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Research Article

Yarn Strength Prediction: A Practical Model Based on Artificial Neural Networks

Rocco Furferi[1] and Maurizio Gelli[2]

[1] *Department of Mechanical and Industrial Technologies, University of Florence, 50121 Florence, Italy*
[2] *New Mill S.P.A. Research Center, 59013 Montemurlo, Italy*

Correspondence should be addressed to Rocco Furferi, rocco.furferi@unifi.it

Yarn strength is one of the most significant parameters to be controlled during yarn spinning process. This parameter strongly depends on both the rovings' characteristics and the spinning process. On the basis of their expertise textile technicians are able to provide a raw and qualitative prediction of the yarn strength by knowing a series of fiber parameters like length, strength, and fineness. Nevertheless, they often need to perform many tests before producing a yarn with a desired strength. This paper describes a Feed Forward Back Propagation Artificial Neural Network-based model able to help the technicians in predicting the yarn strength without the need of physically spinning the yarn. The model performs a reliable prediction of the yarn strength on the basis of a series of roving parameters, commonly measured by the technicians before the yarn spinning process starts. The model has been trained with 98 training data and validated with 50 new tests. The mean error in prediction of yarn strength, using the validation set, is less than 4%. The results have been compared with the one obtained by means of a classical method: the multiple regression. Nowadays, the developed model is running in the laboratory of New Mill S.p.A., an important textile company that operates in Prato (Italy).

1. Introduction

During yarn spinning, textile experts commonly controls a series of parameters like the fiber strength, the fiber length, the twist yarn, the yarn count, and the fineness. Strength parameters of yarns are especially important for rotor-spun yarns. More in detail a very important parameter that technicians want to control is the yarn strength. This is defined as the breaking force of a spinning yarn, and it is commonly measured in cN. On the basis of their skill, the expert operators are capable of giving a qualitative, raw prediction of the yarn strength; unfortunately the empirical estimation of the actual value of the yarn strength is not straightforward. The assessment of such parameter is essential for obtaining high quality of the yarn. Accordingly, in the last two decades, the modeling of yarn properties has become one of the most important and decisive tasks in the textile research field. A considerable number of predictive models have been implemented to evaluate some yarn properties like strength, elongation, evenness, and hairiness. The relationship between fiber properties and yarn properties has been the focal point of several works [1–3]. The studies in literature have shown that the relationship between yarn strength and fiber properties is nonlinear. Accordingly mathematical models based on the fundamental mechanics of woven fabrics often fail to reach satisfactory results. Some studies have been performed so far for modeling the yarn strength using linear regression [4–6]. The main limitation of these studies is related to the need of defining a predefined linear model. In order to model a nonlinear relationship between input and output it is possible to devise an Artificial Intelligence-based approach. For this reason the problem of yarn properties prediction has been faced by some researchers by employing some knowledge-based approaches like artificial neural networks (ANNs) [7, 8] and neuro-fuzzy models [9]. Ramesh et al. [10], Zhu and Ethridge [11], Guha et al. [12], and Majumdar et al. [13] have successfully used the artificial neural network (ANN) and

neuralfuzzy methods to predict various properties of spun yarns. The fabric strength was modeled by Zeydan using neural networks and Taguchi methodologies [14]. Support vector machines (SVMs), based on statistical learning theory, have been developed by Yang and Xiang [15] for predicting yarn properties. The investigation indicates that in the small data sets and real-life production, SVM models are capable of maintaining the stability of predictive accuracy. A comparison between physical and artificial neural network methods has been presented recently. The results show that the ANN model yields a very accurate prediction with relatively few data points [16]. Moreover, it is proved that the parameters of the raw material that significantly influence the basic quality parameters of the yarns are length, strength, and fineness of fibers [17–19]. The effect of yarn count and of twist yarn in the final yarn strength is also well established [20].

The objective of the present work is to propose an approach for predicting the yarn strength based on Feed Forward Back-propagation Artificial Neural Network (FFBP ANNs). In authors' opinion this work, strongly based on scientific literature, has its advantage in the fact that the FFBP ANN model has been trained by means of fiber parameters that are typically measured by the technicians for controlling the yarn spinning. In other words, the technicians are not supposed to carry out none of adjunctive experimental test than they commonly assess. The reliability and goodness of results, in comparison with linear regression models, prove that the present work may be considered a practical method for assessing the yarn strength.

The developed system does not require technicians to produce a yarn and to measure its strength. The experts have only to test the rovings in order to assess some fiber properties. This operation is normally done before producing the yarn. Accordingly, by means of the devised model, the experience of the technicians is merged together with a simple approach in order to give an accurate prediction of the yarn strength.

2. Material and Methods

With the aim of developing a model of the yarn spinning, three tasks have been carried out:

  (i) database creation,

  (ii) definition of training parameters,

  (iii) artificial Neural Network construction and training.

