RELATIONSHIP OF FIBER PROPERTIES TO VORTEX YARN QUALITY VIA PARTIAL LEAST SQUARES

Jonn Foulk
USDA-ARS
Clemson, SC
Calvin Price
Philadelphia, PA
Herman Senter
Clemson University
Department of Mathematical Sciences
Clemson, SC
Gary Gamble
USDA-ARS, Cotton Quality Research Station
Clemson, SC
William R. Meredith
USDA-ARS
Stoneville, MS

Abstract

The Cotton Quality Research Station (CQRS) of the USDA-ARS, recently completed a comprehensive study of the relationship of cotton fiber properties to the quality of spun yarn. The five year study, began in 2001, utilized commercial variety cotton grown, harvested and ginned in each of three major growing regions in the US (Georgia, Mississippi, and Texas). CQRS made extensive measurements of the raw cotton properties (both physical and chemical) of 154 lots of blended cotton. These lots were then spun into yarn in the CQRS laboratory by vortex spinning with several characteristics of the yarn and spinning efficiency measured for each lot. This study examines the use of a multivariate statistical method, partial least squares (PLS), to relate fiber properties to spun yarn quality for vortex spinning. Two different sets of predictors were used to forecast yarn quality response variables: one set being only HVI variables, and the second set consisting of both HVI and AFIS variables. The quality of predictions was not found to significantly change with the addition of AFIS variables.

Introduction

Cotton is a natural agricultural product whose chemical and physical properties cannot be completely controlled. Cotton quality is affected by cotton variety and growing conditions, which vary by year and harvesting location. Fiber processing and spinning can be affected by fiber properties. The following items need to be addressed in order to improve the utilization of cotton: 1.) new methods to more fully characterize cotton quality, 2.) assessment of the impact of cultivation practices and fiber varieties on fiber utilization, and 3.) relationship of fiber properties to utilization. Using our existing equipment, this study evaluated fiber properties and their relationship to processing performance and product quality. These fiber property results provide the potential to predict multiple yarn quality variables using statistical methods.

The primary statistical method used in this paper is partial least squares (PLS). PLS is a technique that can be used to create predictive regression models for multiple response variables when there is a high degree of collinearity in the predictor variables, or when there are very many predictor variables (Tobias, 1997). When the number of predictors is close to or even greater than the number of observations, the ordinary least squares (OLS) estimators of slope coefficients may be unstable or may not exist. In order to overcome these deficiencies, the method of PLS can be used to yield stable results with superior predictive ability. Emphasis is on developing a model for prediction, with no cause and effect relationship assumed between the independent variables and dependent variables. Similarly, one is not able to judge which variables are important in "causing" any of the dependent variables. PLS is not a data reduction technique nor does it directly provide evidence or support as to which variables should be removed or as to which variables are not important in explaining the Y variables. However, PLS can be used with different sets of X variables, to determine which sets of variables lead to better predictions, and to determine how much better predictions are with different sets of X variables.

PLS replaces the original set of numerous X variables with a smaller set of orthogonal factors (also called components) that are extracted from these variables. This is similar to the more commonly used statistical procedure of principal components, where factors are extracted from a set of variables so as to maximize the variance accounted for in that set of variables. However, in PLS, the factors extracted from the X variables are chosen so as to maximize the covariance accounted for between the X and Y variables. Thus, for each number of components that could be pulled from X, there is a corresponding PLS model with its own set of predictions on all of the Y variables. Generally, these predictions are different than those that result from any other PLS model that uses a different number of components. The total number of components extracted from the X matrix ranges from 1 to the number of variables (p). As the number of components increases, the PLS model converges to the regular multiple regression model, where it becomes exactly the same when the number of components extracted is equal to the rank of the design matrix. It is often difficult to determine how many factors from the X matrix should be used in the optimal model. Some Y variables may be predicted best with one number of components, while other Y variables are predicted better with a different number of components.

Output after PLS regression includes information on the fit of each Y variable corresponding to each possible number of components pulled from the X matrix. So, for example, if we wanted to predict 5 Y variables from 20 X variables, the 1st Y variable would be fit with 20 different models, the 2nd Y variable would also be fit with 20 different models, as would the 3rd Y variable, and so on with the end result a total of 100 different models and a corresponding 100 different measures of predictive ability. Consequently, we might find the 1st Y variable is predicted best with 7 components, the 2nd Y variable may be predicted best with 10 components, and so on. The measure of "best predictive ability" used in this study is called the Prediction Error Sum of Squares (PRESS) statistic.

Measurements on one group of 14 predictors (high volume instrumentation, HVI) are performed on all cotton bales while measurements on 12 other predictor variables (advanced fiber information system, AFIS) are often available. The goal of this work was to make the best possible predictions on 12 yarn quality variables from the vortex spinning method. Benchmark determinations will determine how good predictions are with the initial set of 14 HVI variables; subsequently PLS will be performed with the combined 26 HVI and AFIS predictor variables to evaluate any changes in prediction quality.

Preliminary Inspection of the Data

A preliminary inspection of the data was performed on the 12 response variables (measurements of diverse properties of yarn spun by the vortex method) and 26 predictor variables. These predictor variables were grouped into the following categories (with the corresponding number of variables in each category): HVI (14) and AFIS (12). The resultant database utilized in this analysis included 152 observations on 38 variables. All HVI (X) variable observations were in pairs, so the 152 yarn quality variable (Y) observations correspond to 76 distinct HVI variable observations. Linear relationships existed between each yarn quality variable and all HVI variables; except for the variable micronaire, which demonstrates a quadratic relationship with many of the yarn quality variables (Figure 1). The micronaire variable required a transformation (micronaire squared) to remove non-linearity.

