determination of the degree of disintergation of plastic materials and textiles under simulated soil conditions in a laboratory-scale test. A method of determining the weight loss" (PN-EN ISO 11 266: 1997, PN-EN ISO 11 721-1: 2002, and PN-EN ISO 11 721-2: 2002).

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The following methods are applied in the assessment of biodegradation: gel chromatography (GPC), infrared spectroscopy (IR), thermogravimetric analysis (TGA) and scanning electron microscopy (SEM).

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