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Slub Yarn Quality Optimization by using Desirability Function and Neural Networks

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Abstract: Yarn quality is an essential concept defined by customer which requests the satisfaction of several properties simultaneously. The objective of this study is to optimize Slub yarn quality and then predict it. The approach used to characterize Slub yarn quality is the desirability functions. The present method allowed us to qualify yarn quality by an index belonging to the interval [0, 1] which includes the major physical properties of cotton Slub yarn. Each yarn response is to be maximized, minimized or targeted. These goals have contributed to get a better yarn quality representation. The second step of this study involves the prediction of the overall yarn quality with the consideration of the construction parameters by using artificial neural networks. The artificial neural network is trained to foresee only one response which is the Slub yarn quality index that includes all yarn responses. The definition of the yarn quality can be modified according to customer demands. The model elaborated has presented a good performance and flexibility.

Key words: Slub yarn, quality, neural network, desirability, optimization

INTRODUCTION

Now-a-days, the structure, fiber characteristics and color of effect yarns, unlike normal yarns, are being increasingly required from the customer oriented flexibility and market niche policy. Among the frequently used effect yarns in industry is the Slub yarns (Amsler, 2004). The quality of the resulting yarns is very important in determining their application possibilities. In fact, the random variation in the count of the base yarn which contains thick places of different thicknesses and lengths, gives a wide range of effects. This ensures the use of Slub yarns in many applications like denim, shirting, knitwear, casual wear and also in ladies dress material (Sampath, 2004).

Generally, the quality of a yarn is defined in two main characteristics which are namely its tenacity and elongation. Nevertheless, customers usually require much more quality criterion. Over the past several years, methods for predicting yarn performance treat yarn properties separately (Cheng and Adams, 1995; El Mogahzy *et al*., 1990; Ramesh *et al*., 1995; Rajamanickam *et al*., 1997; Morris *et al*., 1999; Pan *et al*., 2001; Ramey *et al*., 1977; Maatoug *et al*., 2007; Das *et al*., 2011; Sami and Naima, 2009). Therefore, it is desirable to predict an overall yarn quality that considers all yarn characteristics simultaneously.

Slub yarn properties have been firstly combined into one index belonging to the closed interval [0, 1]. For the case, an algorithm based on the desirability functions has been developed. This approach, first introduced by Harrington (1965), presents an important method for multi-criteria optimization in industrial quality management (Ahmad *et al*., 2002; Kuang-Cheng *et al*., 2008; Krishnaiah *et al*., 2011). After defining a Slub yarn quality index with desirability approach, neural networks have been used, in the second stage, to predict it. This method is of high interest in predictive modeling for the non-linear relationship between responses and variables (Dreyfus *et al*., 2002; Yedjour *et al*., 2011; Dastorani *et al*., 2010). In this study, we have studied Slub yarns used in denim industry. We have introduced, in addition to yarn tenacity and elongation, yarn work, regularity, hairiness, yarn count, twist and some construction parameters related to yarn aspect.

As yarn quality is primarily influenced by fiber properties, we have introduced these parameters, in addition to construction parameters, for a better modeling.

MATERIALS AND METHODS

In order to study Slub yarn overall quality, we have used the international standards using the Uster Tester 3 and Uster Tensiorapid 3 testing systems. The main yarn characteristics studied are shown in Table 1. The database is developed in an integrated Tunisian factory during the year 2007. The Slub yarn is spun with "programmable" characteristics-electronically controlled

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Table 1: Summary statistics for Slub yarn properties

Yarn property	Symbol	Mean	Standard deviation	Minimum value	Maximum value
Tenacity (CN/Tex)	RKM	17.32	1.23	14.64	22.12
Tenacity evenness (%)	CVRKM	6.85	3.17	4.54	7.96
Breaking elongation (%)	E%	7.87	0.77	6.27	9.72
Breaking elongation evenness (%)	CVE%	4.10	2.64	3.77	8.76
Breaking work (Joule)	TR	2.83	0.85	1.27	6.58
Breaking work evenness (%)	CVTR%	12.07	3.39	0.00	6.27
Irregularity (%)	U%	8.97	2.31	10.70	16.47
Hairiness	PILO	8.21	1.00	5.71	10.74
Pause count/yarn count	T_{pause}/T_{yarn}	0.932	0.03	0.832	0.957
Number of Slubs/meter (m^{-1})	N_{Slubs}	2.47	0.98	1.18	5.36
Twist value (turns/m)	Twist	463.00	8.65	364.00	629.00
Yarn count(m/10^{-3} kg)	T_{yarn}	13.07	3.46	10.10	21.12

