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Prediction and Quantitative Analysis of Yarn Properties from Fibre Properties Using Robust Regression and Extra Sum Squares

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Abstract
The main aim of this study is the prediction and quantity evaluation of important yarn properties (tensile, unevenness, hairiness and imperfections of yarn) from fibre properties by the robust regression and extra sum squares methods. We used cotton fibre and yarn properties measured by means of an HVI system and Uster tester. Properties of 87 Controlled samples of ring-spun cotton yarn with linear densities ranging from 19.2 to 37.4 tex with twist multiple: α_{tex} = 3927.8 (from from 19.2 to 37.4 tex) were used. In this way we selected the effective variables by considering all possible regressions and through the criteria of the mean square error (MSE) and adjusted R^2. Optimum equations with appropriate variables and relative importance of various variables were also investigated. After the fit, desirable MSE statistics and large adjusted R^2 values were observed.

Key words: *robust regression, extra sum squares, yarn imperfections, cotton spinning, yarn quality properties.*

Introduction

The physical characteristics of fibres determine its processing behaviour, production efficiency and finally yarn and fabric quality. In staple yarn, variations in yarn parameters such as count, twist, strength, elongation, imperfections etc, are unavoidable. However, these variations cause problems both during production processes and after production. Thus the relationships between these fibre characteristics must be clearly established for avoiding problems.

The main purpose of many studies in recent decades has been predicting the important yarn characteristic such as the tensile, unevenness and hairiness of yarn from fibre properties. Two main approaches were used in these studies: the statistical approach and theoretical approach. However, one of the most common statistical approaches is the multiple regression method.

So far, mathematical and empirical models for the prediction of single yarn tenacity from fibre properties and some yarn parameters have been established by many authors[1 - 4]. Hearle reviewed various mathematical and empirical studies about yarn strength published between 1926 and 1965 [5]. Hunter reported many researches about the prediction of tensile properties up to 2004 [6].

Another important parameter that influences the performance of spun yarns during winding, warping, and weaving is yarn breaking elongation. Yarn elongation is chiefly influenced by fibre properties, yarn twist and yarn count. Mathematical models related to cotton yarns have been proposed [3, 7, 8]. In this topic, statistical and ANN models have also been developed [1, 9].

Unevenness is a very important factor for yarn and fabric quality. Cross-sectional fibre variation is the basic reason for unevenness. In addition to machine parameters, the spinning method, yarn count and some fibre parameters have decisive influence on the unevenness of the yarn. Some models have been determined for yarn irregularity by using fibre parameters [1, 10].

Hairiness, another measurable yarn characteristic, is usually an undesirable property. Although the prediction of blended yarn hairiness has been reported in some papers [11, 12], so far few research articles have been published on the estimation of the hairiness of 100% cotton yarns using fibre parameters. Kilic and Okur investigated the relationships between yarn diameter/diameter variation and yarn strength. They used nine types of 100% combed cotton ring yarns (from the same blend which had three yarn counts with three levels of twist). Multiple linear regression models were established to estimate the yarn strength from the other yarn parameters such as yarn diameter, diameter and twist variation, and capacitive and optical unevenness [13].

In addition, Ureyen and Kadoglu used the linear multiple regression method for estimation of yarn quality characteristics. They found that yarn count, twist and roving properties had considerable effects on the yarn properties [14]. Recently, Fattahi et al. used statistical various methods for estimation of yarn quality characteristics. They obtained that yarn count and roving properties had considerable effects on the yarn properties in the optimum twist factor [15].

It should be mentioned that some researchers, [1, 2, 10, 14] have found some results which are not consistent with the real facts. They noted that their results show the autocorrelation between fibre properties as well as the nonlinearity between the independent variables and dependent variables. However, in this work, in addition to considering HVI fibre properties, we used yarn imperfections as the dependent variable in our research, as well as appropriate statistical methods so that we could remove the problems mentioned. On the other hand, so far, few research papers have been published about quantitative analysis of cotton yarn properties using fibre properties. Thus in this work we used extra sum squares so that we could obtain quantitative values of yarn properties from fibre properties.

Background

Robust regression

In statistical models, an outlier is an extreme observation. Outliers are data points that are not typical of the rest of the data. Depending on their location in "X-Space", outliers can moderate severe effects on the regression model. Therefore, outliers should be carefully investigated to see if a reason for their unusual behaviour can be found.

