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PREDICTING YARN QUALITY PROPERTIES VIA OVERCOMING THE MULTICOLLINEARITY OF COTTON FIBER PROPERTIES

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ABSTRACT

When predicting yarn quality properties, the collinearity or common variance of cotton fiber characteristics as predictors, result in unreal regression models. The approach of this study is using Principle Component Analysis (PCA) to avoid this issue by extracting independent factors in their effect from each other summarizes cotton fiber properties. Four lint cotton grades of five of Egyptian cotton varieties belong to Extra-long (Giza 88 and Giza 92) and Long staple (Giza 86, Giza 90 and Giza 95) classes used to perform fiber tests. Cotton Classification System (CCS-$V_{5.3}$) used to measure cotton fiber characteristics as predictors. Yarn strength in terms of Lea product, single yarn strength and yarn unevenness of Ne 40 and 60 counts of ring spun yarns were the dependent variables. The results showed significant intercorrelations matrix among CCS measurements. The initial solution extracted only three factors that have eigenvalues more than 1.00. These 3 factors accounted for 89.716 % of the common variance shared by all measurements. The communalities or % variance in each cotton fiber measurement of CCS accounted for by the three factors was not the same. The 3 factors as predictors could predict yarn quality characteristics significantly, and with high contributions (% R^2). But % R^2 valued less than that of ordinary regression models. This audit is a satisfactory improvement to predict yarn quality characteristics from cotton fiber properties accurately.

Keywords: *Collinearity, cotton fiber properties, Eigenvalue, modeling yarn quality.*

1. INTRODUCTION

Cotton is one of the most strategically agricultural products that have various utilization areas in agricultural, industrial and trade sectors. Although, the synthetic fiber production increased, cotton remains important among other raw materials used in the world textile industry (Ute and Kadoglu, 2014). Globalization is growing rapidly, consequently in terms of cotton fiber testing, speaking the same language is becoming more important to prevent ambiguity and misunderstanding. For this purpose, new test methods should be free of variation and human error and should be based on scientific principles, clearly and accurately defined, reproducible and generally accepted (Hunter, 2002).

Yarn strength, which is the most important property of spun yarns, is largely influenced by the tenacity, length, uniformity, short fiber index and micronaire value (Hussein *et al.,* 2010**)**. Spinners require UHM length information to set the drafting rollers at the proper distance to avoid yarn unevenness, floating fibers and yarn breakage (Perkins *et al.,* 1984 and Behery, 1993). Yarn quality parameters such as strength, elongation, hairiness and unevenness are correlated strongly with fiber length (Perkins *et al.,* 1984 and El-Mogahzy and Chewning, 2001). Zeng *et al.* (2004) and Majumdar *et al.* (2005) reported that fiber elongation and length uniformity index were the dominant parameters on breaking elongation.

In recent decades there has been a significant increase in application of data mining techniques of machine learning in textile engineering, especially in forecasting the quality of yarn spinning. This is because the relation slips between fiber and yarn properties are still more complex and nonlinear. Therefore, modeling of yarn quality parameters is widely studied (Majumdar *et al.,* 2005; Nurwaha and Wang 2012 and Abakar and Yu, 2013). In illustration the calculation of predicted index values for a new lot of cotton, only the four benchmark HVI properties, *i., e.,* Micronaire value, fiber strength, length and uniformity (Foulk *et al.*, 2007). Tallant *et al.* (1963) explained that there should be a minimum fiber length for significantly contributing to yarn strength. It was found that fibers shorter than about 3/8 inch do not contribute to yarn tenacity. Yarn quality is an essential concept defined by customer which requests the satisfaction of several properties simultaneously (Souid and Cheikhrouhou, 2011). Yarn quality is generally qualified through one parameter which is namely its strength. Yunus and Rhman, (1990) established a yarn quality index including three parameters of fibers which are; Yarn Quality Index = Elongation × Strength / Uniformity.

In a study to investigate the optimum compact spinning / fiber-property interactions, Krifa *et al.* (2002) and Krifa and Ethridge (2006) stated that, with some combinations of fiber characteristics did not lead to significant hairiness reduction. However, yarn strength and elongation did not appear to be directly affected by these interactions.