Table 2: Summary statistics for fiber parameters

Fiber property	Symbol	Mean value	Standard deviation	Minimum value	Maximum value
Micronaire index(μg $inch^{-1}$)	Mic	4.30	0.13	4.00	4.70
Maturity	Mat	0.88	0.01	0.85	0.91
Upper Half Mean Length (UHML) (10^{-3} m)	Len	28.44	0.68	27.40	30.60
Uniformity Index (%)	Unif	81.14	0.73	79.40	84.10
Short Fiber index (%)	Sfi	7.92	1.82	4.10	10.90
Strength (CN/tex)	Str	29.32	1.56	26.00	34.90
Elongation (%)	Elg	6.53	0.80	4.90	8.20
Trash count	Tr cnt	11.52	4.47	2.00	24.00
Trash area	Tr area	0.14	0.03	0.07	0.24
Trash grade	Tr grade	2.25	1.18	1.00	4.00
Greyness (color reflectance)	Rd	75.43	1.13	72.30	80.00
Yellowness	+b	10.08	0.88	9.20	14.30

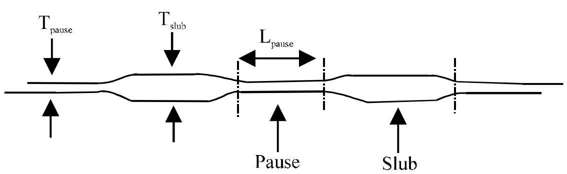

Fig. 1: Slub yarn configuration

and reproducible by means of the Amsler device (Amsler, 2004). These characteristics are produced via a program controlled drafting system which varies acceleration of back and middle rollers. At the same time, the front roller of the Ring spinning is maintained at a constant speed. This controlled acceleration produces variation in Slub (or flames) count (T_{slub}), spacing (or pause) length (L_{pause}) and spacing count (T_{pause}) (Fig. 1).

The determinant structural parameters introduced in the Amsler device program conferring to the Slub yarn configuration are, respectively:

- The number of Slubs per meter (N_{Slubs})
- And the quotient of Pause count by yarn count (T_{pause}/T_{yarn})

The database is made basing on the major cotton fiber characteristics which is composed of twelve characteristics measured by means of the High Volume Instrument (HVI). The summary of statistics of fiber parameters including mean, maximum, minimum values and standard deviation of micronaire index, maturity, length, uniformity index, short fiber index, strength, elongation, impurity trashes and color parameters is shown in Table 2.

Determination of an overall Slub yarn quality index: The desirability approach is a method that becomes widely used for the optimization of multiple responses. It is based on the idea that the "quality" of a product or process has multiple quality characteristics in the same time. If one of the quality characteristics is outside of some "desired" limits, it is considered completely unacceptable. The method finds operating conditions that provide the "most desirable" response values.

For each yarn response Y_i, an individual desirability function d_i (Y_i) assigns numbers between 0 and 1 to the possible values of Y_i, with d_i (Y_i) representing a completely undesirable value of Y_i and d_i (Y_i) = 1 representing a completely desirable or ideal response value. The individual desirabilities of all yarn responses are then combined using the geometric mean which gives the overall yarn quality index D (Eq. 1):

$$D = \sqrt[s]{d_1^{s_1} \times d_2^{s_2} \times \ldots \times d_n^{s_n}} \quad (1)$$

with n denoting the number of yarn responses. s = Σs_i; s_i is the weight of ith response.

Depending on whether a particular response Y_i is to be maximized, minimized or assigned a target value, the different desirability functions d_i (Y_i) used are those proposed by Derringer and Suich (1980).

Let L_i, U_i and T_i be the lower, upper and target values, respectively, that are desired for response Y_i, with $L_i \leq Y_i \leq U_i$.

If a response is of the "target is the best" kind, then its individual desirability function is:

$$d_i = \begin{cases} \left[\dfrac{Y_i - L_i}{T_i - L_i}\right]^p \text{ if } L_i \leq Y_i \leq T_i \\ \left[\dfrac{Y_i - U_i}{T_i - U_i}\right]^q \text{ if } L_i \leq Y_i \leq T_i \\ 1 \quad \text{if} \quad Y_i = T_i \\ 0 \text{ if } Y_i \leq L_i \text{ or } Y_i = U_i \end{cases} \quad (2)$$

With the exponents p and q determining how important it is to hit the target value. For p = q = 1, the desirability function increases linearly towards target T_i (Fig. 2) for p<1, q<1, the function is convex and for p>1, q>1, the function is concave.