The square of micronaire is an appropriate transformation by evaluating the residuals of response variables (neps, thick, and yarn CV) when they are each regressed on both micronaire and the square of micronaire (Tables 1, 2, and 3). The random scatter shown in these residual plots (Figures 2, 3, and 4) and the large sequential sum of squares suggest that adding the Square of micronaire is advisable. The predictive abilities of the developed model also increases with the addition of this variable, as does the variation explained in the response variables. References to "HVI variables" from hereon include the square of the micronaire variable. A search for outliers in the data was performed using a distance plot (Figure 5) which provides a scatter point corresponding to each observation. A point's distance along the horizontal axis signifies how close the observation is to the orthogonal (uncorrelated) components that were created to represent the predictor variables. Similarily, a point's distance along the vertical axis signifies the distance of the observation from the orthogonal (uncorrelated) components created to represent the response variables.

In the distance plot, observations 41 and 42 are outliers with respect to the HVI variables, and observations 1, 2, and 41 are outliers with respect to the set of yarn quality variables. The analysis that follows was done in the absence of these 4 observations, and yielded essentially identical results as when they were included. There is a large amount of evidence that the long thick variable is not significantly related to any of the HVI variables. When outliers are excluded, the long thick variable formally tests as not being significant to any of the HVI variables.

Results and Discussion

Following a preliminary inspection of the data, PLS regression was performed using 12 yarn quality variables against 15 HVI variables. In PLS, each yarn quality variable is modeled with 1-15 components, and measures of fit are provided for every model corresponding to each possible number of components used. For each yarn quality variable, we need to choose the optimal number of components to use in making a predictive model for that variable. While this can be done in a variety of subjective ways, the approach to be used here is a combination of highest R-square and highest predicted R-square.

The predicted R-square is a measure of predictive ability based on the PRESS statistic. Whereas the usual R-square (also called fitted R-square) uses the error sum of squares when accounting for variation not explained, predicted R-square uses the PRESS statistic. Values for the PRESS statistic will always be larger than values for the regular error sum of squares and the predicted R-square will always be smaller than the fitted R-square. The number of components chosen will not be solely determined by which model has the highest predicted R-square; a lower predicted R-square will be accepted if it is accompanied by a significant increase in the fitted R-square or a significant decrease in the number of components used. The ideal case includes an obvious ‘elbow’ where additional components begin to add on only negligible increases to both predicted R-sq and fitted R-square (see Figure 6 for the Statimat strength response variable).

Figure 6 demonstrates that additional components past 4 components yield only negligible increases to both predicted R-square (denoted by “cross-validated”) and fitted R-square. However, not all response variables were as clear as the Statimat strength response variable. For example, the long thin response variable (Figure 7) displayed an obvious elbow at 4 components for predicted R-square, but the fitted R-square still has considerable gains for larger number of components; thus 9 components was selected. It should be noted that the choice in number of components is not directly related to choosing which variables are important or how many variables are suitable for predicting the yarn quality. Regardless of whether 2 components or 10 components are chosen, every single component is a linear combination of all HVI variables. After considering similar results for each of the 12 response variables, Table 4 includes the optimal number of components chosen for each variable.

The long thick response variable is difficult to predict as indicated by a 0.00 predicted R-square. This result is not dependent at all on how many components were selected, as can be seen from Figure 8. Considering the low value of predicted R-square and fitted R-square values across all possible number of components, we conclude that this variable has essentially no relationship to the HVI variables and has very little of its variation explained by them. If the long thick variable is removed from the model we get better predictions on the remaining yarn quality variables because the components extracted from the data do not have to be created with the intent of trying to explain a variable that cannot be explained. In a sense, long thick is an outlier variable that skews the creation of the extracted components, which are in turn used in making predictions for all other response variables. As demonstrated in Table 5, with the removal of the long thick response variable the average fitted R-square improves by 3% (from 0.65 to 0.68) and the average predicted R-square improves by 5% (from 0.57 to 0.62).

These two mean R-square values serve as the HVI benchmark for comparisons when we perform PLS with the additional set of predictors (12 AFIS variables). If the corresponding numbers from PLS are significantly higher than these, we can consider AFIS variables to contribute significantly to predictions on the yarn quality response variables. Conversely, if the corresponding R-square numbers are roughly the same, we will conclude that the AFIS variables do not contribute significantly to predictions on the yarn quality response variables when HVI variables are present.

In addition to assessing the fit and predictive ability of our model, we can make an indirect attempt at variable reduction by interpreting the correlations (also known as loadings) of the predictor variables with each of the extracted components. The PLS components are created so that the 1st component explains the largest amount of covariance, and the 2nd component explains the 2nd largest amount of covariance, and so on. Thus, if there is a certain group of variables that correlate highly on the 1st PLS component, we may be able to attach an interpretation based on similarities between the variables, and conclude that the underlying common feature represented by those variables is important in explaining the covariance between our predictor variables and our set of response variables. Since each of the components explains a decreasing amount of covariance, only the first two components will be of interest. Figure 9 is a graphical representation of the loadings of each HVI variable on the first two components.