A large number of predictive models have been exercised to prognosticate yarn properties. There are three distinguished modeling methods called statistical regression, mathematical and intelligent models. Statistical regression models are very simple to understand and the beta coefficient analysis gives an indication of relative importance of various inputs on yarn quality properties. However, foretelling the type of relationship (linear or non-linear) is essential for developing a regression model (Majumdar and Ghosh, 2008). Mathematical models based on theories of basic sciences give good understanding about the mechanics of the process. However, due to the assumptions or simplifications used while building these models, the prediction accuracy, is not very accurate of encouraging (Frydrych, 1992; Majumdar and Ghosh, 2008). The advent of artificial intelligence models of yarn properties such as artificial neural network (ANN) and neural-fuzzy methods have been used successfully by several researchers such as (Ramesh *et al.*, 1995 ; Zhu and Ethridge, 1997). The problematic high intercorrelation among the predictive variables is known as multicollinearity or collinearity. Cavell *et al.* (1998), Mofenson *et al.*, (1999), and Kamita *et al.*, (2002) pointed out that collinearity increases the estimate of standard error of regression coefficients, causing wider confidence intervals and increasing the chance to reject the regression test statistic. Hair *et al.* (1998) and Yoo *et al.* (2014) stated that, as collinearity increases, it is more difficult to ascertain the effect of any single variable produce biased estimates of coefficients and a loss of power for regressors because the variables have more interrelationships. Methodologies such as principle component analysis (PCA) and partial least square (PLS) are used for dimension reduction in regression analysis when some of the independent are intercorrelated Saikat and Yan (2008)**.** PLS has some similarity with PCA, but PLS is less restrictive (Wold *et al.*, 1994, and Yoo *et al.*, 2014). The Workflow of this study is to diagnose the collinearity of cotton fiber measurements of Cotton Classifying System (CCS) Instrument, therefore describe the process of building principle components in a multivariate regression set-up for modeling yarn quality characteristics.

2. MATERIALS AND METHODS

The materials used in this study were five commercial varieties of Egyptian cotton, Giza 88 and Giza 92 varieties belonging to the Extra-long staple category, whereas Giza 86, Giza 90 and Giza 95 belonging to the Long staple class. According to the local classifying system, four lint cotton grades, namely: Good/Fully Good (G/FG), Good (G), Fully Good Fair/Good (FGF/G) and Fully Good Fair (FGF), were used for each variety. A bulk sample was brought from cotton gin mills, where each variety followed its own region for the cotton crop of 2016 and 2017 seasons. Five sub samples from each grade were used to determine cotton fiber characteristics by Cotton Classification System (CCS-$V_{5.3}$) equipment. Cotton samples were conditioned prior to testing in the BINDER equipment for at least 48 hours at 65 % $\pm$ 2 % Rh and 21^0 C ± 2^0 C. Cotton fiber tests were conducted at the laboratories of the Egyptian &International Cotton Classification Center (EICCC), Cotton Research Institute (CRI), Agricultural Research Center (ARC), Egypt. Cotton fiber Samples were spun at 3.6 twist factor for Ne 40 and Ne 60 counts. Yarn strength in terms of Lea product in pound x count was measured by the Good Brand Lea tester. Single yarn strength was measured using TensoLab 3; and yarn unevenness measured by MT Evenness Tester. Glossary of variable names is listed in Table (1).

Table (1): Glossary of variable names.

+ b	Degree of yellowness
Rd %	Percent of Reflectance
FE %	Fiber Elongation
FS (g / tex)	Fiber Strength
UI %	Uniformity index
ML (mm)	Mean length
UHM (mm)	Upper Half Mean
SFI %	Short Fiber Index
Mike	Micronaire value
MR	Maturity Ratio
LD (Milletex)	Linear Density
LP 40s	Le Product Ne 40s
LP 60s	Le Product Ne 60s
SYS 40s	Single Yarn Strength Ne 40s
SYS 60s	Single Yarn Strength Ne 60s
CV % 40s	Unevenness Ne 40s
CV % 60s	Unevenness Ne 60s

Using the Statistical Package for Social Science (SPSS V.12), the collected data were subjected to the proper analysis of descriptive statistics, Simple correlations and multiple regressions. These models were applied to establish the quantitative relationship between yarn quality properties and fiber characteristics. To reduce the number of predictive variables and solve the collinearity problem, the Principal Component Analysis (CPA) was used as a method of factor analysis.