2.1. Database Creation. The first step for the development of the ANN-based system able to predict the yarn strength on the basis of some fibers parameters was to perform a series of experimental tests. The main intent of such an experimental approach was to create a database of fiber parameters to use as input of an ANN-based algorithm. A total of 6 different families of rovings (obtained mixing together different kinds of fibers) were collected from an important spinning mill operating in Prato (Italy). For each of them, several different values for fiber strength, fiber length, twist yarn, and yarn

count have been tested (see Table 1). The result is a set of 98 different tests. The fiber length has been evaluated by means of a Classifiber Model KCF/LS. The output of the Classifiber measurement (see Figure 1) is given by the mean value of length (ML), the humidity values (UHM and UI%), and the standard deviation in % (CV%). The fineness was measured with an OFDA100, an image analysis system recognized with a Test Method from the (International Wool Textile Organization) IWTO. The OFDA instrument is used to certify mean fiber diameter. The output of the measurement is a statistical distribution of the fineness. The mean value is assumed as the fineness parameter (see Figure 2(a)). The fiber strength was measured with a precision fiber dynamometer. In Table 2 the value of the parameters of some of the 98 tests is listed.

As may be noticed, each roving is composed by different kinds, in different percentages, of fibers. Each fiber is characterized by a different value of length and fineness. For instance the roving named "velox 2" belongs to the family "Velox" composed by 25% viscose, 25% nylon, 10% cashmere, and 40% wool. These fibers are characterized by different length and fineness. In order to use these data for modeling the yarn spinning, it is possible to evaluate a single parameter for both length and fineness.

This can be easily carried out by defining, for each roving:

  (i) weighted average length (W_L), computed as the average weighted length of the fibers from a roving composed by a number i of different materials and defined by the following equation:

$$W_L = \sum_1^n \alpha_i \cdot L_i \quad [\text{mm}], \tag{1}$$

  (ii) fiber weighted average fineness (W_F), computed as the average weighted fineness of the fibers from a roving composed by a number i of different materials and defined by the following equation:

$$W_F = \sum_1^n \alpha_i \cdot F_i \quad [\text{m} \cdot 10^{-6}], \tag{2}$$

  (iii) fiber weighted average strength (W_S), computed as the average weighted strength of the fibers from a roving composed by a number i of different materials and defined by the following equation:

$$W_S = \sum_1^n \alpha_i \cdot R_i \quad [\text{cN/tex}]. \tag{3}$$

In the example of the roving named "velox 2", the values for W_L, W_F, and W_S might be evaluated as follows:

$$
\begin{aligned}
W_L &= 0.40 \cdot 42 + 0.25 \cdot 40 + 0.25 \cdot 35 + 0.25 \cdot 34 \\
&= 38.95\,\text{mm}, \\
W_F &= 0.40 \cdot 19.5 + 0.25 \cdot 15.5 + 0.25 \cdot 13 + 0.25 \cdot 15 \\
&= 16.43\,\text{m} \cdot 10^{-6}, \\
W_S &= 0.40 \cdot 11.21 + 0.25 \cdot 47.91 + 0.25 \cdot 18.35 \\
&\quad + 0.25 \cdot 10.19 = 22.07\,\text{cN/tex}.
\end{aligned}
\tag{4}
$$

By means of (1), (2), and (3), for each of the 98 different tests a set of 5 input parameters may be defined. In Table 3 a subset of this input set is listed. It is important to remark that the parameters α_i, L_i, F_i, and R_i might be used for training the ANN as well, thus probably leading to accurate results. However, when the number of components composing a roving increases, the number of inputs increases as well thus resulting in a more complex ANN architecture. Moreover, as already mentioned, the aim of the present work is to propose a practical approach to be used by the technicians and practitioners using parameters (like W_L, W_F, and W_S) that they typically assess during the spinning process.

From each of the 98 selected rovings, the textile technicians produced a yarn by using a ring frame machine (Marzoli ring spinning frame RST-1, see Figure 2(b)). The process parameters adopted for producing the yarn were maintained constants with the exception of the twist yarn. This is due to the fact that, as already stated, the twist yarn influences the yarn strength; therefore such a parameter has been used as an input for the devised model. Once produced, the yarn strength of the 98 different yarns has been measured by means of a dynamometer. Some of the values of yarn strength (YS) are listed in the last column of Table 3.

2.2. Definition of Training Parameters. The result of the experimental process consists in a dataset of 98×5 fiber parameters and of 98 values for yarn strength. For instance, in Table 4 the whole dataset related to cashmere family is showed.

The dataset may be used as a training set for the FFBP ANN model. In detail, the training set P is composed by a matrix 5×98 composed by 98 vectors of 5 elements:

$$P = \begin{bmatrix} Y_{c1} & Y_{c2} & \cdots & Y_{ci} & \cdots & Y_{c98} \\ Tw_1 & Tw_2 & \cdots & Tw_i & \cdots & Tw_{98} \\ W_{L1} & W_{L2} & \cdots & W_{Li} & \cdots & W_{L98} \\ W_{F1} & W_{F2} & \cdots & W_{Fi} & \cdots & W_{F98} \\ W_{S1} & W_{S2} & \cdots & W_{Si} & \cdots & W_{S98} \end{bmatrix}. \tag{5}$$