For example, the variable uniformity has a correlation of approximately -0.40 with the 1st component, and approximately zero correlation with the 2nd component. This is the pattern we would like to see when choosing a group of variables to associate with a component: a strong correlation with a given component, and morever, a near zero correlation with other components. This ensures that the feature represented by the variable is isolated to the given component. Looking across all of the variables, we can see none of them have particularily strong correlations with either of the first two components (all are smaller than 0.50 in magnitude), so any interpretations drawn here should be regarded as simple suggestions. Nevertheless, we can see that the predictor variables Uniformity, Mike stdev, and +b stdev have the largest isolated correlations with the first component, and Rd, Trash, and Trash stdev have the highest isolated correlations with the second component. The 1st set of variables – uniformity, mike stdev, and +b stdev – appear to be capturing the common yarn quality features of strength and elongation. The 2nd set of variables – Rd, trash, and trash stdev – appear to be capturing the common yarn quality features of thick and low places. These results are generally in agreement with Deussen (1993) who stated that key properties for vortex spinning systems are as follows: length, fineness, strength, friction, cleanliness.

PLS regression was run on response variables using both HVI and AFIS variables. Linear relationships between the response variables and the 12 AFIS predictor variables all appear acceptable. Inspection for outliers does reveal some potential outliers, but the model resulting from their exclusion differs only slightly when they are included. In order to determine the optimal number of components to model each yarn quality variable 11 response variables (long thick excluded) were regressed against the 15 HVI variables and the 12 AFIS variables (27 predictors total).

The general pattern in the results is that a slightly larger number of components was chosen as optimal across all of the response variables, and further, there was no change in the average predicted R-square and only a slight increase in the average fitted R-square (Table 6). Considering the lack of improvement in predictive ability, we can conclude that adding AFIS variables is not worthwhile when making predictions for the vortex yarn quality response variables. In fact, five of the response variables saw a decrease in predictive ability after the AFIS variables were included. These included particularly large decreases in the response variables Major and Minor, where the predicted R-square fell by 4% and 9% respectively. The notable increases occurred in the response variables Statimat strength and Statimat elongation, where the predicted R-square increased by roughly 4% and 12% respectively.

Using HVI and AFIS variables, an indirect attempt at variable reduction was made by interpreting the correlations (loadings) of each predictor variable on the extracted components. The corresponding loadings for the first two components is shown in Figure 10. As was the case before, none of these correlations are particularly large (all are less than 0.50 in magnitude) so any interpretations here are merely suggestions. The first component correlates highly with the AFIS predictors maturity ratio and neps, and the second component is characterized by AFIS predictor UQL and HVI predictor length. The 1st set of variables – maturity ratio and neps – appear to be capturing the common yarn quality feature of thick and low places. The 2nd set of variables – UQL and length – appear to be capturing the common yarn quality feature of strength and elongation. Again these results are generally in agreement with Deussen (1993) who stated that key properties for vortex spinning systems are as follows: length, fineness, strength, friction, cleanliness.

Having completed PLS analysis, it is interesting to compare these results with other regression alternatives such as stepwise and OLS. Since these methods require a single response variable, these methods will be performed on two separate response variables: one that PLS predicts quite well (Statimat strength) and one PLS was not able to predict very well (major). Using the basic OLS model, we will use all of the HVI and AFIS variables as predictors (27 total). Results for the response variable Statimat strength are in Table 7. The foremost result to be noted here are the large Variance Inflation Factor (VIF) values, indicating a high degree of collinearity, and essentially invalidating any other conclusions that could be drawn about which predictors are significant. Both the fitted and predicted R-square are on the same level as that drawn from the PLS model, though the PLS model did so with a considerably smaller dimension of predictors (only 8, versus the 27 here), further indicating excessive collinearity. OLS results for the other response variable are omitted, as the results are identical to these: that is, compared to OLS, PLS achieved the same quality of fit and predictive ability, but with the added feature of removing collinearity and ensuring more stable results.

Stepwise regression for response variable Statimat strength yielded a fitted R-square of 0.90 and a predicted R-square of 0.89, compared to the PLS values of 0.89 and 0.86 ; thus we can see that there was a slight increase in the predicted R-square. However, this increase comes at the expense of introducing collinearity into the model, as about one-third of the selected predictors had large VIF's. Compared to the 8 prediction factors used in PLS, the stepwise procedure selected the following 16 predictors (Table 8) as significant.

Likewise, when predicting for the Major response variable, the fitted and predicted R-square from a stepwise procedure were 0.43 and 0.35, a 9% increase over the predicted R-square found with PLS. Collinearity was also not as severe a problem in this model, with only two variables having a large VIF. The results are shown below in Table 9. These results suggest that a stepwise procedure may be able to make more accurate predictions than PLS for some response variables. This result should not be surprising, since this stepwise procedure only took one single response variable into account, whereas the PLS method creates predictions for 11 yarn quality response variables simultaneously. There are many studies that detail the pitfalls of using stepwise procedures (Judd and McClelland,1989; Tibshirani, 1996) where it is known that resulting models could fit well only by chance, and the final model is also likely to be unstable. This work used "leave one out" criteria related to the PRESS statistic and predicted R-square. However, there is evidence that this method may result in overly optimistic views on prediction ability, and other alternatives (eg, "leave k out") may prove more appropriate (Shao, 1993).