3. RESULTS AND DISCUSSION

3.1. Variation in fiber and yarn quality properties

A compilation of the significant statistical parameters of fiber and yarn properties is given in **Table (2).** This Table includes: Minimum (MIN), Maximum (MAX), Mean, Median, Range and Coefficient of Variation (CV% =SD/mean *100). The descriptive statistics were the most sensitive with the large values of range and the great CV%, for approximately all fiber and yarn properties. This acceptable for uniformity index, maturity ratio and linear density that have the least discriminating and had small values of CV %. The mean and median values of these three variables seem to be close, indicating symmetric distribution with slight negative skewness.

3.2. Interrelationship among cotton fiber properties

The correlation matrix (person's r- values) is shown in **Table (3)**. Coefficients of correlation between the eleven variables indicate that the correlation coefficients among these variables are often significant. It is not surprising that the higher r- values were among fiber length parameters and between micronaire value and linear density. Micronaire value and SFI showed negative correlations. On the other hand, micronaire value and linear density show insignificant correlations with other measurements. Whereas, their correlation

Table (2): Descriptive statistics of CCS measurements and yarn quality properties.

	MIN	MAX	Mean	Median	Range	CV %	SD
+b	8	12.6	10.4	11.4	4.6	14.86	1.55
Rd %	60	82	68.02	67.15	22	8.14	5.54
FE %	6	8.5	7.1	6.9	2.5	9.43	0.668
FS	32	50.6	41.64	42.05	18.6	12.56	5.22
UI%	80.5	89.1	84.91	85.05	8.6	2.35	2
ML	22.03	31.82	26.85	27.53	9.79	9.78	2.61
UHM	27	36	31.75	32.2	9	7.78	2.45
SFI %	5.3	9.7	7.13	7	4.4	14.56	1.04
Mike	3.5	4.7	4.09	4.1	1.2	7.31	0.299
MR	0.80	0.89	0.84	0.84	0.09	2.73	0.023
LD	141	170	158	158	29	4.28	6.74
LP 40s	2100	3940	3002	3045	1840	19.2	576.5
LP 60s	1900	3560	2678	2580	1660	19.1	511.3
SYS 40s	10.4	27.8	17.6	16	17.4	30.06	5.29
SYS 60s	10	25	15.84	15	15	26.6	4.24
CV% 40s	14%	20%	19.33	20%	9%	12.8	2.48%
CV% 60s	10%	20.4%	20.03	20.%	13%	11.6	2.32%

Table (3): Intercorrelation coefficients among CCS cotton fiber measurements

	+b	Rd%	FS	FE%	UHM	ML	UI%	SFI	Mike	MR
LD	**0.135**	**0.115**	**0.042**	**0.256***	**-0.092**	**-0.019**	**0.226***	**-0.698****	**0.935****	**0.553****
MR	**-0.213***	**0.566****	**0.644****	**-0.339***	**0.487****	**0.545****	**0.660****	**-0.630****	**0.446****	
Mike	**0.058**	**0.135**	**-0.087**	**0.359****	**-0.240***	**-0.162**	**0.119**	**-0.622****		
SFI	**0.367****	**-0.47****	**-0.313***	**-0.009**	**-0.137**	**-0.195***	**-0.37****			
UI%	**-0.37****	**0.631****	**0.850****	**-0.650****	**0.819****	**0.899****				
ML	**-0.37****	**0.576****	**0.947****	**-0.760****	**0.991****					
UHM	**-0.37****	**0. 539****	**0.937****	**-0.761****						
FE%	**0.434****	**-0.51****	**-0.73****							
FS	**-0.51****	**0.708****								
Rd%	**-0.83****									

coefficients are significant with maturity ratio and short fiber index. It is worthy to mention that the high degree of correlation among these variables increase the variance in estimates of the regression parameters. Finally, the intercorrelation matrix showed the collinearity or common variance among CCS measurements.

