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Using Intelligent Control Systems to Predict Textile Yarn Quality

Abstract
This study describes the application of intelligent control systems in textile engineering and how to use these approaches for developing a spun yarn quality prediction system. The Multilayer Perceptron Neural Network(MLPNN), Support Vector Machines(SVMs), the Radial Basic Function Network(RBFN), the General Neural Network(GNN), the Group Method of Data Handling Polynomial Neural Network (GMDHPNN) and Gene expression Programming (GEP), generally called intelligent techniques, were used to predict the count-strength-product (CSP). Fiber properties such fibre strength (FS), micronaire (M), the upper half mean length (UHML), fibre elongation(FE), the uniformity index (UI), yellowness (Y), grayness (G) and short fibre content (SFC) were used as inputs. The prediction performances are compared to those provided by the classical Linear Regression (LR) model. The SVMs model provides good prediction ability, followed by the GEP and LR models, respectively. Graphs illustrating the relative importance of fibre properties for CSP were plotted. Fiber strength (FS) is ranked first in importance as a contributor to CSP by the five models, while fibre elongation (FE) ranks second. By means of the yarn strength learned surfaces on fibre properties, the study shows how to control yarn quality using knowledge of fibre properties.

Key words: *intelligent techniques, CSP, fibre properties.*

Introduction

As yarn strength is the principle component yarn quality and the most important index of spinning quality, predicting yarn strength is very important from a technological point of view. The relationship between fibre properties and yarn properties has been the focus of extensive research, and considerable success has been achieved. Many mathematical models have been used to understand and predict the complex relationships between fibre parameters and yarn characteristics, and substantial research has been done to determine methods of predicting yarn properties. The classical linear regression (LR) approach has been used more intensively for the prediction of yarn strength. But it also has limitations due to its inability to show how such fibre properties contribute to yam strength. In recent years, artificial intelligent techniques have been widely used in mapping highly nonlinear and complex relationships in many areas of engineering. They have been used as model predictive control technologies and it was shown that they can calculate control variables where classical mathematical and statistical models have failed [1 - 6]. However, their power performances are still questionable and many other studies have to be conducted in order to assess the approximate power performance of each model. In textile engineering, some studies using those methods have been conducted and it was shown that they can lead to a quick convergence of the predefined quality specifications with a small number of trials and low cost [5, 6]. Moreover, multifunctional textile materials have been significantly developed, with such materials being mostly used for producing high-valued products. Furthermore engineers are strongly involved in the development of new advanced materials in order to satisfy complex customer requirements and specifications. In this study, the strength of yarn was chosen as one of the most important qualities. As yarn strength depends on fibre properties, it is very important to establish the relation between yarn strength and fibre properties. However, the nonlinear relationship between yarn strength and its components has complicated the problem. Therefore, the development of predictive modelling of yarn strength is still significant both in theory and in practice.

The main objective of this study was to explore the new intelligent technologies and attempt to use them as new approaches to predict and control yarn quality. The Multilayer Perceptron Neural Network (MLPNN), Support Vector Machines (SVM), the Radial Basis Function Network (RBFN), the General Regression Neural Network (GRNN), the Group Method of Data Handling Polynomial Neural Network (GMDHPNN), and Gene Expression Programming (GEP), generally called intelligent technique models, were used to predict the spun yarn strength from fibre properties, and their performances were compared to those of the Linear Regression (LR) model. We used these methods to determine the relative importance of fibre properties for yarn strength. More details

Table 1. *Cotton fibre properties selected; *Measured by Uster AFIS.*

Variables	Description of variables	Units
FS	Fiber strength	g/tex
UHML	Upper half mean length	mm
UI	Uniformity index	%
M	Micronaire	μg/mm
G	Grayness	Rd
Y	Yellowness	+b
E	Elongation	%
SFC	Short fibre content*	%by weight
YC	Yarn count	tex

Table 2. *Spinning parameters.*

Spinning parameter	Values
Nominal yarn number, tex	19.68
Rotor speed, r.p.m.	55000
Opening roller speed, r.p.m.	6700
Draft (approximate)	198
Twist multiplier, t.p.m.	188.18
Yarn speed, m/min	53.31