Conclusions

This work examines the use of PLS to predict multiple yarn quality variables based on a number of cotton quality predictor variables. The data set indicated that OLS regression was inappropriate with the large number of predictors compared to the number of observations, and the presence of strong collinearity in the predictor variables. Partial least squares was evaluated as a method that could overcome these difficulties and still provide accurate predictions. Two different sets of predictors were used to forecast the yarn quality response variables: one set being only HVI variables, and the second set consisting of both HVI and AFIS variables. The quality of predictions was not found to significantly change with the addition of AFIS variables, implying that effort spent on gathering observations for these variables is not worthwhile for the sake of predicting the vortex yarn quality response variables. Relevant tasks for future work include judging predictions of the response variables based on other groups of predictor variables beyond HVI and AFIS. PLS was indirectly used to suggest which variables are "important" for explaining response variables (data reduction), however, other multivariate techniques are specifically designed for this, such as factor analysis.

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Table 1. Regression model analysis and parameter estimates for yarn CV response variable.

Predictor	Coefficient	Standard Error Coefficient	T	Prob>T
Constant	49.451	4.104	12.07	0
X1	-14.500	1.993	-7.27	0
squareX1	1.6537	0.2395	6.90	0
Source	DF	Sequential Sum of Squares		
X1	1	29.852		
squareX1	1	67.099		

Table 2. Regression model analysis and parameter estimates for nep response variable.

Predictor	Coefficient	Standard Error Coefficient	T	Prob>T
Constant	5000	474.5	10.54	0
X1	-2082.7	230.5	-9.04	0
squareX1	228.90	27.69	8.26	0
Source	DF	Sequential Sum of Squares		
X1	1	29.852		
squareX1	1	67.099		

Table 3. Regression model analysis and parameter estimates for thick response variable.

Predictor	Coefficient	Standard Error Coefficient	T	Prob>T
Constant	6455.5	560.8	11.51	0
X1	-2704.4	272.3	-9.93	0
squareX1	299.39	32.73	9.15	0
Source	DF	Sequential Sum of Squares		
X1	1	2365579		
squareX1	1	2199212		

Table 4. Best number of components in the PLS model for each variable using only HVI results.

		Number of components	R-square	Predicted R-square
YV1	Ends down	10	0.60	0.51
YV2	Statimat strength	4	0.84	0.82
YV3	Statimat elongation	9	0.68	0.62
YV4	Neps	15	0.77	0.70
YV5	Thick	15	0.85	0.81
YV6	Low	10	0.77	0.72
YV7	Yarn CV	15	0.86	0.82
YV8	Major	10	0.43	0.30
YV9	Minor	15	0.70	0.60
YV10	Long thick	15	0.25	0.00
YV11	Long thin	9	0.45	0.37
YV12	Yarn board appearance	7	0.56	0.51
Mean			0.65	0.57

Table 5. Best number of components in the PLS model for each variable using HVI results with the variable long thick removed.

Variables		Number of Components	R-square	Predicted R-square
YV1	Ends down	10	0.60	0.51
YV2	Statimat strength	3	0.83	0.82
YV3	Statimat elongation	10	0.69	0.63
YV4	Neps	15	0.77	0.70
YV5	Thick	15	0.85	0.81
YV6	Low	11	0.78	0.73
YV7	Yarn CV	15	0.86	0.82
YV8	Major	10	0.43	0.30
YV9	Minor	15	0.70	0.60
YV10	Long thick	na	na	na
YV11	Long thin	8	0.45	0.37
YV12	Yarn board appearance	7	0.57	0.51
Mean			0.68	0.62

Table 6. Best number of components in the PLS model for each variable using HVI and AFIS results.

Variable		Number of Components	R-square	Predicted R-square
YV1	Ends down	15	0.66	0.52
YV2	Statimat strength	8	0.89	0.86
YV3	Statimat elongation	14	0.83	0.75
YV4	Neps	18	0.78	0.69
YV5	Thick	13	0.85	0.79
YV6	Low	10	0.80	0.73
YV7	Yarn CV	10	0.87	0.83
YV8	Major	12	0.47	0.26
YV9	Minor	12	0.64	0.51
YV10	Long thick	na	na	na
YV11	Long thin	10	0.47	0.36
YV12	Yarn board appearance	10	0.60	0.51
Mean			0.72	0.62

Table 7. Components in the OLS model for Statimat strength using HVI and AFIS results.

Predictor	Predictor	Coefficient	Standard Error of Coefficient	T	P	VIF
Constant		-15.92	10.28	-1.55	0.124	
HVI1	Mic	-3.717	1.436	-2.59	0.011	506.6
HVI2	Mic stdev	-0.9316	0.3635	-2.56	0.012	5
HVI3	Strength	0.32413	0.05002	6.48	0	7.4
HVI4	Strength stdev	0.1773	0.1686	1.05	0.295	2.7
HVI5	Rd	0.13656	0.02397	5.7	0	4.3
HVI6	Rd stdev	0.82	0.2463	3.33	0.001	2
HVI7	+b	-0.1001	0.1073	-0.93	0.353	3.6
HVI8	+b stdev	-0.0414	0.1463	-0.28	0.778	8.1
HVI9	Trash	0.13134	0.04101	3.2	0.002	9.5
HVI10	Trash stdev	-0.2087	0.1956	-1.07	0.288	5.6
HVI11	Length	8.704	4.097	2.12	0.036	18
HVI12	Length stdev	-0.0404	0.1348	-0.3	0.765	5
HVI13	Uniformity	0.27947	0.09509	2.94	0.004	5.9
HVI14	Uniformity stdev	0.7254	0.3503	2.07	0.04	1.4
AFIS1	Fineness	-0.02796	0.01395	-2	0.047	10.7
AFIS2	Fineness stdev	0.00219	0.03061	0.07	0.943	1.5
AFIS3	UQL	-7.869	3.004	-2.62	0.01	14.7
AFIS4	UQL stdev	6.963	4.856	1.43	0.154	1.5
AFIS5	SFC	-0.19455	0.0443	-4.39	0	7
AFIS6	SFC stdev	0.07916	0.0799	0.99	0.324	1.4
AFIS7	Maturity ratio	2.114	2.893	0.73	0.466	6.7
AFIS8	Maturity ratio stdev	-2.276	6.499	-0.35	0.727	1.4
AFIS9	Nep	-0.0024	0.000994	-2.42	0.017	16.1
AFIS10	Nep stdev	0.000209	0.002568	0.08	0.935	1.5
AFIS11	VFM	0.08766	0.08914	0.98	0.327	2.8
AFIS12	VFM stdev	-0.0817	0.1437	-0.57	0.571	1.5
HVI1sq	Mic squared	0.3351	0.1588	2.11	0.037	429