For dimension reduction in yarn quality regression models, there is an urgent need to reduce the number of predictive variables (cotton fiber measurements of CCS) and solve the collinearity problem. The traditional statistical method commonly used in this regard, is Principle Component Analysis (PCA). So, the question is the intercorrelation matrix of fiber measurements is factorable?

There are two ways to determine the factorability:

1- Kaiser- Meyer- Olkin measure of sampling adequacy (KMO).

2- Bartletts Test of sphericity.

Kaiser- Meyer-Olkin (KMO)	0.727
Bartletts Test Approx. Chi-square	2000.42
DF	55
Sig.	0.000

According to Kaiser- Meyer–Olkin interpretation, the degree of common variance among CCS measurements (0.727) is "Middling". In matrix algebra, the determent of an identity matrix is equal to 1.00. So, the sample intercorrelations matrix did not come from population in which the matrix is an identity. The statistical decision is; if a factor analysis is conducted, the factors extracted will account for fare amount of variance but not a substantial amount.

3.3. Initial solution using the principle components method

In the initial solution, each variable of CCS measurements is standardized to have a mean of 0.00 and a standard deviation of $\pm$ 1.00. Thus the variance of each variable = 1.00; and the total variance to be explained is 11(number of variables). Otherwise the factor extracted explains variance no more a single variable. Since a single variable can account for more than 1.00 unit of variance (eigenvalue), a useful factor must account for more than 1.00 eigenvalue (λ > 1.00).Total variance explained in Table (4) identifies three factors that have values of eigenvalues more than 1.00. The first factor has an eigenvalue = 5.692. Since this is greater than 1.00, it explains more variance than a single variable, in fact 5.692 times as much. The percentage of variance derived as (5.692/11 units of variance) × (100) = 51.748 %. The same, 2nd factor has an eigenvalue λ = 2.989 and the percent of variance = 27.169 %. The 3rd factor has an eigenvalue λ = 1.188 and the percent of variance = 10.80 %. On the other hand, the remaining factors i.e., factor 4 through factor 11 have eigenvalues less than 1.00., and therefore explain variance less than a single variable. The sum of the eigenvalues associated with each factor (component) sums to 11 is; 5.692 + 2.989 + 1.188 + ……+ 0.00 = 11

The cumulative percentage of variance explained by the first three factors is 89.716 %. In other words, 89.716 % of the common variance shared by the eleven variables can be accounted for by the first three factors. This is reflective of the KMO of 0.727 values, a "Middling" % of variance.

Cattell's plot (Cattell, 1952) illustrates the way to determine the number of factors to extract in the final solution (Fig. 1). This is a plot of the eigenvalues associated with each of the factors extracted vs. each factor. At the point that the plot begins to level off, the additional factors explain less variance than a single variable. Accordingly, could obtain three main factors, that higher than the line of 1.00.

Table (4): Total Variance Explained

Component	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	5.692	51.748	51.7481
2	2.989	27.169	78.916
3	1.188	10.80	89.716
4	0.309	2.805	92.521
5	0.293	2.667	95.187
6	0.259	2.358	97.546
7	0.138	1.259	98.804
8	0.063	.575	99.379
9	0.038	0.345	99.725
10	0.030	0.274	99.999
11	0.00	0.001	100.00