Various statistical methods have been proposed for detecting outliers. We apply the robust regression method in this research. The main purpose of robust regression is to detect outliers and provide consistent results in their presence. Many methods have been developed in response to this problem. However, in statistical applications of outlier detection and robust regression, the methods most commonly used today are Huber M estimation, high breakdown value estimation, and combinations of these two methods [16].

Least trimmed (sum of) squares

Least trimmed squares (LTS) estimation is a high breakdown value method introduced by Rousseeuw [16]. The breakdown value is a measure of the proportion of contamination that an estimation method can withstand and still maintain its robustness. The LTS estimator is found by finding the regression model parameters that satisfy

$$\underset{\beta}{Minimize} \sum_{i=1}^{h} e_{(i)}^2$$

Where $e_{(1)}^2 < e_{(2)}^2 < ... < e_{(n)}^2$ are the ordered squared residuals and h must be determined. The best robustness properties are obtained when $h = n/2$ approximately, in which case a breakdown point of 50% is attained. However, since a 50% breakdown point can sometimes produce poor results, it may be better to use a large value of h to increase efficiency. The LTS estimate has several advantages:

1 Its objective function is smoother, making the LTS estimate less jumpy (i.e. sensitive to local effects).
2 Its statistical efficiency is better because the LTS estimate is asymptotically normal.
3 The LTS estimate also takes less computing time and is more accurate

Collinearity diagnostic

When a regressor is nearly a linear combination of other regressors in the model, the estimates affected are unstable and have standard errors. This problem is called collinearity and the tolerance is an important collinearity diagnostic. In general, the tolerance for the j^{th} regression coefficient can be written as

$$TOL_j = 1 - R_j^2$$

Where R_j^2 is the coefficient of multiple determination obtained from regressing X_j on the other regressor variables. Clearly, if X_j is nearly orthogonal to the remaining regressors, R_j^2 is small and Tol_j is close to unity, while if X_j is nearly linearly dependent on some subset of the remaining regressors, R_j^2 is near unity and Tol_j is near zero. Practical experience indicates that tolerances smaller than 0.1 imply serious problems with collinearity [17].

Weight least squares regression

Linear regression models with nonconstant error variance can also be fitted by the method of weighted least squares. In this method of estimation the deviation between the observed and expected values of y_i is multiplied by a weight w_i chosen inversely proportional to the variance of y_i. For the case of the multiple regression model, the weight least squares normal equations are:

$$(X'WX)\hat{\beta} = X'WY$$

and the weighted least squares estimator is:

$$\hat{\beta} = (X'WX)^{-1} X'WY$$

Note that observations with large variance will have smaller weights than those with small variances [17].

Extra sum of squares

We may also directly determine the contribution to the regression sum of squares of a regressor, for example x_j, given that other regressors x_i $(i \neq j)$ are included in the model by using the extra-sum-of-squares method. In general, we can find

$$SS_R(\beta_j \mid \beta_0, \beta_1, ..., \beta_{j-1}, \beta_{j+1}, ..., \beta_k),$$
$$1 \leq j \leq k$$

which is the increase in the regression sum of squares due to adding x_j to a model that already contains x_1, …, x_{j-1}, x_{j+1}, …, x_k. Some find it helpful to think of this as measuring the contribution of x_j as if it were the last variable added to the model. When we think of adding regressors one at a time to a model and examining the contribution of the regressor added at each step, given all regressors added previously, we can partition the regression sum of squares into marginal single degree-of-freedom components. For example, consider the model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$$

with the corresponding analysis-of-variance identity

$$SS_T = SS_R(\beta_1, \beta_2, \beta_3 \mid \beta_0) + SS_{Res} \quad (7)$$

We may decompose the three-degree-of-freedom regression sum of squares as follows:

$$SS_R(\beta_1, \beta_2, \beta_3 \mid \beta_0) =$$
$$= SS_R(\beta_1 \mid \beta_0) + SS_R(\beta_2 \mid \beta_1, \beta_0) + \quad (8)$$
$$+ SS_R(\beta_3 \mid \beta_1, \beta_{\cdot}$$

Where, each sum of squares on the right-hand side has one degree of freedom. In a special case, if the columns in X_1 are orthogonal to those in X_2, we can determine the sum of squares due to β_2 , that is free of any dependence on the regressors in X_1. Therefore

$$SS_R(\beta) = SS_R(\beta_1) + SS_R(\beta_2),$$
$$SS_R(\beta_1 \mid \beta_2) = SS_R(\beta) - SS_R(\beta_2) = SS_R(\beta_1),$$

and

$$SS_R(\beta_2 \mid \beta_1) = SS_R(\beta) - SS_R(\beta_1) = SS_R(\beta_2)$$

Consequently $SS_R(\beta_1)$ and $SS_R(\beta_2)$ measure the contribution of regressors X_1 and X_2 to the model unconditionally, respectively. We can unambiguously determine the effect of each regressor when the regressors are orthogonal [17].