As previously mentioned the FFBP ANN is required to find a nonlinear correlation between this training set and a target set T, defined as a vector (size 1×98) whose elements are the yarn strength values of the 98 yarns:

$$T = [YS_1, YS_2, \ldots, YS_i, \ldots, YS_{98}]. \tag{6}$$

2.3. Artificial Neural Network Construction and Training. In order to model the yarn spinning process, it is necessary to devise a proper neural network able to predict reliably the value of yarn strength, the yarn count, the twist yarn, the weighted average length, the weighted average fineness, and the weighted average strength of a roving. This is possible if the ANN is properly training by means of the training and target sets. Both structure and training of the ANN have been developed by using the Artificial Neural Network Toolbox working into Matlab environment. The constructed FFBP ANN, showed in Figure 3, has the following characteristics:

(i) three layers: input, hidden, and output layer;

(ii) hidden layer made of logistic neurons followed by an output layer of linear neurons;

(iii) 5 input, h hidden, and 1 output units.

The number of hidden neurons of feed-forward neural networks, generally decided on the basis of experience [21], is an important factor for the training, in order to avoid over fitting in the function approximation. From one point of view the number of hidden units may be stated *a priori* by means of empirical equations provided by the literature [22].

On the other hand it is possible to select the best network by estimation, for a given problem, of the network architecture and parameters within a set of candidate configurations [23]. In the present work the value h was evaluated varying from 2 to 14 with a step of 2 units, monitoring the performance of response using the training data. As known, during the training, the weights and the biases of the network are iteratively adjusted to minimize the network error function. The network error used in this work is the mean square error (MSE) correspondent to the training set elements. This error is monitored during the training process and will normally decrease during the initial phase of the training. However, when the network becomes excessively specialized in reproducing the training data, the early stopping error will typically begin to rise. When the early stopping error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum early stopping error are returned. The selected network is characterized by $h = 10$ units. The training was carried out using a training rule based on the Levemberg-Marquardt descent backpropagation algorithm with an adaptive learning rate [24]. Training set (input and target) has been scaled in the range [0-1] with a min-max algorithm. Training was automatically performed until the early stopping error increases for a specified number of iterations. This goal was obtained in 22 epochs (see Figure 4).

3. Results

Once trained, the network is able to correlate the training set elements to the target ones. In other words the ANN is able to receive any vector of 5 elements composed by the fiber parameters of any roving in input and to give, as output, the prediction of the yarn strength of the yarn produced with that roving. Hence,

$$\text{input (ANN)} = [Y_{\text{cin}}, Tw_{\text{in}}, W_{\text{Lin}}, W_{\text{Fin}}, W_{\text{Sin}}],$$
$$\text{output (ANN)} = \left[YS_{\text{predicted}} \right]. \tag{7}$$

The predicted value of the yarn strength ($YS_{\text{predicted}}$) must be compared with the real value (YS_{real}) in order to assess the reliability of the prediction. The comparison may be evaluated, in percentage, by defining a coefficient η, called "prediction error", given by

$$\eta = \frac{\left| YS_{\text{real}} - YS_{\text{predicted}} \right|}{YS_{\text{real}}}. \tag{8}$$

Classifiber Series model KCF/LS version 4.20.0 <Basic> p.1

New MILL S.p.A.
Purchased date: Oct/16/2009
Brand Name: Ws38kvv
Lot. No.: 118955
Database: Fiber Resources
Print Date: Oct/16/2009

Group no. 1									
No.	SL 2.5%	SL50%	UR%	SFC%	ML	UHM	UI%	SL66,0%	CV%
1	56.5 mm	21.4 mm	37.9%	0.3%	41.8 mm	48.8 mm	85.7%	17.3 mm	29.4%
2	56.8 mm	21.6 mm	38%	1.1%	42.5 mm	53.1 mm	80.0%	16.9 mm	30.6%
3	55.0 mm	19.8 mm	36%	0.0%	40.2 mm	51.0 mm	78.8%	15.8 mm	32.9%
4	57.2 mm	22.8 mm	39.9%	0.7%	44.8 mm	53.8 mm	83.3%	18.3 mm	28.7%
Total Evaluation	$N = 4$								
	SL 2.5%	SL50%	UR%	SFC%	ML	UHM	UI%	SL66,0%	CV%
Mean	56.4 mm	21.4 mm	38.0%	0.5%	42.3 mm	51.7 mm	81.9%	17.1 mm	30.4%
Min	55.0 mm	19.8 mm	36.0%	0.0%	40.2 mm	48.8 mm	78.8%	15.8 mm	28.7%
Max	57.2 mm	22.8 mm	39.9%	1.1%	44.8 mm	53.8 mm	85.7%	18.3 mm	32.9%
STD. DEV.	1.0	1.2	1.6	0.5	1.9	2.3	3.1	1.0	1.8

Figure 1: Example of output of the Classifiber Model KCF/LS measurement: the mean value of length (ML), the humidity values (UHM and UI%), and the standard deviation in % (CV%) of a lot of rovings are showed.

Table 1: Number of different tests performed for each roving in order to train the ANN system.

