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Identification of Cotton Properties to Improve Yarn Count Quality by Using Regression Analysis

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Abstract. Identification of raw material characteristics towards yarn count variation was studied by using statistical techniques. Regression analysis is used to meet the objective. Stepwise regression is used for model selection, and coefficient of determination and mean squared error (MSE) criteria are used to identify the contributing factors of cotton properties for yarn count. Statistical assumptions of normality, autocorrelation and multicollinearity are evaluated by using probability plot, Durbin Watson test, variance inflation factor (VIF), and then model fitting is carried out. It is found that, invisible (INV), nepness (Nep), grayness (RD), cotton trash (TR) and uniformity index (UI) are the main contributing cotton properties for yarn count variation. The results are also verified by Pareto chart.

Keywords: autocorrelation, cotton properties, regression analysis, stepwise regression, yarn count, yarn quality

Introduction

Yarn is used for manufacturing fabrics, which is used in apparel, home textile furnishing and industrial products. Apparel includes trousers, shorts, shirts and jeans. Yarn is an input for knitters, it produces fabric and demand high quality of yarn to produce fine quality of fabric.

The textile industry contains different subunits, i.e., spinning, weaving, knitting, dying, and finishing. There are three methods for yarn manufacturing, cotton yarn is one of these and the most important textile spinning production method. (Jackowski *et al.,* 2002). A high quality of yarn is always demanding for the textile products by knitters and weavers. Hard global competition, however, usually prevents turning yarn quality improvements into higher sales prices. Yarn is produced in different counts, which range from 10s, 20s, and 30s to 80s and above (where‘s’ stands for single). These different counts of hank (a unit of length) yarn are used to produce different types and quality of cotton cloth. The lower counts of yarn, below 40s, are used to produce lower quality cotton cloth, while the higher counts are used to produce higher quality segment of the cloth. There is a relationship between the quality of raw materials and the end products. The lower the quality of cotton fibers results in lower quality of yarn produced. Cotton is the main natural fibre, which presents a large variation in its properties (Price *et al.,* 2009; Majumdar and Majumdar, 2004). Physical properties of cotton affect the production efficiency and yarn quality. These physical properties include colour, elongation, invisible, maturity ratio, micronair, moisture, nippiness, fibre strength, trash, upper half mean length and uniformity index. High quality cotton blends are superior with respect to properties such as length, fineness, elongation, brightness, sufficiently mature and without any trash particles, and displaying a high capacity of spinning consistency. Yarn English count for natural fibre (yarn count) is one of the important yarn quality measuring parameter. Yarn count is very important for yarn count lea strength product (CLSP) because yarn product with high CLSP produced good quality of cloth. Therefore, consistency in yarn count parameter is necessary for good quality of yarn. Objective of this study was to determine the most important cotton quality factors, which affect the quality of yarn regarding yarn count, by using regression analysis.

Koo and Suh (2005), have used a regression analysis to study the effect of fibre properties and process parameters in the textile industry on yarn quality characteristics and found that fibre length is the significant factor for all manufacturing processes and these results are misleading due to multicolinearity among independent variables. Ureyen and Kadoglu (2007), used a linear regression model to predict the cotton yarn properties

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on the basis of fibre properties. They have studied different yarn characteristics separate by on fibre physical properties and found that these properties have great affect on all yarn characteristics. Üreyen and Gürkan (2008a) used artificial neural network (ANN) and regression models to predict the yarn tensile properties and found that fibre strength and elongation were the most significant factors for yarn tensile properties. Also they compared the ANN and regression method on the basis of Adjusted-R^2 and MSE and found that ANN is more powerful than regression method. The same study was then applied by Üreyen and Gürkan (2008b) to predict the yarn hairiness and unevenness and the same conclusions were drawn. Majumdar *et al.* (2008) tested the accuracy of two computing approaches i.e., ANN and neural-fuzzy system to forecast the unevenness of ring spun yarns and compared these two methods with regression on the basis of cotton properties and yarn count. They have found that these two computing approaches are better and consistent than linear regression method. Same study was conducted by Nurwaha and Wang (2009) on the strength of rotor yarn. Fattahi *et al.* (2010) have used robust regression to study the fibre factors for yarn quality characteristics. Bo (2010) applied a multiple regression and neural network model to predict the cotton yarn hairiness on the basis of spinning process parameters i.e., roller speed (F), spindle speed (S), nip gauge (N), back draft zone time (B), and roving twist (R). They have found that both methods give reliable results. But they have not identified the most important spinning process parameters for predicting the yarn hairiness. Lewandowski *et al.* (2010) conducted a comparative analysis of ring spinning process by using regression analysis. Gauri (2011) applied weighted principal component and principal component analysis to improve yarn quality electronically and found that by using these techniques yarn quality is substantially improved. Nurwaha and Wang (2012) predicted textile yarn quality, characteristics on the basis of cotton physical properties and found that for yarn quality count strength product (CSP) the most important factors are fibre strength elongation. Souid *et al.* (2012) applied neural network method to predict yarn quality based on fiber properties elongation, strength and uniformity. Fattahi *et al.* (2012) applied fuzzy least square method to predict yarn properties using yarn count as dependent and other yarn properties i.e., strength, elongation, unevenness, and hairiness. They have found that all yarn properties are influenced by cotton properties. Ahmed *et al.*(2012) studied the yarn quality parameters in ring spinning on the basis of bamboo and cotton fibre characteristics. They used only descriptive measures and found that the moisture regain capacity of bamboo was higher than cotton and tensil strength was decreased for blending bamboo yarn.