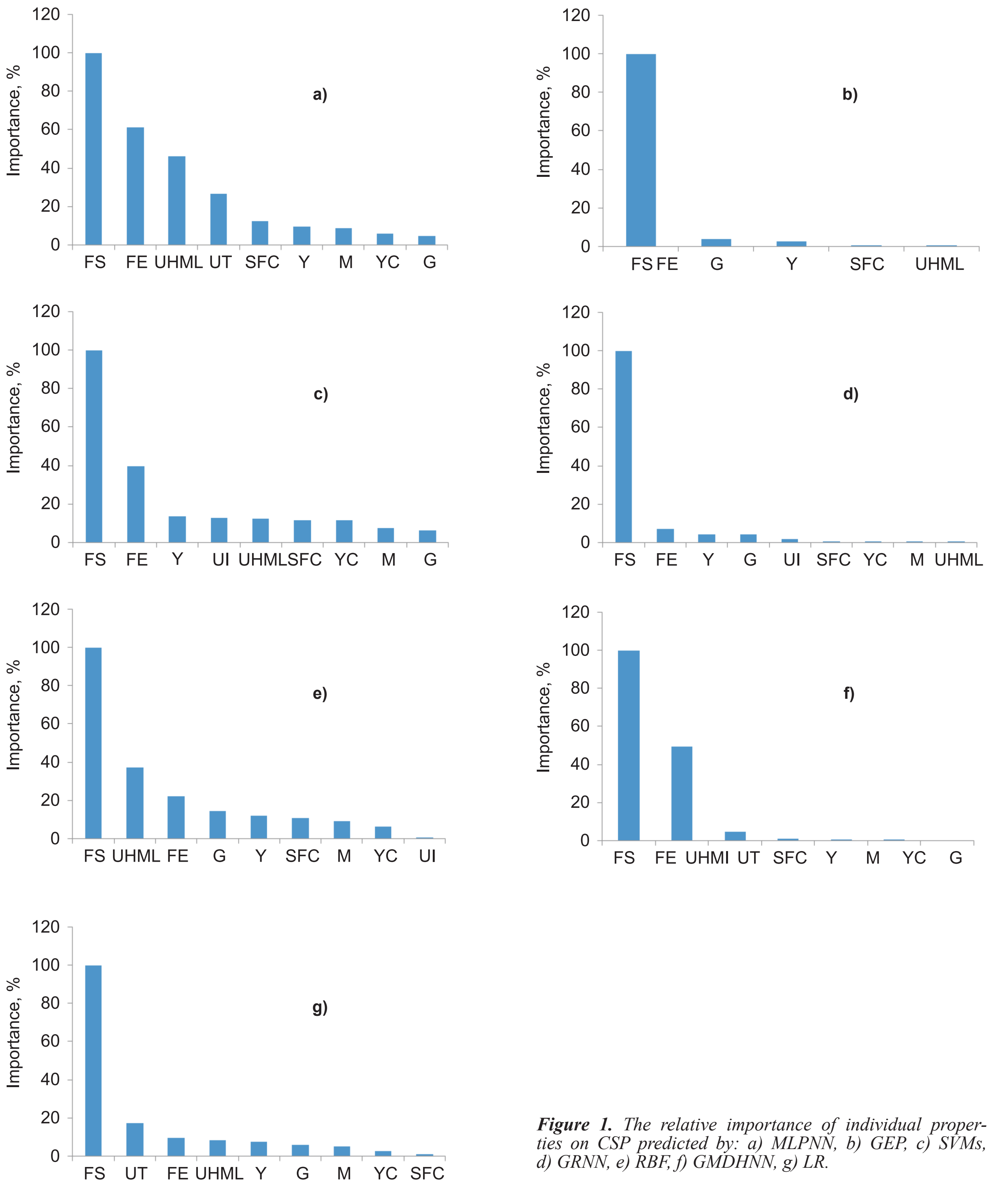

Figure 1. *The relative importance of individual properties on CSP predicted by: a) MLPNN, b) GEP, c) SVMs, d) GRNN, e) RBF, f) GMDHNN, g) LR.*

on the theory and applications of these new intelligent technologies can be found in a number of publications [8 - 15].