If a response is to be maximized instead, the individual desirability is defined as shown in Eq. 3:

$$d_i = \begin{cases} 0 & \text{if} \quad Y_i \leq L_i \\ \left[\dfrac{Y_i - L_i}{T_i - L_i}\right]^p & \text{if} \quad L_i \leq Y_i \leq T_i \\ 1 & \text{if} \quad Y_i \geq T_i \end{cases} \quad (3)$$

When we want to maximize a response, the function of individual desirability is constant and equals to one, for response values superior to the target. Under the lower limit, the desirability is equal to zero. Between lower and target values, the individual desirability varies linearly (p = 1) with a slope equals to:

$$\frac{1}{T_i - L_i}$$

Figure 3 shows the illustration of this function.

Finally, if a response is to be minimized, the desirability function used is shown in Fig. 4. The individual desirability (d_i) is calculated according to Eq. 4.

$$d_i = \begin{cases} 1 & \text{if} \quad Y_i \leq T_i \\ \left[\dfrac{Y_i - U_i}{T_i - U_i}\right]^q & \text{if} \quad T_i \leq Y_i \leq U_i \\ 0 & \text{if} \quad Y_i \geq U_i \end{cases} \quad (4)$$

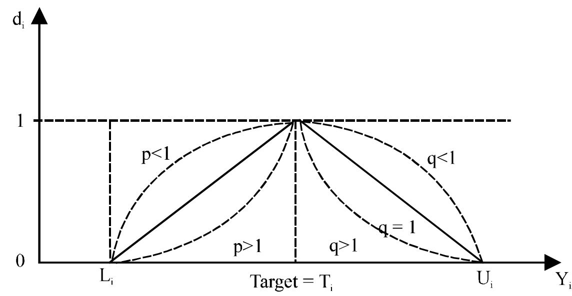

Fig. 2: Function of desirability to reach a target value

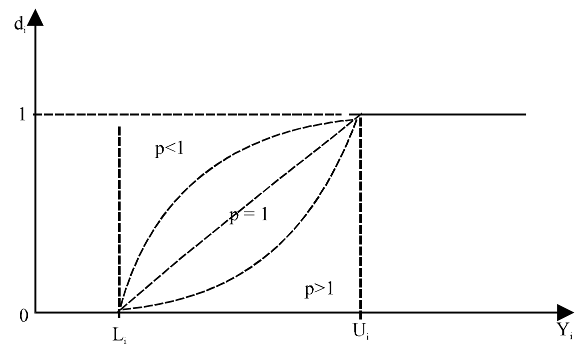

Fig. 3: Desirability function to maximize

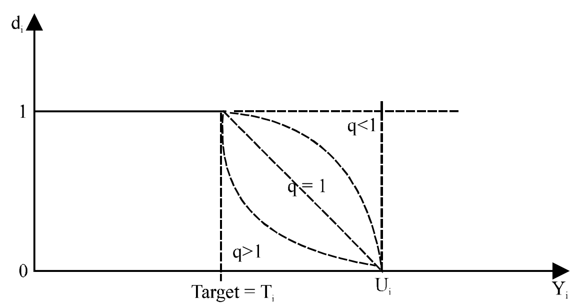

Fig. 4: Desirability function to minimize

Neural network modeling

Model parameters: In this study, we implemented a back-propagation neural network. The network structure is composed of one single hidden layer connected to an input layer and an output layer from each end. In our application, the input units are composed of fiber properties and yarn construction parameters. The output unit is the yarn properties summarized in the yarn quality index D (Table 3). The connection strengths are the weights which were adjusted, in each input-output training pair. The update of weights and bias values was achieved according to the one-step secant method (Dreyfus *et al*., 2002).

Table 3: Input and output parameters of the neural network model

Status	Parameters	Micronaire index (μg inch^{-1})	Mic
Inputs	Fiber properties	Maturity	Mat
		Upper Half Mean Length (UHML) (10^{-3} m)	Len
		Uniformity Index (%)	Unif
		Short Fiber index (%)	Sfi
		Strength (CN/tex)	Str
		Elongation (%)	Elg
		Trash count	Tr cnt
		Trash area	Tr area
		Trash grade	Tr grade
		Greyness (color reflectance)	Rd
		Yellowness	+b
	Construction parameter	Yarn count	T_{yarn}
		Twist value	Twist
		Pause count/yarn count	T_{pause}/T_{yarn}
		Number of Slubs/meter (m^{-1})	N_{Slubs}
Output	Slub yarn global quality	D	

RESULTS AND DISCUSSION

In order to build our neural network model, an overall yarn quality has been calculated for each experience of the database. The objectives and boundaries of maximizing, minimizing or targeting a response depends on customer quality requirements. In our study, the Slub yarn quality definition chosen is described in Table 4. The values p = q = 1 were chosen in all cases to put an equal importance to all responses.