Materials and Methods

Data concerned to present study was obtained from the Colony Textile Mills (CTM) Multan, Pakistan. Data is related to yarn quality characteristics i.e., yarn count (NEC) and cotton physical properties of yarn product 40/1s. These physical properties are given in Table 1.

Table 1. Variables description of fibre and yarn quality characteristics

Variable	Description	Unit	Symbol
Y	Yellowness	b+	A
ELG	Elongation	%	B
INV	Invisible	g	C
MR	Maturity ratio	%	D
MIC	Micronaire	µg/mm	E
Moist	Cotton moisture	%	F
Nep	Nepness	G	G
RD	Grayness	rd	H
Str	Fibre strength	g/tex	I
TR	Trash	g	J
UHML	Upper half mean length	mm	K
UI	Uniformity index	%	L
Yc	Yarn count	tex	Y

where:

Y is the dependent (out put) and A to L are independent variables (input parameters). In Table 1, the term symbol is further used in regression model i.e., used for model selection. Further details about yarn and cotton quality parameter are followed by Lawrence (2003).

Regression analysis. Modeling yarn characteristics is an important field of the textile spinning research. In modeling regression analysis tools are very useful (Majumdar *et al.,* 2008) for yarn quality improvement. These tools quantify the relationship between yarn quality characteristics and cotton properties.

Regression model. To study the effect of cotton properties on yarn count quality, the following regression model was used:

$$Y = X\beta + \in$$

where:

Y = the vector of response variable of dimension $(n \times 1)$, X = the matrix of independent variables of dimension

$(n \times p)$, β = the matrix of unknown parameters of dimension $(p \times 1)$, and $\in$ = random error of dimension $(n \times 1)$, and following a normal distribution with zero mean and constant error variances.

In present study, the yarn characteristics, i.e., yarn count, with its cotton as an input parameters were concerned. The resulted model, using symbols for cotton properties, available in Table 1, is given by:

$$Y = \beta_o = \beta_1 A + \beta_2 B + \beta_3 C + \beta_4 D + \beta_5 E + \beta_6 F + \beta_7 G + \beta_8 H + \beta_9 I + \beta_{10} J + \beta_{11} K + \beta_{12} L + \in$$

where:

Y = the dependent, A to L = the independent variables, p = the number of unknown parameters in regression model, β_o = the intercept, and β_1 s = the slope coefficients of independent variables.

The assumptions of the linear regression model includes normality, zero mean, constant variance of the error term, no correlation among regressors, independence of the error term, etc., (Drapper and Smith, 1998). To validate these assumptions probability plot (normality), Durbin Watson test (autocorrelation) and VIF for multi-collinearity were calculated and inferences were drawn accordingly. Details are given by Gujarati (2003), and Drapper and Smith (1998).

Stepwise regression. Stepwise regression is used to identify important input (trash, fibre strength, etc.) are cotton properties, which contribute maximum determination of yarn count variation. To proceed for model selection by stepwise regression, initially, average yarn count on fibre strength was regressed and the results were noted i.e., Adjusted-R^2, MSE and Mallows Cp etc. In the next step, average yarn count on cotton properties, fibre strength and micro-naire was regressed (i.e., an other input to the average yarn count was added) and note the results. It was continued until all cotton properties were included in the model. This process is known as forward selection. Similarly, starting from the full model and then removing the independent variable one by one is known as backward elimination method. The model, which contains maximum Adjusted-R^2 and minimum MSE (Bingham and Fry, 2010; Paulson, 2007; Kutner *et al.,* 2004).

Results and Discussion

The results of stepwise regression for model selection is given as in Table 2.

Table 2. Models with largest Adjusted-R^2 for yarn count

MSE	R^2 (%)	Adjusted-R^2 (%)	Mallows Cp	Included variables
0.0092	76.7973	69.9729	0.7389	CGHJL
0.0106	71.7519	65.4745	1.2916	CGHJ
0.0109	72.5185	64.4357	2.9037	CGHJK
0.0306	4.5455	0.0000	29.7826	L
0.0306	4.5455	0.0000	31.5620	K
0.0306	0.0000	0.0000	29.5930	Constant

In this analysis, there are 1586 models fitted for yarn quality characteristic, yarn count on the basis of 12 cotton properties are shown in Table 1. The model, which gives the largest Adjusted-R^2 and minimum MSE values is the best fitted. By using stepwise regression for model selection, the best model for yarn count includes variables C, G, H, J, and L (Adjusted-R^2 = 69.9729 and MSE = 0.0092) as shown in second row of Table 2 and corresponding input parameters INV, Nep, RD, TR and UI.