Data collection

In this study cotton crop study results of the International Textile Center (U.S.A) were used [19]. Summary statistics of seven cotton fibre properties measured by HVI (fibre bundle tenacity, elongation, upper half mean length (UHML), uniformity index, micronaire, reflectance degree and yellowness), yarn unevenness measured by an Uster Tester (imperfections, hairiness and capacitive irregularity), tensile properties, and yarn count are shown in ***Table 1***.

Statistical analyses

Each yarn quality property is analysed, respectively, as follows:

- Least squares or weighted least squares according to residual plot.
- Robust regression and LTS estimator for detecting and then deleting the outliers.
- Variable selection using all possible regression methods with the criteria of MSE, and R^2.
- Relative importance of appropriate variables using extra sum of squares.

Yarn tenacity

We used robust regression with least trimmed squares (LTS) estimation and n = 45 for detecting outlier data. ***Ta-***

Table 1. Summary statistics for fibre and yarn properties.

Fibre and yarn	Min.	Max.	Mean	S.D.	Index
Fibre tenacity, cN/tex	26.5	34.0	28.95	1.41	X_1
Fibre elongation, %	5.3	6.9	6.24	0.46	X_2
UHML, mm	24.5	30.5	26.5	1.3	X_3
Uniformity index, %	79.1	83.2	81.5	1.05	X_4
Micronaire, μg/in	3.1	5.0	4.2	0.45	X_5
Reflectance degree, °	70.5	80.4	76.93	2.28	X_6
Yellowness, -	8	11.4	9.35	0.72	X_7
Linear density (Yarn count - Ne) from 19.2 to 37.4 tex	15.8	30.8	23.9	5.28	X_8
Yarn tenacity, cN/tex	12.28	18.02	14.73	1.13	Y_1
Yarn elongation, %	4.23	7.5	5.9	0.77	Y_2
Irregularity, %CV	16.35	26.42	20.01	2.31	Y_3
Hairiness index (3 mm), -	4.31	6.66	5.3	0.59	Y_4
Imperfection (I.P.I), -	286	5298	1473	1071	Y_5^*

Table 2. Outlier point diagnostics for tenacity (Y_1).

Observations	11	14	26	32	34	52	53	54
Standardised robust residuals	-3.03	3.22	-3.35	-3.26	-3.52	3.72	4.15	5.79

Table 3. MSE selection method for tenacity (Y_1).

Number in model	R^2	R^2_{adj}	MSE	Variables in model
6	0.747	0.726	0.315	$X_1, X_2, X_3, X_4, X_5, X_8$
5	0.740	0.722	0.320	X_1, X_2, X_4, X_5, X_8
5	0.739	0.721	0.321	X_1, X_2, X_3, X_4, X_8
6	0.742	0.720	0.322	$X_1, X_2, X_4, X_5, X_7, X_8$
4	0.727	0.714	0.330	X_1, X_3, X_4, X_8

Table 4. Parameter estimates for tenacity (Y_1).

Variable	Parameter estimate	t-value	Pr > |t|	TOL
Intercept	-21.021	-3.73	0.0004	0
X_1	0.478	9.21	<0.0001	0.754
X_2	0.395	2.26	0.026	0.648
X_3	-0.084	-1.44	0.154	0.766
X_4	0.281	3.39	0.001	0.556
X_5	0.258	1.52	0.133	0.661
X_8	-0.098	-8.14	<0.0001	0.973

ble 2 displays outlier point diagnostics. Standardised robust residuals are computed based on the parameters estimated. Observations in ***Table 2*** are outliers because their standardised robust residuals exceed the cutoff value at the absolute value (cutoff value = 3). Therefore due to incorrect recording of data or failure of the measuring instrument, these observations were deleted from the data set.

Then the model-selection method is used to calculate R^2, R^2_{adj} and MSE for all possible combinations of independent variables. These results are shown in ***Table 3***.