Table 8. Components in the stepwise regression model for Statimat strength using HVI and AFIS results.

Predictor Coefficient		Standard Error	Coefficient	T	P	VIF
Constant		-11.298	8.407	-1.34	0.181	
HVI3	Strength	0.34589	0.0301	11.49	0	2.8
HVI5	Rd	0.11665	0.01884	6.19	0	2.8
HVI13	Uniformity	0.27911	0.08025	3.48	0.001	4.4
HVI1	Mic	-4.341	1.279	-3.4	0.001	415.6
HVI14	Uniformity stdev	0.7529	0.324	2.32	0.022	1.3
HVI2	Mic stdev	-1.1289	0.251	-4.5	0	2.5
HVI6	Rd stdev	0.7485	0.2211	3.39	0.001	1.7
HVI11	Length	9.465	3.921	2.41	0.017	17.1
HVI9	Trash	0.07719	0.02412	3.2	0.002	3.4
HVI7	+b	-0.17952	0.08859	-2.03	0.045	2.6
HVI1sq	Mic squared	0.3888	0.1403	2.77	0.006	346.7
AFIS1	Fineness	-0.02141	0.013	-1.65	0.102	9.6
AFIS5	SFC	-0.19543	0.03986	-4.9	0	5.9
AFIS9	Nep	-0.00277	0.000867	-3.2	0.002	12.7
AFIS3	UQL	-8.601	2.878	-2.99	0.003	14
AFIS4	UQL stdev	7.856	4.682	1.68	0.096	1.4

Table 9. Components in the stepwise regression model for major places using HVI and AFIS results.

Predictor Coefficient		Standard Error	Coefficient	T	P	VIF
Constant		-38.59	16.82	-2.29	0.023	
AFIS9	Nep	-0.00237	0.005395	-0.44	0.661	8.2
HVI10	Trash stdev	-2.642	0.9168	-2.88	0.005	2.1
HVI2	Mic stdev	9.367	2.628	3.56	0.001	4.5
HVI8	+b stdev	-2.107	0.9697	-2.17	0.031	6.2
AFIS5	SFC	0.8157	0.2124	3.84	0	2.8
HVI7	+b	2.1904	0.557	3.93	0	1.7
HVI11	Length	57.81	26.28	2.2	0.029	12.8
AFIS3	UQL	-31.59	20.34	-1.55	0.123	11.7
HVI4	Strength stdev	0.96	1.121	0.86	0.394	2.1
HVI14	Uniformity stdev	-5.631	2.509	-2.24	0.026	1.3
HVI6	Rd stdev	3.814	1.672	2.28	0.024	1.6
HVI12	Length stdev	1.6594	0.9011	1.84	0.068	3.9
HVI1	Mic	-1.785	1.28	-1.39	0.165	7