Yarn Type	Composition	Number of tests performed varying the fiber parameters for training the net	Number of tests performed varying the fiber parameters for testing the net
Cashmere	100% cashmere	18	8
Maghreb	80% wool 20% nylon	16	8
Joy	60% viscose 35% nylon 5% cashmere	14	8
Beta	28% viscose 15% nylon 7% angora 10% cashmere 40% wool	15	8
Gamma	30% viscose 15% nylon 20% cashmere 35% wool	14	8
Velox	25% viscose 25% nylon 10% cashmere 40% wool	21	10
Total number of Tests		**98**	**50**

Smaller is the value of η and better is the prediction.

In order to validate and test the approach a new series of experimental test (called "validation set") has been carried out. This new experimental phase consisted in collecting the parameters of 50 new rovings (see last column of Table 1). These parameters are used as a test set for the devised ANN.

More in detail the ANN has to give a response closer to the real value of the really produced yarn strength. In Table 5 some of the 50×5 parameters are showed. In order to clarify the approach described above, an example is provided below. Let suppose we want to predict the yarn strength of the "gamma 19" roving whose parameters are listed in Table 5.

TABLE 2: percentage, yarn count, twist, length, fineness, and fiber strength of some rovings within the 98 tested ones.

Yarn type	Fiber	Percentage	Yarn count [tex]	Twist [g/m]	Length [mm]	Fineness [m∗10⁻⁶]	Fiber strength [cN]
	Cashmere	18.3			38	16	10.19
Cashmere 1	Cashmere	80.19	35.52	416	40	15	10.19
	Cashmere	1.78			34	15	10.19
	Cashmere	1.5			33	15	10.19
	Cashmere	0.33			39	15	10.19
Cashmere 2	Cashmere	10.5	36.48	413	34	16.5	10.19
	Cashmere	23.83			39	16	10.19
	Cashmere	37.01			38	15.5	10.19
	Cashmere	26.83			40	15.5	10.19
Maghreb 1	Wool	80	66.48	290	38	21	11.21
	Nylon	20			40	15.5	47.91
Maghreb 2	Wool	80	52.95	302	38	21	11.21
	Nylon	20			40	15.5	47.91
	Viscose	60			35	13	18.35
Joy 1	Nylon	35	57.52	317	40	15.5	47.91
	Cashmere	5			34	15	10.19
	Viscose	60			35	13	18.35
Joy 2	Nylon	35	50.76	329	40	15.5	47.91
	Cashmere	5			36	15	10.19
	Viscose	28			35	13	18.35
	Nylon	15			40	15.5	47.91
Beta 1	Angora	7	65.2	291	38	14	9.17
	Cashmere	10			36	15	10.19
	Wool	40			40	19.5	11.21
	Viscose	28			35	13	18.35
	Nylon	15			38	15.5	47.91
Beta 2	Angora	7	65.35	316	20	14	9.17
	Cashmere	10			35	15	10.19
	Wool	40			40	19.5	11.21
	Viscose	30			35	13	18.35
Gamma 1	Nylon	15	64.08	281	40	15.5	47.91
	Cashmere	20			34	15	10.19
	Wool	35			38	19.5	11.21
	Viscose	30			35	13	18.35
Gamma 2	Nylon	15	76.23	312	40	15.5	47.91
	Cashmere	20			36	15	10.19
	Wool	35			38	19.5	11.21
	Wool	40			42	19.5	11.21
Velox 1	Nylon	25	62.09	294	40	15.5	47.91
	Viscose	25			35	13	18.35
	Cashmere	10			34	15	10.19
	Wool	40			42	19.5	11.21
Velox 2	Nylon	25	60.9	304	40	15.5	47.91
	Viscose	25			35	13	18.35
	Cashmere	10			34	15	10.19

The input set for the ANN is given by the following vector:

$$\text{input (ANN)} = [Y_{\text{cin}}, Tw_{\text{in}}, W_{\text{Lin}}, W_{\text{Fin}}, W_{\text{Sin}}]$$
$$= [15.22, 313, 30.25, 16.3, 18.653]. \quad (9)$$

The ANN response to this input vector is given by

$$\text{output (ANN)} = \left[\text{YS}_{\text{predicted}} \right] = 350.5 \quad [\text{cN}]. \quad (10)$$

TABLE 3: Values of yarn count, twist, W_L, W_F, W_R, and yarn strength for 12 of the 98 different tests.

Yarn type	Yarn count [tex]	Twist [g/m]	W_L [mm]	W_F [m∗10^{-6}]	W_S [cN/tex]	Yarn strength [cN]
Cashmere 1	35.52	416	39.64	15.22	10.19	118.1
Cashmere 2	36.48	413	38.28	15.72	10.19	137.3
Maghreb 1	66.48	290	38.40	19.90	18.55	333.5
Maghreb 2	52.95	302	38.40	19.90	18.55	270.7
Joy 1	57.52	317	36.70	13.98	28.29	589.7
Joy 2	50.76	329	36.80	13.98	28.29	496.7
Beta 1	65.20	291	38.06	16.25	18.47	402.8
Beta 2	65.35	316	36.40	16.25	18.47	428.4
Gamma 1	64.08	281	36.60	16.05	18.65	323.4
Gamma 2	76.23	312	37.00	16.05	18.65	406.4
Velox 1	62.09	294	38.95	16.43	22.07	313.6
Velox 2	60.90	304	38.95	16.43	22.07	379.1

TABLE 4: values of yarn count, twist, W_L, W_F, W_R, and yarn strength (YS) related to "cashmere" family.