Collection of data

Fiber and yarn data, along with detailed explanations of equipment and procedures were collected from the cotton crop study data of 1997 published by the International Textile Center [7]. Eight cotton fibre properties measured by a High Volume Instrument (HVI) and Uster AFIS were selected, given in ***Table 1.*** All the spun yarns were produced on an open-end spinning machine with 30/1 yarn counts (YC) in tex. The spinning machine parameters and their values are given in ***Table 2***. The rotor speed, opening roller speed and twist multiplier were held constant during the processing. The skein method was used to test the yarn strength. A set of 34 samples was used to train and test the models. Since multiple yarn sizes were spun from each cotton bale sampled, the yarn count (YC) was also included as an input variable.

Methods

For implementation, commercially available predictive modeling software, namely Decision Tree and Regression (DTREG) [16] was used to execute both of the models. The prediction performance of each method was evaluated using the following statistical metrics, namely, the Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). RMSE and MAE are measures of the deviation between the actual and predicted values. The smaller the values of RMSE and MAE, the closer the predicted CSP values are to the actual CSP values. All these methods of comparison are defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(o_i - o_p)^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - O_p\right| \quad (2)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|O_i - O_p\right|}{\left|O_i\right|}\times 100\% \quad (3)$$

where n is the number of pairs; O_i and O_p are i-th desired output and calculated output, respectively.

As a validation method, the ten-cross validation method was used for all methods, except for GEP and GRNN. With the ten-cross validation method, one subset was chosen for testing, and the remaining nine subsets were used for training. The process was repeated until all the subsets were chosen for testing.

For the GRNN method, the leave one out method was used for validation. The process of removing unnecessary neurons is an iterative process. Leave-one-out validation was used to measure the error of the model with each neuron removed. The neuron that caused the least increase in error (or possibly the largest reduction in error) was then removed from the model. The process was repeated with the remaining neurons until the stopping criterion is reached.

For the GEP model, fitness was based on how well the individual modelled the data. As the target variable had continuous values, the fitness was based on the difference between predicted values and actual values. Evolution stopped when the fitness of the best individual in the population reached a certain limit that

Table 3. *Summary of the results from LR statistical analysis.*

Fibre properties	Coefficient	Std. Error	t	P(t)
FS	42.54	8.82	4.82	0.00006
UHML	364.42	333	1.09	0.28477
UI	29.03	20.7	1.40	0.17320
M	-71.21	56.8	-1.25	0.22224
G	5.59	6.19	0.90	0.37491
Y	23.20	21.7	1.07	0.29527
FE	-50.16	28.9	-1.74	0.09556
SFC	-2.87	5.72	-0.50	0.62013
YC	-34.88	66	-0.53	0.60223
Constant	-954.71	2945	-0.32	0.74859

Table 4. *Anova and F statistics (validation).*

Source	DF	Sum of squares	Mean square	F value	Prob (F)
Regression	9	602762.8	66973.64	2.451	0.038450
Error	24	655683.5	27320.14		
Total	33	1258446			

Table 5. *Comparison analysis of the training results of the seven models.*

Statistical parameter	SVMs	RBFN	GMDHNN	MLPNN	GRNN	GEP	LR
RMSE	75.56	65.12	62.85	81.97	59.48	93.07	82.27
MAE	44.34	50.41	45.55	62.32	43.37	75.57	64.85
MAPE	2.24	2.55	2.30	3.18	2.19	3.84	3.29

Table 6. *Comparison analysis of the validation results of the seven models.*

Statistical parameter	SVMs	RBFN	GMDHNN	MLPNN	GRNN	GEP	LR
RMSE	120.03	208.44	425.17	162.73	148.82	124.52	138.86
MAE	82.87	131.63	180.05	100.91	89.65	93.69	97.73
MAPE	4.07	6.39	9.31	4.89	4.28	4.70	4.84

was specified for the analysis or when a specified number of generations had been created or a maximum execution time limit was reached. After the generation of the population, the individual fitness value was computed using the following expression:

$$F = \left(\sum (M - \left|C - T\right|)\right)\frac{100}{M \times n} \quad (4)$$

where M is the range of selection; C denotes the value returned by the target gene; T is the target value, and n is the population size.

Thus each chromosome has a fitness value. The greater the fitness value, the better it describes the data. More details can be found in [14].