After model selection for yarn count with input parameters INV, Nep, RD, TR and UI, yarn count on these selected input parameters was regressed to identify the most important input parameters. Tables 3-4 show the regression analysis of the selected model.

Table 3. Analysis of variance (ANOVA) for yarn count model

Source	Sum of squares	DF	Mean square	F-ratio	P-value
Model	0.5170	5.0000	0.1034	11.2500	0.0001
Residual	0.1562	17.0000	0.0092	-	-
Total	0.6732	22.0000	-	-	-

R^2= 76.79%; Adjusted-R^2 = 69.97%; Durbin Watson = 1.2045 (P-value= 0.3343).

Multiple linear regression model was fitted to describe the relationship between yarn count and five input parameters. The equation of the fitted model is;

$$Y = 24.7902 + 0.1815\ INV + 0.0020\ Nep + 0.1548\ RD + 0.1932\ TR - 0.0248\ UI$$

ANOVA results are given in Table 3, indicate that the dependence of yarn count on selected input parameters is significant. Now, to identify which parameter actually contributes maximum variation to explain in yarn count quality.

The results which are given in Table 4, indicate that INV, Nep, RD, and TR are significant ($P < 0.05$) in all

Table 4. Regression analysis for yarn count model

Parameter	β	SE (β)	t-stat	P-value	VIF
Constant	24.7902	2.6520	9.3479	0.0000	-
INV	0.1815	0.0468	3.8803	0.0012	2.0104
Nep	0.0020	0.0006	3.1882	0.0054	2.0240
RD	0.1548	0.0282	5.4794	0.0000	2.2104
TR	0.1932	0.0299	6.4641	0.0000	2.2083
UI	0.0248	0.0129	1.9227	0.0714	1.5442

these cases. But UI has no significant effect on yarn count.

The Adjusted-R^2 (= 69.9729 %) indicates the quality of input parameters and shows about 70% good forecast in yarn count due to these input parameters. To validate the assumption of independence of residuals, Durbin Watson statistic, assures the independence (P-value = 0.3343). Also small VIF's (i.e. VIF<5) shows that all input parameters are independent to each other. To check the normality of residuals, a probability plot of residuals was drawn, which shows that residuals follow normal distribution (Fig.1).

From the Pareto plot (Fig. 2), it was found that the main factor which affects yarn count is the TR (fiber trash). So for purchasing cotton, the higher concentration should be given to cotton trash, i.e., for the high quality of yarn count, the spinner should prefer to purchase the cotton with minimum trash.

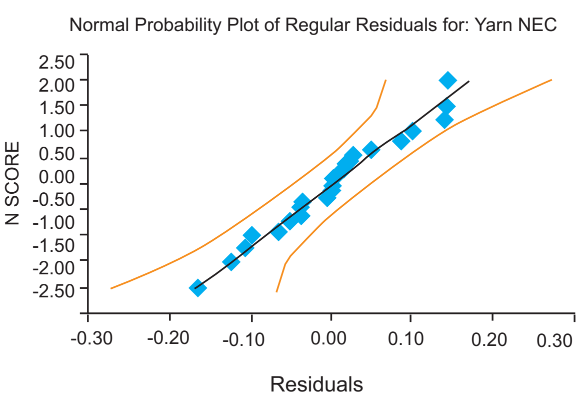

Fig. 1. Probability plot for yarn count.

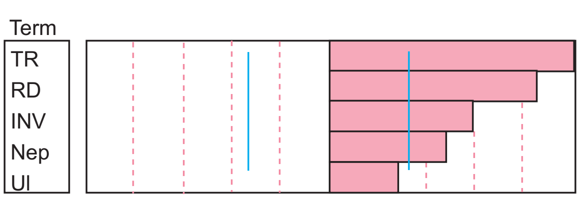

Fig. 2. Pareto plot for yarn count input parameters.

Conclusion

Material factors which affect on yarn quality characteristic, i.e., yarn count were studied by using regression analysis. Yarn count on 12 independent variables (input parameters) was regressed to select the regression model by stepwise regression. The model having largest Adjusted-R^2 and minimum MSE was supposed to be the best. There are 1586 models fitted for yarn quality characteristic and the best model to explain yarn count variation contains INV, Nep, RD, TR and UI as explanatory variables. Statistical assumptions of the model are tested through standard techniques and then applied regression analysis, having validation of assumptions.

The main factor for yarn count quality on the basis of cotton properties is TR (cotton trash) as signified by t-test and Pareto chart. This indicates that lower trash in cotton produced good quality of yarn regarding yarn count. Therefore, spinner purchase and use the cotton with lower trash for manufacturing good quality of yarn to satisfy their customer demands.

The current study addresses the input parameters of cotton that cause the improvement in the yarn count quality, hence, the textile industry may enable major improvements in the final product that follow customer obligations.

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