Yarn type	Yarn count [tex]	Twist [g/m]	W_L [mm]	W_F [m∗10^{-6}]	W_S [cN/tex]	YS [cN]
Cashmere 1	35.52	416.00	39.64	15.22	10.19	118.10
Cashmere 2	36.48	413.00	38.28	15.72	10.19	137.30
Cashmere 3	37.15	416.20	38.92	15.85	11.10	134.21
Cashmere 4	37.17	416.42	38.65	16.07	10.86	138.26
Cashmere 5	37.18	420.01	39.04	16.57	11.35	128.21
Cashmere 6	38.14	425.00	39.12	16.82	11.33	123.20
Cashmere 7	38.91	428.31	39.13	17.56	11.49	121.98
Cashmere 8	38.96	432.01	40.12	18.50	12.02	132.10
Cashmere 9	39.44	432.16	40.50	19.25	12.80	123.90
Cashmere 10	39.57	432.53	40.86	20.09	13.02	138.09
Cashmere 11	40.08	433.98	40.89	20.63	13.88	137.85
Cashmere 12	40.91	438.01	40.90	20.72	14.83	120.22
Cashmere 13	37.06	439.55	39.22	16.28	11.19	137.69
Cashmere 14	37.48	432.87	39.59	16.84	11.45	124.98
Cashmere 15	37.68	421.87	38.95	16.27	11.75	119.54
Cashmere 16	38.49	425.76	39.07	16.34	12.71	139.76
Cashmere 17	38.71	430.42	39.90	17.20	13.37	140.70
Cashmere 18	39.39	431.75	40.20	18.17	13.72	142.87

The real value of yarn strength measured with a dynamometer (after producing the yarn) is given by

$$YS_{real} = 356.6. \tag{11}$$

Finally the prediction error is given by

$$\eta = 1.71\%. \tag{12}$$

In Table 5 the results of 11 of the whole set of 50 new inputs are provided. Referring to Table 5 the mean error in prediction of yarn strength is 3.07% with a standard deviation equal to 0.0127. The maximum value in error prediction is equal to 5.17%. These results may be compared with the one obtained by means of a multiple regression-based model. The regression equation (evaluated using, as input, the values of Y_c, Tw, W_L, W_F, and W_S normalized in the range [0-1]) is given by

$$YS = 1.027 - 0.334 \cdot Y_c - 0.59 \cdot Tw + 1.072 \cdot W_L$$
$$- 1.090 \cdot W_F + 0.8602 \cdot W_S. \tag{13}$$

This linear regression model, as depicted in the last column of Table 5, leads to an average estimation error equal to 5.55%. In Table 6 the results of simulation performed with the FFBP ANN model on the whole set of 50 rovings are listed. Referring to this validation set the mean error in prediction by using the FFBP ANN is 3.5%. The standard deviation is equal to 0.015. In some cases, like for instance for the roving named "joy 18", the maximum error may be relevant (in this case it is equal to 7.5%). This higher error may be reduced using more data for training the ANN. Future works will be addressed for the building of a more consistent database.

TABLE 5: Some of the 50 × 5 parameters used for testing the ANN. The mean value in prediction error and the standard deviation for both the ANN and the multiple regression models are showed.

Name	Roving properties		Input data					Target data	ANN output	ANN prediction error	Multiple regression output	Multiple regression prediction error
	Composition %	Fiber	Yarn Count [tex]	Twist [g/m]	W_L [mm]	W_F [m*10^{-6}]	W_S [cN/tex]	Yarn strength [cN]	Predicted yarn strength [cN]	%	Predicted yarn strength [cN]	%
Beta 19	28 / 15 / 7 / 10 / 40	Viscose / Nylon / Angora / Cashmere / Wool	14.59	296	29.2	16.15	18.84	397.2	392.4	1.21%	360.75	9.17%
Beta 20	28 / 15 / 7 / 10 / 40	Viscose / Nylon / Angora / Cashmere / Wool	14.89	287	28.86	16.24	18.64	300.6	304.5	1.30%	354.18	17.83%
Beta 21	28 / 15 / 7 / 10 / 40	Viscose / Nylon / Angora / Cashmere / Wool	15.23	294	28.93	16.34	18.94	372.1	378.6	1.75%	349.01	6.20%
Beta 22	28 / 15 / 7 / 10 / 40	Viscose / Nylon / Angora / Cashmere / Wool	14.56	294	18.28	8.44	13.98	347.2	340.2	2.02%	346.54	0.19%
Gamma 16	30 / 15 / 20 / 35	Viscose / Nylon / Cashmere / Wool	15.87	301	30.32	16.45	18.83	339.7	348.1	2.47%	352.18	3.67%
Gamma 19	30 / 15 / 20 / 35	Viscose / Nylon / Cashmere / Wool	15.22	313	30.25	16.30	18.65	356.6	365.8	2.58%	349.42	2.01%
Velox 23	40 / 25 / 25 / 10	Wool / Nylon / Viscose / Cashmere	13.57	303	30.5	16.75	22.39	428.4	419.3	2.12%	425.85	0.59%

TABLE 5: Continued.