An optimal model is selected with six variables (X_1, X_2, X_3, X_4, X_5, X_8) by desirable MSE, R^2 and R^2_{adj}. ***Table 4*** displays the parameter estimates and other values for the fitted model. This model is as follows:

$$Y_1 = -21.021 + 0.478X_1 + \\ + 0.395X_2 - 0.084X_3 + 0.281X_4 + \\ + 0.258X_5 - 0.098X_8$$

According to ***Table 4***, most of the effects (variables) are significant. Tolerances (TOL) have near unity. These diagnostics indicate that independent variables are approximately orthogonal. We also used an extra sum of squares to obtain the importance and contribution of each independent variable. The related equation is as follows:

$$SS(\beta) = SS(\beta_1) + SS(\beta_2|\beta_1) + \\ + SS(\beta_3|\beta_1, \beta_2) + SS(\beta_4|\beta_1, \beta_2, \beta_3) + \\ + ... + SS(\beta_6|\beta_1, \beta_2, ... \beta_5)$$

$$SS(\beta) = 34.6 + 18.4 + 11.8 + 1.0 + \\ + 0.9 + 0.8 = 67.5 \qquad SS_T = 90.04$$

Therefore the relative importance and contribution of parameters for yarn strength (Y_1) are approximately X_1 - 38%, X_8 - 20%, X_4 - 13%, X_5 - 2%, and X_2, X_3 - 1%, respectively.

Figure 1 shows the scatter plot of predicted values versus experimental values and regression line.

Yarn elongation

As in the previous case, we used the robust regression. After deleting the eight outlier points, the model is fitted for the 79 remaining observations. The results concerning model-selection are shown in ***Table 5***.

The optimal model is selected with seven variables (X_1, X_2, X_3, X_4, X_5, X_7, X_8) by desirable MSE, R^2, and R^2_{adj}. The parameter estimates and other values are shown in ***Table 6***. The final model is obtained as follows:

$$Y_2 = -16.71 - 0.26X_1 + \\ + 0.61X_2 + 0.18X_3 + 0.35X_4 + \\ - 0.80X_5 - 0.21X_7 - 0.098X_8$$

According to this ***Table 6***, all variables are significant and nearly independent. Therefore the extra sum of squares for this model is as follows:

$$SS(\beta) = 11.56 + 7.91 + 4.86 + 4.67 + \\ + 3.74 + 3.15 + 1.76 = 37.65 \qquad SS_T = 49$$

Thus the relative importance and contribution of parameters for yarn elongation (y_2) are nearly X_8 - 23%, X_2 - 16%, X_4 - 10%, X_5 - 9.5%, X_1 - 7.5%, X_3 - 6.5% and X_7 - 3.5%, respectively. ***Figure 2*** displays the diagram of predicted values against experimental values.

Yarn unevenness

By using robust regression, nine outlier points (19-20-21-65-66-69-70-77-78) were observed. After deleting these outliers, the model was fitted with the rest of observations. According to ***Table 7***, the final model is selected with seven variables (X_1, X_3, X_4, X_5, X_6, X_7, X_8).

The parameter estimates and other values are shown in ***Table 8***. Therefore the final model is as follows:

$$Y_3 = 72.21 - 0.566X_1 + \\ + 0.157X_3 - 0.197X_4 - 1.92X_5 + \\ - 0.160X_6 - 1.118X_7 + 0.287X_8$$

According to ***Table 8***, most of the variables are significant (P < 0.0001) and close to independence ($TOL \cong 1$). Therefore the extra sum of squares for the model is as follows:

$$SS(\beta) = 127.85 + 55.60 + 50.85 + \\ + 34.59 + 4.05 + 2.12 + 1.66 = 276.72 \\ SS_T = 382.37$$

Thus the relative importance and contribution of parameters for yarn unevenness are nearly X_8 - 33.5%, X_5 - 14.5%, X_1 - 13.5%, X_7 - 9%, X_6 - 1%, X_4 - 0.5% and X_3 - 0.5%, respectively. ***Figure 3*** shows the scatter plot of predicted values versus experimental values.

Yarn hairiness

By using robust regression, five outlier points (19 - 63 - 65 - 69 - 77) were observed. After deleting the outliers, this model is fitted by the 82 remaining observations. According to ***Table 9***, the final model is selected with six appropriate variables (X_1, X_2, X_4, X_5, X_7, X_8).