Results and discussion

Comparison analysis of the performances of different models

The goal of this part of the research is to compare the prediction results provided by SVMs, RBFN, GMDHNN, MLPNN, GRNN and GEP, generally called intelligent techniques, as well as by the linear regression (LR) model in order to have a concrete idea of the performance power of each model. The training results are given in ***Table 5***. However, the final comment on overall prediction performances should made by analysing the test results. After the training, the models were subjected to unseen testing data. Results from the LR statistical analysis are summarised in ***Tables 3*** and ***4***, and the resulting expressions generated - LR and GEP are given by ***Equations 5*** and ***6***, respectively:

$$\text{LR: } CSP = 42.54 \times FS + 364.42 \times \times UHML + 29.03 \times UI - 71.21 \times M + + 5.59 \times G + + 23.20 \times Y - 20.16 \times FE + + 2.87 \times SFC - 34.88 \times YC - 954.75 \quad (5)$$

$$\text{GEP: } CSP = (((SFC + (18.258451 \times Y)) + - (10.502118 \times G)) + (UHML + + ((FS - 10.05878) \times G))) - (-1193.8948) \quad (6)$$

A comparison of the validation results is in ***Table 6***. We can now look at the differences in the results obtained by the different methods. The lowest values of RMSE, MAE and MAPE were provided by the support vector machines (SVMs) model, followed by gene expression programming (GEP) and linear regression (LR), respectively. These results are acceptable for test data, indicating the ability of the three models to generalise training data well for the prediction of new conditions. Hence, the results imply the acceptable prediction ability of the models. The highest values of RMSE, MAE and MAPE were provided by GMDHNN, followed by RBFN, MLPNN and GRNN, respectively. These models do not generalise the training data in this study.

Importance of individual properties of fibres for CSP

In this section, we analyse the importance of individual properties of fibre for CSP. The models determine the most important variables. Graphs representing the order of importance of individual properties of fibre for the CSP obtained by each method are shown in ***Figure 1*** (see page 23). From ***Figure 1*** we can see that the CSP is influenced, to a greater or lesser degree, by fibre properties. Fibre strength (FS) is ranked first in importance as a contributor to CSP by five models: MLPNN, GEP, SVMs, GRNN, RBF and LR. This is in agreement with previous observations in textile literature. Fibre elongation (FE) ranks seconds, and the remaining fibre properties may contribute to CSP to a lesser degree.

CSP quality control decision by learned surface analysis

In order to qualitatively study the effects of fibre properties on yarn strength, response surfaces plots were generated using the relationships obtained. The surface viewer provides a 3-dimensional view of the relationship between the two inputs and the output of the system, which allows to check the behaviour of the output across the entire range of possible input combinations. The surface viewer shows the entire output surface of the system, which is the entire span of the output set based on the entire span of the input set. Hence a three dimensional output surface can be generated where any two inputs vary while the others must be held constant. ***Figures 2 and 3*** show the learned surfaces for two fibre properties with all other fibre properties held constant. This surface would be an initial estimate of the presence of nonlinearity. Since a combination of two fibre properties has a positive impact on yarn strength, the yarn strength learned surface is smoothly continuous in an upward direction, for example the learned surface on fibre strength and the uniformity index (***Figure 2***). However, when a combination of two fibre properties has a negative impact on yarn strength, the resulting surface exhibits discontinuity, as is shown in the case of the combination of micronaire and fibre strength (***Figure 3***). This type of analysis uses different combinations of fibre properties that assure the quality control desired in the CSP.