Name	Roving properties		Input data					Target data	ANN output	ANN prediction error	Multiple regression output	Multiple regression prediction error
	Composition %	Fiber	Yarn Count [tex]	Twist [g/m]	W_L [mm]	W_F [m∗10^{-6}]	W_S [cN/tex]	Yarn strength [cN]	Predicted yarn strength [cN]	%	Predicted yarn strength [cN]	%
Velox 25	40 25 25 10	Wool Nylon Viscose Cashmere	14.61	345	30.25	16.42	22.28	365.5	348.6	4.62%	388.72	6.35%
Velox 26	40 25 25 10	Wool Nylon Viscose Cashmere	15.34	319	33.9	16.95	22.06	438.3	423.1	3.47%	433.59	1.07%
Velox 27	40 25 25 10	Wool Nylon Viscose Cashmere	15.57	320	29.6	16.57	22.06	417	409	1.92%	381.69	8.47%
Velox 30	40 25 25 10	Wool Nylon Viscose Cashmere	15.67	312	29.85	16.42	22.06	373.8	359.2	3.91%	94.45	5.52%
									Mean	2.49%		5.55%
									Standard deviation	0.011		0.051

New Mill S.p.A.

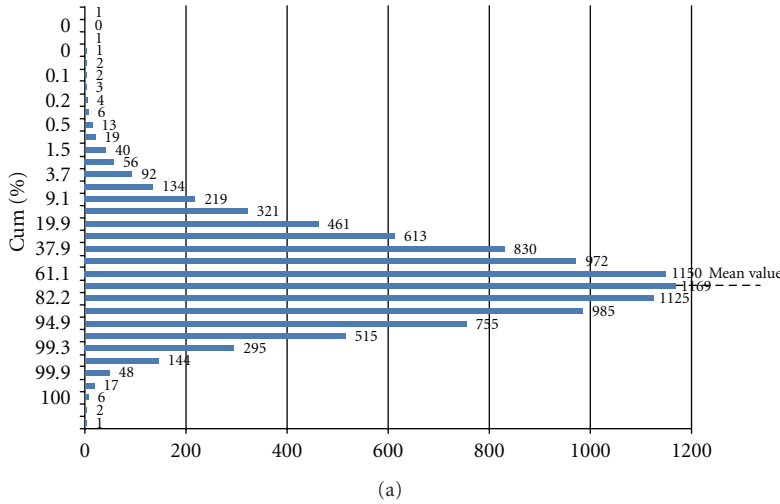| Date | 25 Mar 2009 | Mean | 15.71 u |
Sample Id	Kvss08203	SD	3.53 u
Description	38 mm cal 4	Sample size	10002
5% of fibres 6.7 above mean		Spin fineness	15.5 u
		Comfort factor	99.9%

(a)

(b)

FIGURE 2: (a) Example of output obtained by means of the OFDA instrument: statistical distribution of the fineness. The mean value is assumed as the fineness parameter. (b) Ring frame machine used in the work.
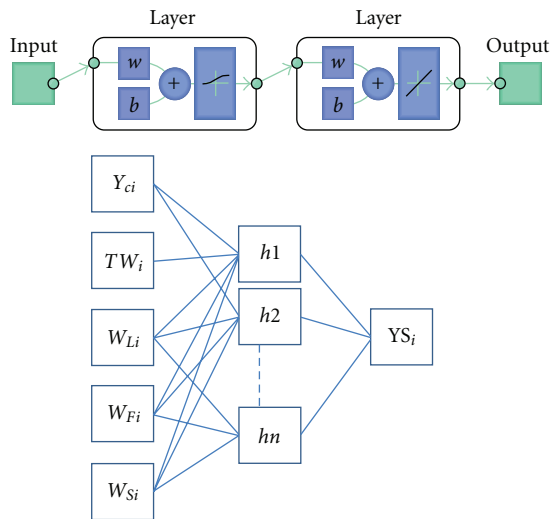

FIGURE 3: A scheme of the devised ANN. The ANN is composed by three layers: input, hidden and output layer. The hidden, layer is made of logistic neurons followed by an output layer of linear neurons. The value for h was set to 10.
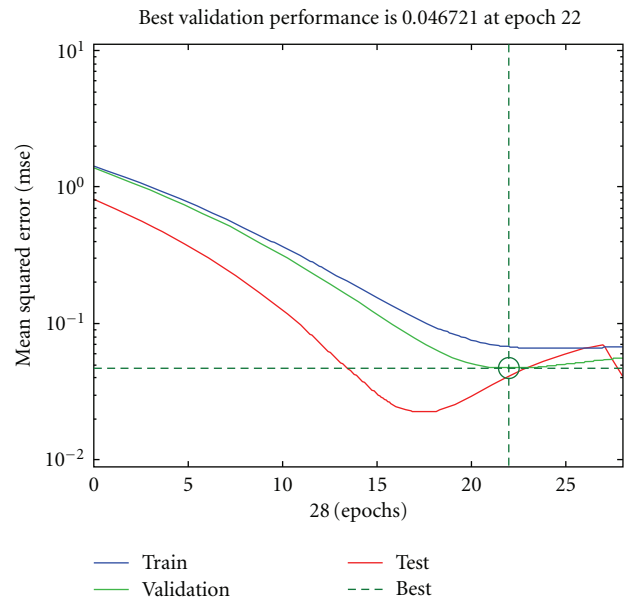

FIGURE 4: Training performance (MSE versus Epochs). The best training has been reached for 22 epochs.