The parameter estimates and other values are shown in ***Table 10***. The final model is derived as follows:

$$Y_4 = 19.271 - 0.066X_1 + \\ - 0.154X_2 - 0.083X_4 - 0.255X_5 + \\ - 0.124X_7 - 0.087X_8$$

According to ***Table 10***, all variables are significant and close to independence. Therefore the extra sum of squares for this model is as follows:

$$SS(\beta) = 19.51 + 5.51 + 1.10 + 0.50 + \\ + 0.50 + 0.29 = 24.2 \qquad SS_T = 27.53$$

Thus, the relative importance and contribution of various Parameters for yarn hairiness are about X_8 - 70%, X_4 - 10%, X_5 - 4%, X_7 - 2%, X_1 - 2% and X_2 - 1%, respectively. ***Figure 4*** displays the diagram of predicted values against experimental values.

Yarn imperfections

The assumption of constant variance is a basic requirement of regression analysis. A common reason for the violation of this assumption is for the response variable Y to follow a probability distribution in which the variance is functionally related to the mean. Thus since the distribution of Y^*_5 (Yarn imperfection) is Poisson, we can regress $Y_5 = \sqrt{Y^*_5}$ against X as the variance of the square root of a Poisson's random variable is independent of the mean. The plot of R-Student residuals versus the fitted values Y_5 is shown in ***Figure 5***. This plot again indicates a violation of the constant variance assumption. Consequently the least squares fit is inappropriate. To correct this inequality-of-variance problem, we should know the weights w_i. The inverse of these fit-

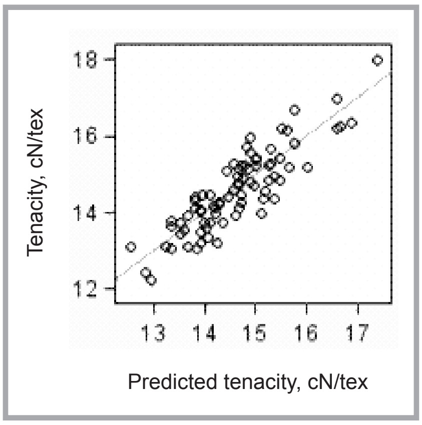

Figure 1. *Plot of tenacity (Y_1) and predicted tenacity (Y_1).*

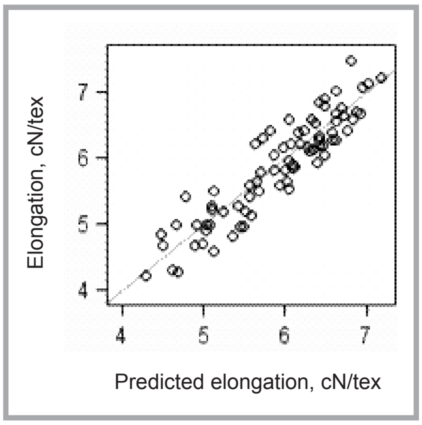

Figure 2. *Plot of elongation (Y_2) and predicted elongation (Y_2).*

Table 5. *MSE selection method for elongation (Y_2).*

Number in model	R^2	R^2_{adj}	MSE	Variables in model
7	0.768	0.745	0.160	$X_1,X_2,X_3,X_4,X_5,X_7,X_8$
6	0.732	0.710	0.182	X_1,X_2,X_3,X_4,X_5,X_8
7	0.733	0.706	0.184	$X_1,X_2,X_3,X_4,X_5,X_6,X_8$
7	0.718	0.690	0.194	$X_1,X_2,X_4,X_5,X_6,X_7,X_8$
6	0.710	0.686	0.197	X_1,X_2,X_4,X_5,X_7,X_8

Table 6. *Parameter estimates for elongation (Y_2).*

Variable	Parameter estimate	t-value	Pr > |t|	TOL
Intercept	-16.71	-4.37	<0.0001	0
X_1	-0.26	-6.45	<0.0001	0.62
X_2	0.61	4.85	<0.0001	0.74
X_3	0.18	4.21	<0.0001	0.78
X_4	0.35	6.52	<0.0001	0.68
X_5	-0.80	-6.85	<0.0001	0.75
X_7	-0.21	-3.31	0.0015	0.95
X_8	-0.06	-6.55	<0.0001	0.96