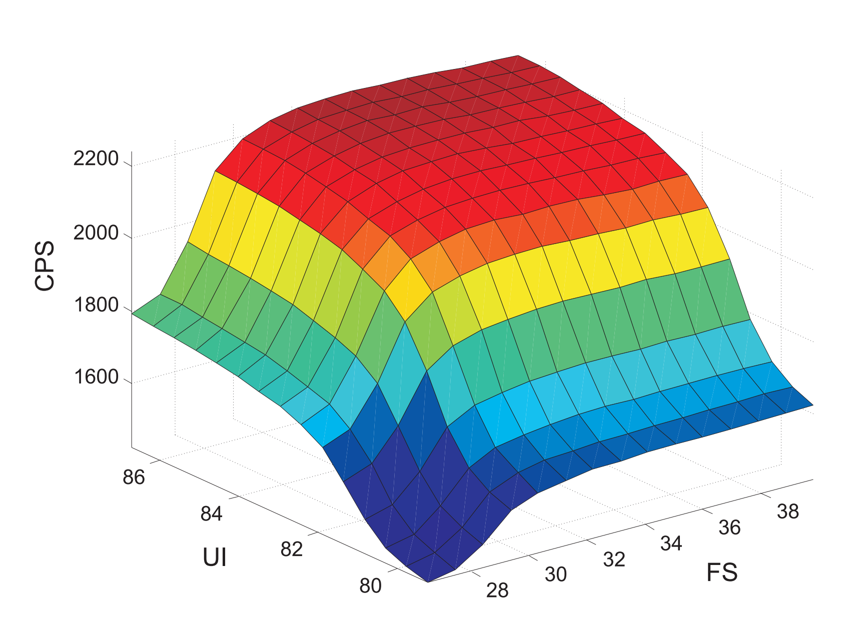

Figure 2. *Response surfaces for yarn strength in terms of fibre strength and micronaire with all other fibre properties held constant.*

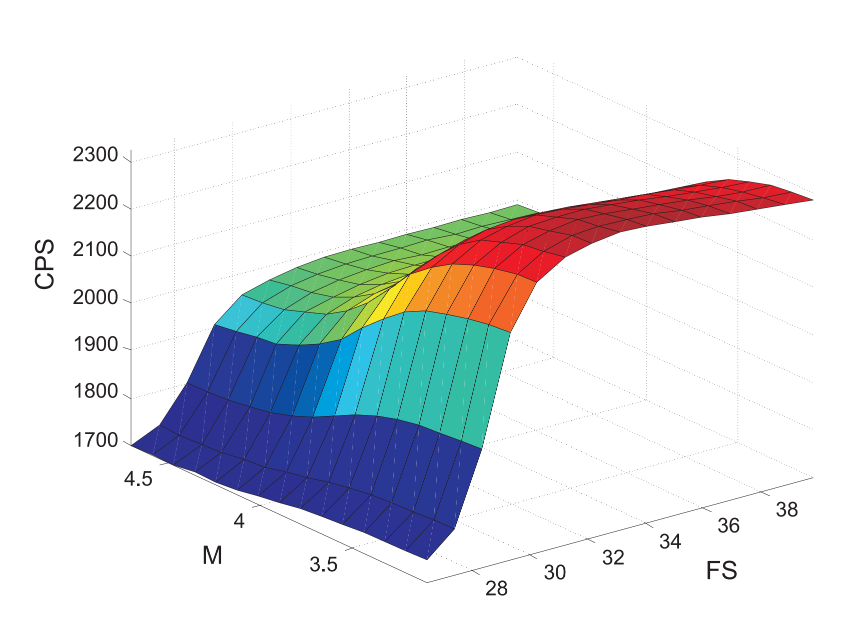

Figure 3. *Response surfaces for yarn strength in terms of fibre strength and micronaire with all other fibre properties held constant.*

Conclusions

This work gives new approaches for predicting yarn quality, specifically the application of the new intelligent techniques to model spun yarn strength prediction. The Multilayer Perceptron Neural Network(MLPNN), Support Vector Machines(SVMs), the Radial Basis Function Network(RBFN), the General Neural Network(GNN), the Group Method of Data Handling Polynomial Neural Network (GMDHPNN) and Gene expression

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Fibre properties such fibre strength (FS), micronaire (M), the upper half mean length (UHML), fibre elongation (FE), the uniformity index (UI), yellowness (Y), greyness (G) and short fibre content (SFC) are used to predict the CSP. The prediction performances have been compared to those provided by the classical Linear Regression (LR) model. Graphs illustrating the relative importance of fibre properties for CSP have been plotted. Fiber strength (FS) was ranked first in importance as a contributor to CSP by the five models, fibre elongation (FE) ranks second, and the remaining fibre properties do not contribute significantly to CSP.

In order to qualitatively study the effects of fibre properties on yarn strength, response surfaces plots were generated using the relationships obtained. The comparison with conventional methods indicated that these new approaches worked better in the prediction of yarn strength. The study has synthetised all the main new intelligent methods in order to evaluate and compare their performances. This will facilitate engineers, with respect to the type of the data, in choosing an appropriate and powerful model.

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