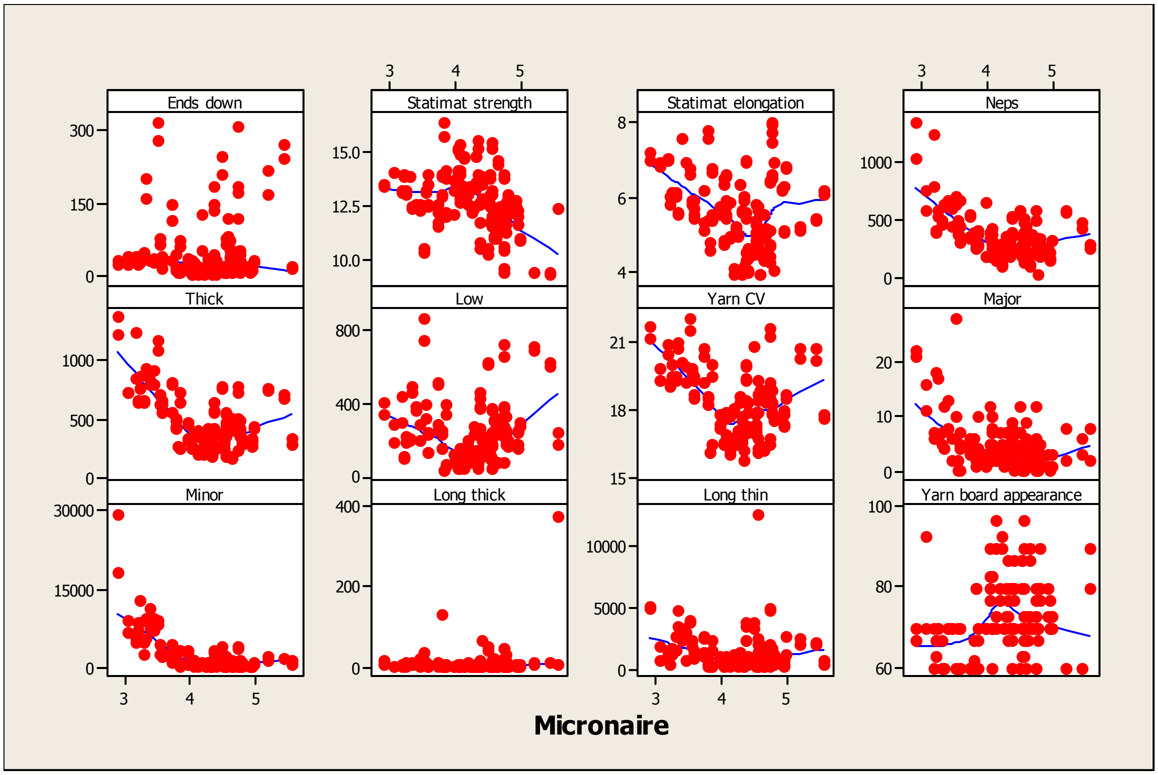

Figure 1. Scatterplot of ends down, Statimat strength, Statimat elongation, neps, thick, low, yarn CV, major, minor, long thick, long thin and yarn board appearance versus micronaire.

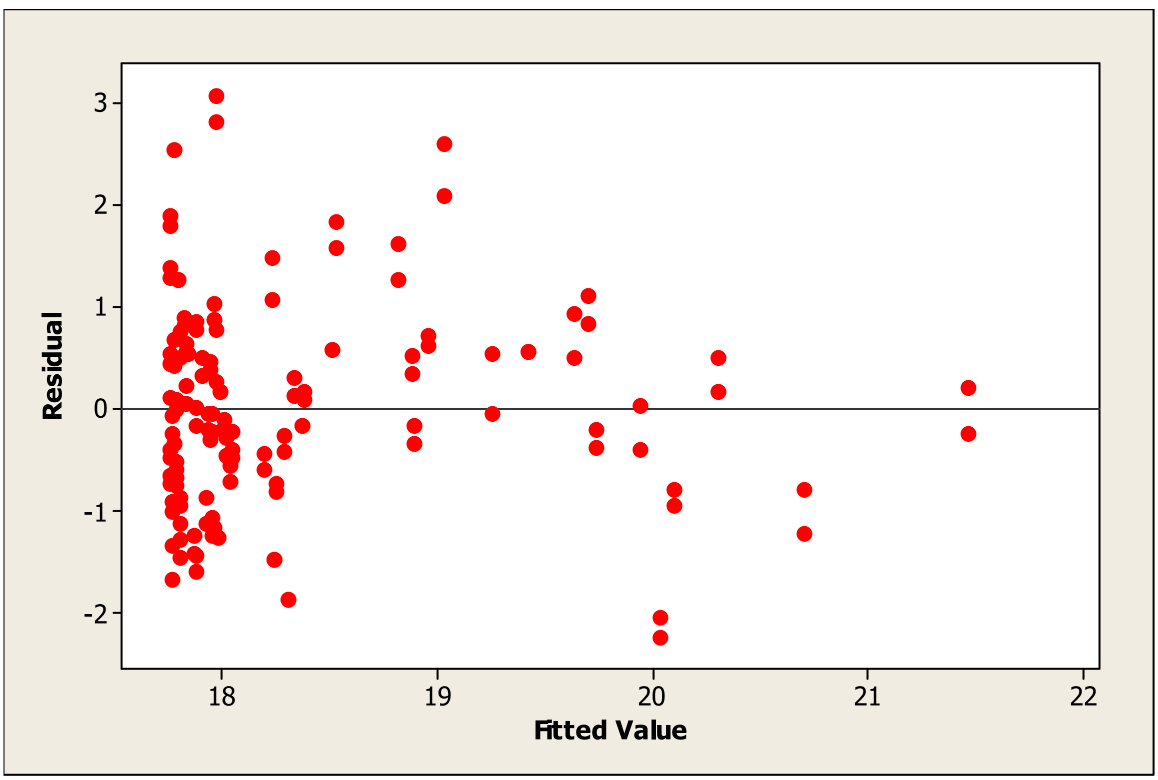

Figure 2. Residuals versus the fitted values (response is yarn CV).