Table 7. *MSE selection method for irregularity (Y_3).*

Number in model	R^2	R^2_{adj}	MSE	Variables in model
7	0.724	0.696	1.509	X_1, X_3, X_4, X_5, X_6, X_7, X_8
6	0.718	0.694	1.518	X_1, X_4, X_5, X_6, X_7, X_8
6	0.718	0.694	1.518	X_1, X_3, X_5, X_6, X_7, X_8
5	0.714	0.694	1.520	X_1,X_5, X_6, X_7,X_8
4	0.703	0.690	1.554	X_1,X_5, X_7, X_8

Table 8. *Parameter estimates for irregularity (Y_3).*

Variable	Parameter estimate	t-value	Pr > |t|	TOL
Intercept	72.21	4.95	<0.0001	0
X_1	-0.566	-4.44	<0.0001	0.60
X_3	0.157	1.19	0.230	0.77
X_4	-0.197	-1.19	0.231	0.69
X_5	-1.92	-5.41	<0.0001	0.77
X_6	-0.160	-1.93	0.0500	0.57
X_7	-1.118	-5.00	<0.0001	0.77
X_8	0.287	10.66	<0.0001	0.95

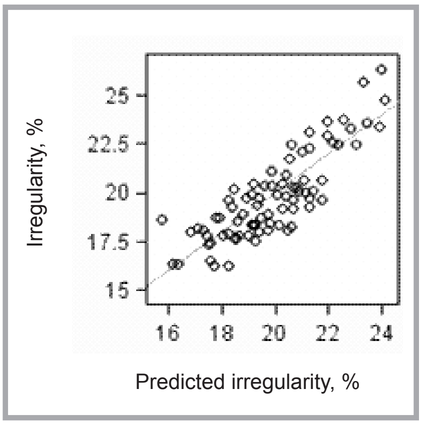

***Figure 3.** Plot of irregularity (Y_3) and predicted irregularity (Y_3).*

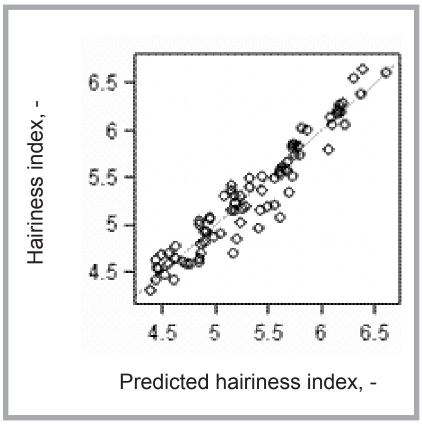

***Figure 4.** Plot of hairiness index (Y_4) and predicted hairiness index (Y_4).*

***Table 9.** C_P selection method for Y_4.*

Number in model	R^2	R^2_{adj}	MSE	Variables in model
6	0.879	0.869	0.0442	X_1, X_2, X_4, X_5, X_7, X_8
7	0.880	0.869	0.0443	X_1, X_2, X_4, X_5, X_6, X_7, X_8
7	0.880	0.868	0.0446	X_1, X_2, X_3, X_4, X_5, X_7, X_8
8	0.881	0.868	0.0448	X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8
5	0.869	0.860	0.0474	X_1, X_4, X_5, X_7, X_8

***Table 10.** Parameter estimates for Y_4.*

Variable	Parameter estimate	t-value	P_r>|t|	TOL
Intercept	19.271	9.94	<0.0001	0
X_1	-0.066	-3.61	<0.0005	0.811
X_2	-0.154	-2.55	0.0127	0.755
X_4	-0.083	-3.05	0.0032	0.686
X_5	-0.255	-4.28	<0.0001	0.763
X_7	-0.124	-3.78	0.0003	0.973
X_8	-0.087	-19.70	<0.0001	0.970

ted values will be reasonable estimates of the weights w_i. Applying weighted least squares to the data gives the appropriate fitted model. We should now examine the residuals to determine if using weighted least squares has improved the fit. To do this, the weighted residuals are plotted against weighted fitted values.

This plot is shown in ***Figure 6***, and is much improved when compared to the previous plot (***Figure 5***) for the least squares fit. We conclude that weighted least squares have corrected the inequality-of-variance problem.

As in previous cases, we used the robust regression. After deleting the outlier points (ten observations), the model is fitted for the 77 remaining observations. The results of model-selection are shown in ***Table 11***.