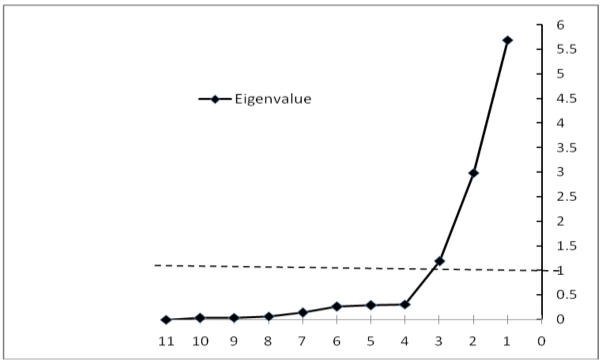

Fig. (1): The Scree Plot of Eigenvalue for the 11 variables

3.4. Factor Loadings

The component matrix which indicates the correlation coefficient of each variable of CCS measurements with each factor is shown in Table (5). Fiber strength correlates 0.960 with factor 1 and – 0.135 with factor 2 and 0.094 with factor 3. The total proportion of the variance in fiber strength explained by the three factors is simply the sum of its squared factor loadings or correlations ($0.960^2 - 0.135^2 + 0.094^2 = 0.948$. This is called the communality of the variable fiber strength. Similarly, the total % variance in mean length explained by the three factors is; $0.920^2 - 0.236^2 + 0.262^2 = 0.971$. Thereafter, the communalities of the remaining measurements are derived the same. As evident, the percentage of variance in each measurement of CCS accounted for by the three factors is not the same. It is worth mentioning that often all measurements load high on the most important factor; 1. Whereas, micronaire value and linear density load lowest on factor 1. There are five measurements that load highest on factor 2, *i.e.*, fiber elongation, maturity ratio, micronaire value, linear density and short fiber index. On the other hand, only yellowness degree is loads highest on the 3rd factor.

3.5. Modeling yarn quality properties

After overcoming the problematic collinearity of cotton fiber properties using factor analysis, noncollinear factors for predicting yarn quality properties could be obtained three . By this way, predicting yarn quality properties seems more realistic and reliable**.** Table (6) indicates the significance and contribution of cotton fiber measurements of CCS equipment explained by the scored three factors on the variation in yarn quality properties. According to "F" values, all models are highly significant. The three factors that summarize the 11 attributes show high contributions (% R^2) ranged from 68.9 %

Table (5): The factor loading and communalities of CCS cotton fiber measurements

	Component			Communality
	Factor 1	**Factor 2**	**Factor 3**	
FS	**0.960**	**-0.135**	**0.094**	**0.948**
ML	**.920**	**-0.236**	**0.262**	**0.971**
UI%	**0.908**	**0.044**	**0.242**	**0.876**
UHM	**0.887**	**-0.309**	**0.356**	**0.948**
Rd%	**0.806**	**0.102**	**-0.506**	**0.916**
FE %	**-0.749**	**0.449**	**-0.055**	**0.766**
MR	**0.720**	**0.487**	**0.186**	**0.790**
Mike	**0.058**	**0.956**	**0.034**	**0.917**
LD	**0.154**	**0.937**	**0.211**	**0.946**
SFI	**-0.452**	**-0.755**	**0.219**	**0.823**
+b	**-0.594**	**0.082**	**0.780**	**0.968**

Table (6): The significance and % R^2 of PCA and % R^2 of the ordinary multiple regression models.

	F Value	**Sig.**	**PCA %R^2**	**Multi. Reg. %R^2**
LP 40s	645.3	0.00	95.3 %	98.3 %
LP 60s	421.1	0.00	92.9 %	97.4 %
SYS 40s	184.3	0.00	85.2 %	96.2 %
SYS 60s	70.70	0.00	68.9 %	90.7 %
CV % 40s	85.60	0.00	72.8 %	89.1 %
CV % 60s	88.00	0.00	73.3 %	84.7 %

through 95.3 %. On the other hand, on the ordinary multiple regression models, the contribution of the eleven variables on the variation in yarn quality properties show the highest values of % R^2 ranged from 84.7 % through 98.3 %. Comparing % R^2 values of multiple regression models with PCA regression models, disclose the shrinkage of % R^2 values after PCA procedure. The differences of % R^2 values are slight for lea product of Ne 40 and Ne 60 counts. For single yarn strength and unevenness of Ne 40 and Ne 60 counts, differences of % R^2 are highest, especially for single yarn strength of Ne 60 count. These results reveal the unreal contribution of fiber properties collected on the variation in yarn quality properties due to the collinearity of predictors. So, the improvement occurred by factor analysis using the principle component method that eschewing the collinearity.