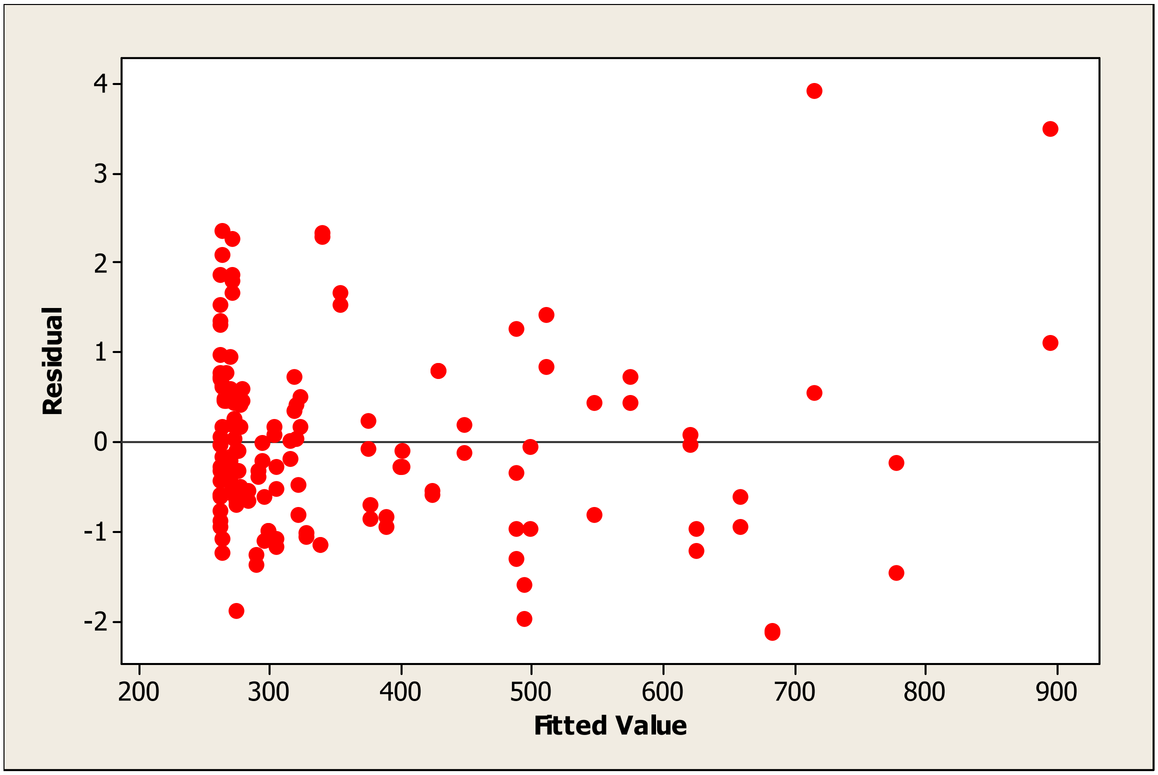

Figure 3. Residuals versus the fitted values (response is neps).

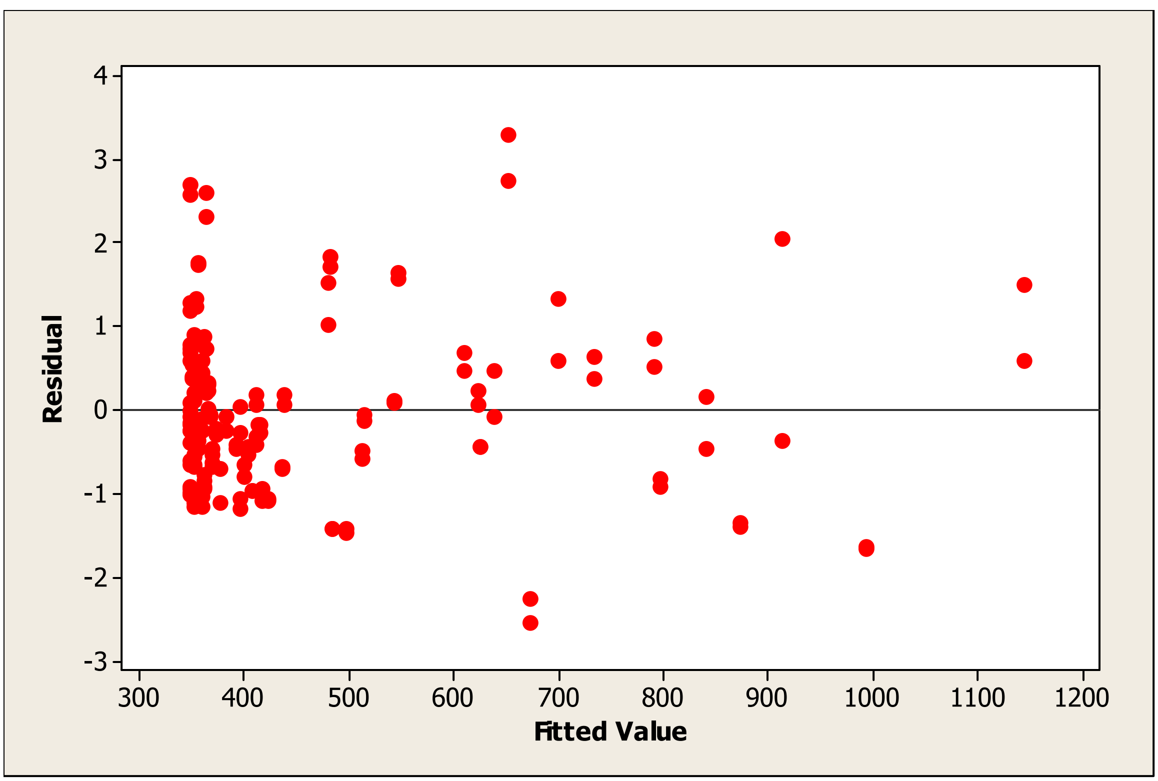

Figure 4. Residuals versus the fitted values (response is thick).