An optimal weighed model is selected with seven variables (X_1, X_3, X_4, X_5, X_6, X_7, X_8). The parameter estimates and other values are shown in ***Table 12***. The final weighted least squares model is as follows:

$$Y_5 = 401.62 - 1.194X_1 + $$
$$+ 1.733X_3 - 3.294X_4 - 7.096X_5 + $$
$$- 1.036X_6 - 3.273X_7 + 1.233X_8$$

According to ***Table 12***, all variables are significant and nearly independent. Therefore the extra sum of squares for this model is as follows:

$$SS(\beta) = 2.65 + 1.33 + 0.45 + 0.39 + $$
$$+ 0.20 + 0.14 + 0.13 = 5.29$$
$$SS_T = 7.416$$

Thus the relative importance and contribution of various parameters for yarn imperfection are about, X_8 - 35%, X_4 - 18%, X_7 - 6%, X_5 - 5.5%, X_6 - 3%, X_1 - 2% and X_3 - 2%, respectively. ***Figure 7*** displays the diagram of predicted values against experimental values.

Results and discussion

The equations obtained show that yarn properties such as strength, elongation, unevenness, hairiness and imperfection are influenced by fibre properties and yarn count in the constant twist factor. The accuracy of the two models (least-squares regression and robust regression) is also evaluated by the R squares (R^2) criterion. These results are shown in ***Table 13***. The predictive accuracy of all the models improves in the case of robust regression. Therefore it is clear that the performance of the robust regression is

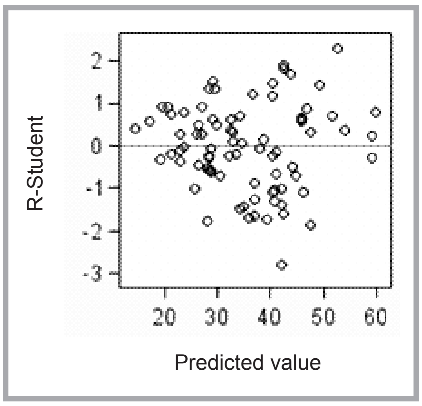

***Figure 5.** Plot of residuals versus $\hat{Y}_5$.*

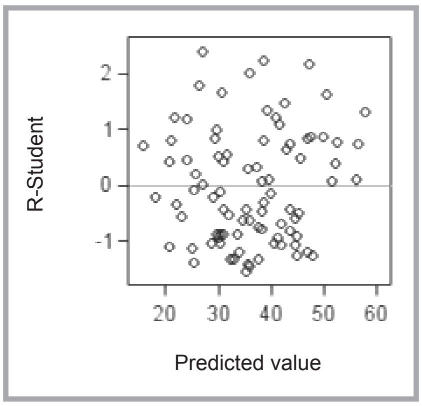

***Figure 6.** Plot of residuals versus weighted $\hat{Y}_5$.*

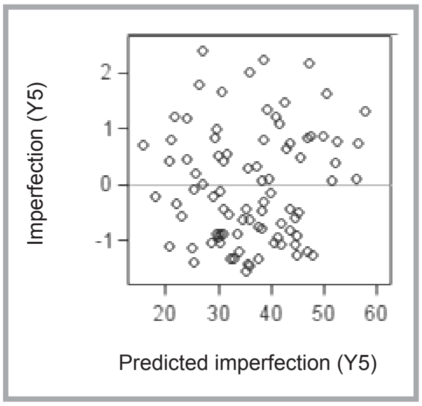

***Figure 7.** Plot of imperfection (Y_5) and predicted imperfection ($\hat{Y}_5$).*

better than that of the least squares. The robust regression model exhibits an increase in predictive power of between 2.2% and 13.1% for various properties. It is also observed from ***Table 13*** that there is the highest value of improvement for Y_3 and the lowest value for Y_4.

The relative importance, contribution, and direction of the effect of various characteristics on different properties of yarn are also shown in ***Table 14***.

Yarn count and uniformity are the most decisive factors for yarn properties. Among the other properties, the strength and micronaire of fibres also have great importance.

As shown by ***Table 14***, as might be expected, yarn strength is highly influenced by fibre strength, yarn count and uniformity. Most of the studies [14, 15, 18, 19] showed that fibre strength has the greatest effect on yarn strength. In order of importance, the contribution and direction of significant properties are fibre strength (+38%), yarn count (-20%), and uniformity (+13%). Yarn elongation is mainly influenced by the yarn count, fibre elongation, uniformity and micronaire, respectively. Some other researchers [7, 9] also found yarn count and fibre elongation to be the first and second most important contributors of yarn elongation. In order of importance, the contribution and direction of significant properties are yarn count (-23%), fibre elongation (+16%), uniformity (+10%), micronair (-9.5%), fibre strength (-7.5%), UHML (+6.5%), and yellowness (-3.5%).