Conclusion

Cotton fiber properties are the predictors for predicting yarn quality properties. The collinearity of cotton fiber properties resulted in unrealistic and inaccurate regression models. One approach is using principle component analysis method to give satisfactory regression models after getting rid of the collinearity of cotton fiber properties.

4. REFERENCES

Abakar K. A. and Yu C. (2013). The performance of Data Mining Techniques in prediction of yarn quality. Int'l. Inn. Manag. and Tech., 4, (4): 390-392.

Behery H. M. (1993). Short fiber content and uniformity index in cotton. Int'l. Cotton Advi. Comm., Rev. Article 4, CAB Int., Wallingford, UK.

Cattell R. B. (1952). Factor Analysis. New York. Harper & Bors.

Cavell A., Lydiate D. and Parkin I. (1998). Collinearity between 30-centimorgan segment of *Arabidopsis thaliana* chromosome 4 and duplicated regions within the *Brassica Napus* Ggenome., 4: 62-69.

EL Mogahzy Y. E. and Chewning C. H. (2001). Cotton fiber to yarn manufacturing Technology. Cotton Incorporated, Cary, NC. USA.

Foulk J., Gamble G., Senter H. and Meredith W. (2007). Cotton Natures High Tech. Fiber. WCRC-4.,10-14 September.

Frydrysh I. A. (1992). A new approach for predicting strength properties of yarn. Text. Res. J., 62: 346-348.

Hair J., Tatham R. and Anderson R. (1998). Multivariate data Analysis.(5thed). Prentice Hall. USA.

Hunter L. (2002). HVI Testing of cotton: Its present status and future prospects. 26th International cotton conference Bremen.,

Hussein K. M., Hassan A. H. and Kamal M. M. (2010). The Multiplicative Analytic Hierarchy Process (MIAHP) as a quality criterion determining the technological value of the Egyptian cotton varieties. Americ. J. Plant Sci., (1):106-112.

Kamita M., Fraudeau N. and Herault Y. (2002). Serial deletions and duplications suggest a mechanism for the collinearity of Hoxd genes in limbs. Nature., 420, 145-150.

Krifa M. and Ethridge D. (2006). Compact spinning effect on cotton yarn quality: interactions with fiber characteristics. Text. Res. J., 76(5): 388-399.

Krifa M., Hequet E. and Ethridge D. (2002). Compact Spinning: New Potential for short staple cottons. Textile Topics., (2):2-8.

Majumdar A., Majumdar P.K. and Sarkar B. (2005). Application of linear regression, artificial neural and Neruo-Fuzzy algorithms to predict the breaking elongation of rotor- spun yarns. Indian Tour. of Fiber and Textiles Res., 30, (1): 1925-1934.

Majumdar A. and Ghosh A. (2008). Yarn strength modeling using Fuzzy Expert System. J. Eng. Fibers and Fabrics. 3 (4):61-68.

Mofenson L., Lambert J. and Stiehm R. (1999). Risk factors for perinatal transmission of human immunodeficiency virus type I in women treated with Zidovudine. The New England J. of Med., 341, (6): 385-393.

Nurwaha D. and Wang X. (2012). Using Intelligent Control Systems to predict textile yarn quality. Fibers & Textiles in Eastern Europe. 90, (1) : 23-27.

Perkins Jr., Ethridge D.E. and Bragg C.K. (1984). Fiber. *In* “Cotton” (R. J. Kohel and C. F. Lewis, eds.). Amer. Soc. of Agron., Madison, WI.

Ramesh M. C., Rajamanickam R. and Jayaraman S. (1995). Prediction of yarn tensile Properties Using Artificial Neural Networks. J. Text. Ins., (86):459-469.

Saikat M. and Yan J. (2008). Principle component Analysis and Partial least squares: Two dimension Reduction Techniques for Regression. Casualty Actuarial Society., Discussion Paper Program., 79- 89.

Souid H. and Cheikhrouhou M. (2011). Slop yarn quality optimization by using desirability function and neural networks. J. App. Sci., 11(7): 3204- 3208.