The new database composed of fiber characteristics, yarn construction parameters, yarn responses and overall quality indexes, constitute the neural network database. The neural network program developed was achieved using Matlab software. The program handles different numbers of neurons in the hidden layer and different epochs until reaching a correlation coefficient R% near to 100%, contributing to the minimum root mean square errors generated by the training and testing data (Dreyfus *et al*., 2002).

The activations of the units in the hidden layer were calculated by using the Log-sigmoid transfer function (Fan and Hunter, 1998). The activation function of the output layer that improved the speed of the training and the best forecasting of the model was the Tan-sigmoid activation function.

The training ended after 300 epochs, when the root mean square errors of training $RMSE_{train}$ and testing $RMSE_{test}$ have, respectively fallen to 0-01, 0-04 (Fig. 5). The two errors were small and of the same order. They were obtained for seven neurons in the hidden layer. The highest correlation obtained with seven hidden neurons was higher and was equal to 0.96. From this investigation, we saw that seven neurons construct the best network model.

Table 4: Slub yarn quality definition

Slub yarn responses	Objective	Inferior Limit (L_i)	Target (T_i)	Superior limit (U_i)
RKM	Maximize	16	19	*
CVRKM	Minimize	*	4.6	6.5
E%	Maximize	7	9	*
CVE%	Minimize	*	0.5	2
TR	Maximize	3.5	6	*
CVTR%	Minimize	*	0	2
U%	Minimize	*	11	13
PILO	Minimize	*	6	8
T_{pause}/T_{yarn}	Target	0.86	0.9	0.93
N_{Slubs}	Target	3.5	4	4.5

*Not defined in the corresponding desirability function

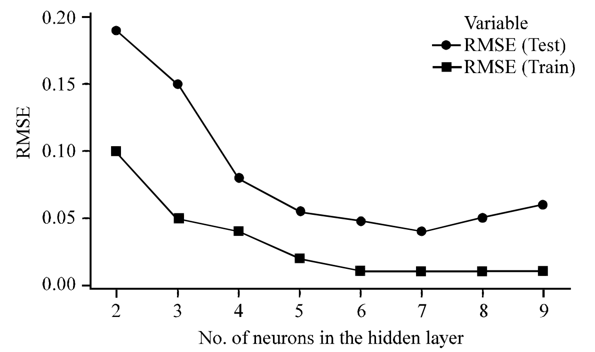

Fig. 5: Time series plot of $RMSE_{train}$ and $RMSE_{test}$ versus the number of neurons in the hidden layer

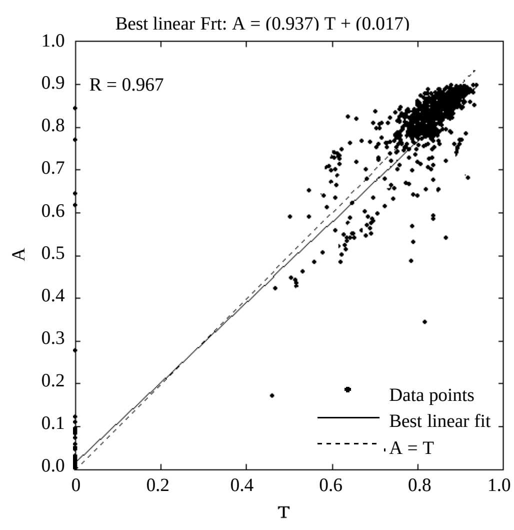

Fig. 6: Relationship between actual and predicted values of the Slub yarn quality index

The model has resulted to a correlation coefficient near to 1 and training and testing errors small and of the same order. These results conferred that the model elaborated was "good" (Dreyfus *et al*., 2002).

Figure 6 illustrates the distribution of the estimated values A of Slub yarn overall quality to measured values T. A linear regression between the network output and the corresponding target was performed in order to check the good quality of the network training. If we have a perfect fit, the slope would be 1 and the estimated values of quality represented would be on the solid line. Here, the output data points seem to track the targets reasonably well and R% value was almost 0.96. Also, the perfect fit line and the best fit line were so close.

CONCLUSION

The present study shows a manner to predict Slub yarn global quality by including different criteria in the same time. As tools, we have used the functions of desirability and the artificial neural networks. The results show that the conditions imposed by desirability functions summarized in each response objectives, boundaries and weights furnish a good reflection of quality as desired by customer. We have implemented a multi-objective optimization into one single valuable index. To predict the quality of the Slub yarn, while considering fiber and construction parameters, we have applied only one neural network model to all yarn quality criterion summed in the overall Slub yarn quality index. The prediction accuracy of the established neural network model has shown a good performance.

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