As we expected, among the various properties, yarn count (+33.5%) has the greatest effect on yarn unevenness. Similar results have been reported about this property by others [14, 15, 18]. Other important factors that influence yarn evenness in order of importance are micronaire (-14.5%), fibre strength (-13.5%) and yellowness (-9%). The hairiness of yarn is mainly influenced by the yarn count (-70%). In addition, the uniformity (-10%) and micronaire (-4%) can affect the hairiness of yarn. Some papers have also shown that there are significant effects of the yarn count and uniformity on yarn hairiness [15, 18].

Among the various properties, yarn count (+35%) has the greatest effect on yarn imperfections. Other important properties that affect yarn imperfections are uniformity (-18%), yellowness(-6%), micronaire (-5.5%), and reflectance (-3%). Fattahi et al. [15] also obtained that micronaire and yarn count have significant effects on yarn imperfections.

Our emphasis is to evaluate the effect of the various properties subjectively (the value of effect), while most of the previous papers found the order of importance of properties [6, 9, 14, 15, 18, 19].

Table 11. *MSE selection method for Y_5.*

Number in model	R^2	R^2_{adj}	MSE	Variables in model
7	0.714	0.685	0.0300	$X_1, X_3, X_4, X_5, X_6, X_7, X_8$
7	0.713	0.684	0.0308	$X_2, X_3, X_4, X_5, X_6, X_7, X_8$
7	0.700	0.670	0.0322	$X_1, X_2, X_4, X_5, X_6, X_7, X_8$
6	0.695	0.669	0.0323	$X_3, X_4, X_5, X_6, X_7, X_8$
6	0.695	0.669	0.0323	$X_2, X_4, X_5, X_6, X_7, X_8$

Table 12. *Parameter estimates for Y_5.*

Variable	Parameter estimate	t-value	$P_r > \|t\|$	TOL
Intercept	401.62	6.66	<0.0001	0
X_1	-1.194	-2.15	0.0350	0.599
X_3	1.733	2.65	0.0100	0.676
X_4	-3.294	-4.61	<0.0001	0.650
X_5	-7.096	-4.18	<0.0001	0.745
X_6	-1.036	-3.07	0.0030	0.665
X_7	-3.273	-3.54	0.0007	0.799
X_8	1.233	9.69	<0.0001	0.935

Table 13. *Validation results of least squares and robust regression by R^2.*

Regression methods	Yarn properties				
	Tenacity (Y1)	Elongation (Y2)	Irregularity (Y3)	Hairiness (Y4)	Imperation (Y5)
(Least squares reg.) R^2, %	63.7	64.0	59.3	85.7	68.1
(Robust reg.) R^2, %	74.7	76.8	72.4	87.9	71.4
(Improvement), %	11.0	12.8	13.1	2.2	3.3

Table 14. *Importance of various characteristics on yarn properties.*

Fibre properties	Yarn properties				
	Tenacity (Y1)	Elongation (Y2)	Irregularity (Y3)	Hairiness (Y4)	Imperation (Y5)
Strength (X1)	+38%	-7.5%	-13.5%	-2%	-2%
Elongation (X2)	+1%	+16%	-	-1%	-
UHML (X3)	-1%	+6.5%	+0.5%	-	+2%
Uniformity (X4)	+13%	+10%	-0.5%	-10%	-18%
Micronaire (X5)	+2%	-9.5%	-14.5%	-4%	-5.5%
Reflectance (X6)	-	-	-1%	-	-3%
Yellowness (X7)	-	-3.5%	-9%	-2%	-6%
Yarn count (X8)	-20%	-23%	+33.5%	-70%	+35%

Conclusions

Yarn properties such as tensile, elongation, unevenness, hairiness and imperfection are influenced by fibre properties and yarn count in the constant twist factor. In this study, we investigated some statistical approaches for the modelling and prediction of important properties of ring spun cotton yarn. The results obtained showed that the predictive accuracy of all the models improves in the case of robust regression as compared to that of the least squares. We also selected yarn imperfection as a dependent variable. The models derived showed better prediction performance than the previous studies.

The relative importance, contribution, and direction of the effect of various characteristics on different properties of yarn are obtained. From a quality-control-in-cotton-spinning point of view, the models obtained are desirable, especially in practical cases.

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