Tallant J. D., Fiori I. A., Litte H. W. and Castillan A.V. (1963). Investigation of the minimum length of Cotton fiber effective in single yarn Tenacity. Text. Res. J., (33): 1005 – 1012.

Ute B.T. and Kadoglu H. (2014). Regressional estimation of cotton Sirospun yarn properties from fiber properties. Autex Res. J., 14 (3): 161-167.

Wold S. (1994). PLS for multivariate linear modeling. In: van de Water-beemed H (Editor), Chemometric Methods in Molecular Design. Verlag-Chemie., 195-218. Weinheim, Deutschland.

Yoo W., Mayberry R., Bae S., Singh K., Qinghua, P. and James W. Jr. (2014). A study of effects multicollinearity in the multivariable analysis. Int’l. J. Appl. Sci. Tech., 4, (5): 9-19.

Yunus M. and Rhman F. (1990). Micronaire effects. Textile Asia., (13): 58-61.

Zeng Y. C., Wang K. F. and Yu C. W. (2004). Predicting the Tensile properties of Air-Jet spun yarns. Text. Res. J., 74, (8): 689 - 694.

Zhu R. and Ethndge D. (1997). The prediction of cotton yarn irregularity based on the AFIS measurements. J. Text. Inst., (87):509-512.

إستنتاج صفات جودة خيوط الغزل من خلال تجنب العلاقة الخطية المتعددة فيما بين صفات جودة تيلة القطن

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ملخص

كثيرا ما تستخدم معادلات الإنحدار لاستنتاج صفات جودة خيوط الغزل بالإعتماد على صفات جودة تيلة القطن. لكن نظراً للعلاقات المتداخلة القوية فيما بين صفات التيلة multicollinearity، يزداد الخطأ القياسى فى معاملات الإنحدار. لذلك استخدم فى هذه الدراسة طريقة تحليل العوامل الرئيسية لتلافى هذه المشكلة. أستخدم لهذا الغرض 5 أصناف من الأقطان التجارية المصرية: جيزة 88 ، جيزة 92 من طبقة الأقطان فائقة الطول، وجيزة 86، جيزة 90 وجيزة 95 من طبقة الأقطان الطويلة. أخذ من كل صنف 4 رتب قطن شعر وهى جود إلى فولى جود (ج/فج)، جود (ج) ، فولى جود فير إلى جود (فجف/ج)، فولى جود فير (فجف). وتم استخدام 5 عينات من كل رتبة لإجراء اختبارات التيلة والغزل. أجريت اختبارات التيلة على جهاز $SCC\text{-}V_{5.3}$ بمعهد بحوث القطن. كما تم الغزل ثم اختبارات جودة خيوط الغزل على جهاز Good Brand لقياس متانة الشلة و جهاز TensoLab لقياس متانة الخيط المفرد وجهاز MT Evenness Tester لتقدير عدم انتظام الخيوط. أظهرت النتائج العلاقات المتداخلة القوية بين صفات التيلة. أمكن تجميع صفات التيلة فى 3 عوامل فقط منفصلة عن بعضها البعض فى تاثيراتها فى التغير فى صفات جودة الخيوط وعبرت هذه العوامل الثلاثة عن % 89.72 من العلاقات المتداخلة بين صفات التيلة. إختلفت نسبة مساهمة كل صفة من صفات التيلة عن الأخرى فى كل عامل من العوامل الثلاثة، ومعظم المساهمات تركزت فى العامل الأول والثانى. أمكن استنتاج صفات جودة الخيوط من خلال معادلات إنحدار تعتمد على تلك العوامل الثلاث الرئيسية فقط بنسب مساهمة عالية و لكن أقل نسبيا من نسب المساهمة لصفات التيلة مجتمعة فى معادلات الإنحدار المتعدد العادى. وبذلك قد أمكن استنتاج صفات جودة الخيوط بدقة مرضية نتيجة تجنب العلاقات الخطية المتداخلة القوية فيما بين صفات تيلة القطن.

المجلة العلمية لكلية الزراعة - جامعة القاهرة - المجلد (70) العدد الثانى (أبريل 2019):103-110.