4. Conclusions

With the devised model the textile technicians may test any kind of rovings composed by different percentages of fibers. As stated above the experts are capable of knowing the yarn strength without physically processing it by using the provided model. The model gives an output in less than 1 sec and uses parameters that are commonly measured by the technicians before starting the spinning process. As a result they can quickly test a large number of rovings until they reach the best desirable strength property. After this phase of testing they may effectively spin the yarn. Furthermore, also

TABLE 6: Results of simulation for the 50 new rovings. The mean value in prediction error and the standard deviation are also showed.

Yarn type	Yarn strength [cN]	Predicted yarn strength [cN]	%	Name	Yarn strength [cN]	Predicted yarn strength [cN]	%	Name	Yarn strength [cN]	Predicted yarn strength [cN]	%
Cashmere 19	123.2	127.9	3.83%	joy 15	456.4	442.1	3.13%	gamma 15	329.4	316.3	3.98%
Cashmere 20	138.3	132.79	3.98%	joy 16	534.2	542.2	1.50%	gamma 16	339.7	348.1	2.47%
Cashmere 21	129.5	134.54	3.90%	joy 17	567.9	589.2	3.75%	gamma 17	404.8	421.6	4.15%
Cashmere 22	144.5	150.34	4.05%	joy 18	532.2	572.1	7.50%	gamma 18	373.9	364.7	2.46%
Cashmere 23	146.8	140.82	4.07%	joy 19	456.9	443.3	2.98%	gamma 19	356.6	365.8	2.58%
Cashmere 24	149.2	155.30	4.09%	joy 20	421.5	403.7	4.22%	gamma 20	421.0	416.3	1.12%
Cashmere 25	128.3	133.28	3.88%	joy 21	394.7	386.6	2.05%	gamma 21	376.3	358.0	4.86%
Cashmere 26	132.5	137.70	3.93%	joy 22	459.2	449.2	2.18%	gamma 22	307.9	301.9	1.95%
Maghreb 17	267.8	281.93	5.28%	beta 16	480.1	469	2.31%	velox 22	408.6	405.3	0.81%
Maghreb 18	302.6	319.62	5.63%	beta 17	562.1	572.2	1.80%	velox 23	428.4	419.3	2.12%
Maghreb 19	332.4	352.09	5.92%	beta 18	528.7	502.7	4.92%	velox 24	359.6	376.2	4.62%
Maghreb 20	321.7	302.98	5.82%	beta 19	397.2	392.4	1.21%	velox 25	365.5	348.6	4.62%
Maghreb 21	298.2	314.84	5.58%	beta 20	300.6	304.5	1.30%	velox 26	438.3	423.1	3.47%
Maghreb 22	276.4	291.22	5.36%	beta 21	372.1	378.6	1.75%	velox 27	417.0	409	1.92%
Maghreb 23	343.1	322.40	6.03%	beta 22	347.2	340.2	2.02%	velox 28	419.3	416.9	0.6%
Maghreb 24	332.5	352.20	5.93%	beta 23	402.3	395.9	1.59%	velox 29	365.9	378.5	3.4%
								velox 30	373.8	359.2	3.91%
								velox 31	428.3	447.9	4.58%
Mean	**3.50**%										
Standard deviation	**0.0162**										

an unskilled user is able to correctly choose the best roving for a desired yarn after a few trials. This is translated into a lossless time process. The devised model is running in the New Mill S.p.A. Laboratory and will be subjected to further implementations.

Nomenclature

L_i: Length of the ith fiber composing a roving
F_i: Fineness of the ith fiber composing a roving
R_i: Resistance of the ith fiber composing a roving
α_i: Percentage of the ith fiber composing a roving
Y_{c_i}: Yarn count of the ith roving
Tw_i: Twist yarn of the ith roving
W_{Li}: Weighted average length of the fibers from ith roving
W_{Fi}: Weighted average fineness of the fibers from the ith roving
W_{Ri}: Weighted average strength of the fibers from the ith roving
YS_i: Strength of the ith yarn.

References

[1] C. Price, H. Senter, J. Foulk, G. Gamble, and W. Meredith, "Relationship of fiber properties to vortex yarn quality via partial least squares," *Journal of Engineered Fibers and Fabrics*, vol. 4, no. 4, pp. 37–46, 2009.

[2] M. E. Üreyen and H. Kadoğlu, "Regressional estimation of ring cotton yarn properties from HVI fiber properties," *Textile Research Journal*, vol. 76, no. 5, pp. 360–366, 2006.

[3] M. W. Suh, K. Hyun-Jui, and C. Xiaoling, "Prediction of yarn tensile properties based on HVI testing of 36 U.S. Upland cottons," in *Proceedings of the Beltwide Cotton Conferences*, pp. 786–790, San Diego, Calif, USA, January 1998.

[4] S. Ertugrul and N. Ucar, "Predicting bursting strength of cotton plain knitted fabrics using intelligent techniques," *Textile Research Journal*, vol. 70, no. 10, pp. 845–851, 2000.

[5] Y. E. El Mogahzy, "Selecting cotton fiber properties for fitting reliable equations to HVI data," *Textile Research Journal*, vol. 58, no. 7, pp. 392–397, 1988.

[6] M. D. Ethridge, J. D. Towery, and J. F. Hembree, "Estimating functional relationships between fiber properties and the strength of open-end spun yarns," *Textile Research Journal*, vol. 52, no. 1, pp. 35–45, 1982.

[7] P. K. Majumdar and A. Majumdar, "Predicting the breaking elongation of ring spun cotton yarns using mathematical, statistical, and artificial neural network models," *Textile Research Journal*, vol. 74, no. 7, pp. 652–655, 2004.

[8] L. Cheng and D. L. Adams, "Yarn strength prediction using neural networks. I. Fiber properties and yarn strength relationship," *Textile Research Journal*, vol. 65, no. 9, pp. 495–500, 1995.

[9] N. Ucar and S. Ertugrul, "Predicting circular knitting machine parameters for cotton plain fabrics using conventional and neuro-fuzzy methods," *Textile Research Journal*, vol. 72, no. 4, pp. 361–366, 2002.

[10] M. C. Ramesh, R. Rajamanickam, and S. Jayaraman, "Prediction of yarn tensile properties by using artificial neural networks," *Journal of the Textile Institute*, vol. 86, no. 3, pp. 459–469, 1995.

[11] R. Zhu and M. D. Ethridge, "The prediction of cotton yarn irregularity based on the 'AFIS' measurement," *Journal of Textile Institute*, vol. 87, no. 3, pp. 509–512, 1996.

[12] A. Guha, R. Chattopadhyay, and B. Jayadeva, "Predicting yarn tenacity: a comparison of mechanistic, statistical, and neural network models," *Journal of the Textile Institute*, vol. 92, no. 1, pp. 139–145, 2001.

[13] A. Majumdar, A. Ghosh, S. S. Saha et al., "Empirical modelling of tensile strength of woven fabrics," *Fibers and Polymers*, vol. 9, no. 2, pp. 240–245, 2008.

[14] M. Zeydan, "Modelling the woven fabric strength using artificial neural network and Taguchi methodologies," *International Journal of Clothing Science and Technology*, vol. 20, no. 2, pp. 104–118, 2008.

[15] J.-G. Yang, Z.-J. Lv, and Q. Xiang, "Yarn properties prediction using support vector machines: an intelligent reasoning method," in *Proceedings of the 4th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD '07)*, vol. 1, pp. 696–700, Haikou, China, August 2007.

[16] Z. Bo, "Predicting fiber diameter of Polypropylene (PP) spunbonding nonwovens process: a comparison between physical and artifical neural network methods," in *Proceedings of the International Conference on Computational Intelligence and Security (CIS '09)*, vol. 1, pp. 639–642, Beijing, China, December 2009.

[17] B. Chylewska and D. Cyniak, "Requirements for fibres used for rotor-spun yarns," *Bulletin of the Gdynia Cotton Association*, no. 4, pp. 33–47, 1998 (Polish).

[18] T. Jackowski and I. Frydrych, "What i learnt in fibre quality: practical experience," in *Proceedings of the 58th Plenary Meeting of the International Cotton Advisory Committee*, Charleston, SC, USA, October 1999.

[19] M. Frey, "Influence of fibre parameters and values of their variation on the spinning process," in *Proceedings of the 4th International Conference on Grid Computing and Applications*, Gdynia, Poland, 1995.

[20] M. Kiliç and A. Okur, "Relationships between yarn diameter/diameter variation and strength," *Fibres and Textiles in Eastern Europe*, vol. 14, no. 5, pp. 84–87, 2006.

[21] H. C. Yuan, F. L. Xiong, and X. Y. Huai, "A method for estimating the number of hidden neurons in feed-forward neural networks based on information entropy," *Computers and Electronics in Agriculture*, vol. 40, no. 1–3, pp. 57–64, 2003.

[22] J. M. Kinser, "The determination of hidden neurons," *Optical Memories and Neural Networks*, vol. 5, no. 4, pp. 245–262, 1996.

[23] L. Ren and Z. Zhao, "An optimal neural network and concrete strength modeling," *Advances in Engineering Software*, vol. 33, no. 3, pp. 117–130, 2002.

[24] A.-H. Tan, G. A. Carpenter, and S. Grossberg, "Intelligence through interaction: towards a unified theory for learning," in *Proceedings of the 4th International Symposium on Neural Networks (ISNN '07)*, vol. 4491 of *Lecture Notes in Computer Science*, pp. 1094–1103, June 2007.