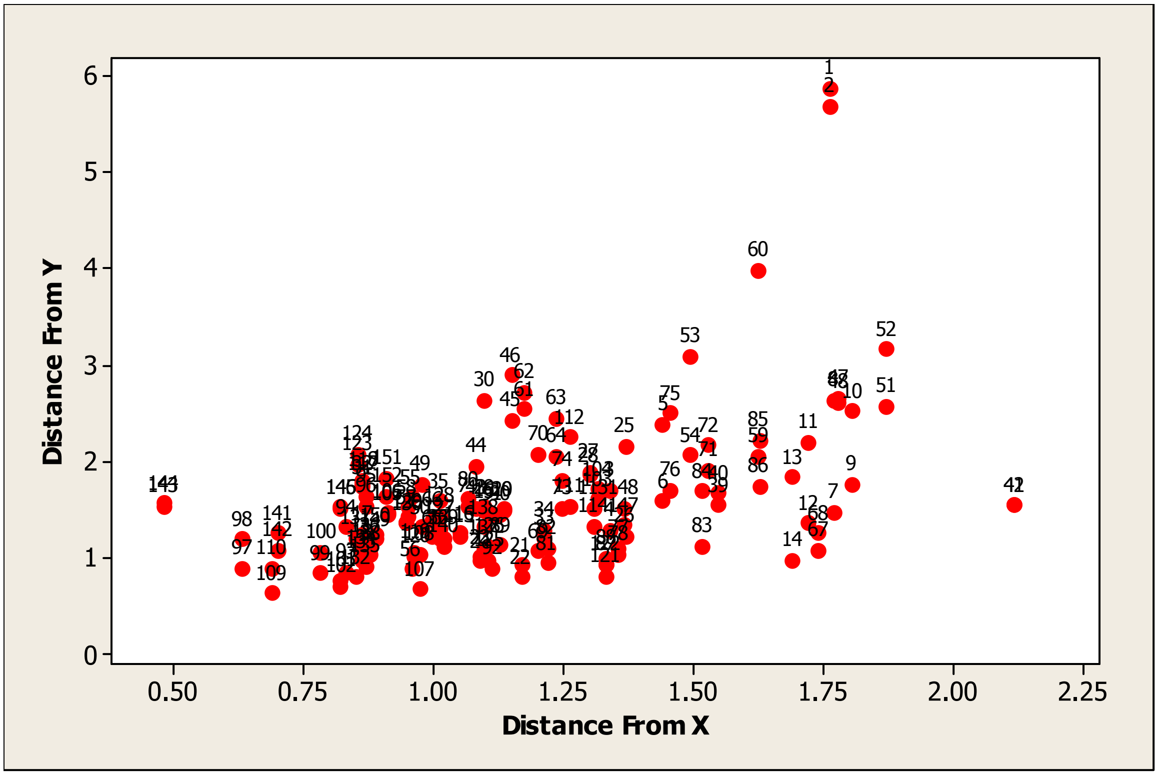

Figure 5. PLS distance plot with 8 components.

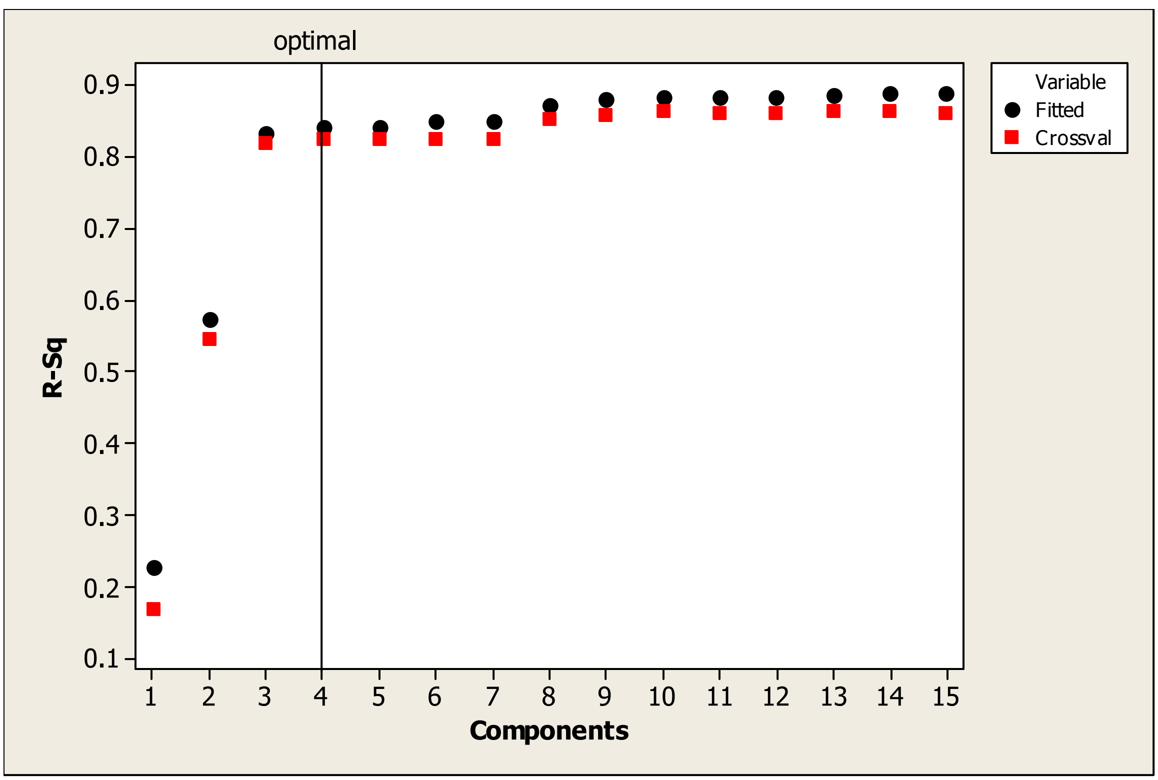

Figure 6. PLS model selection plot (response is Statimat strength).

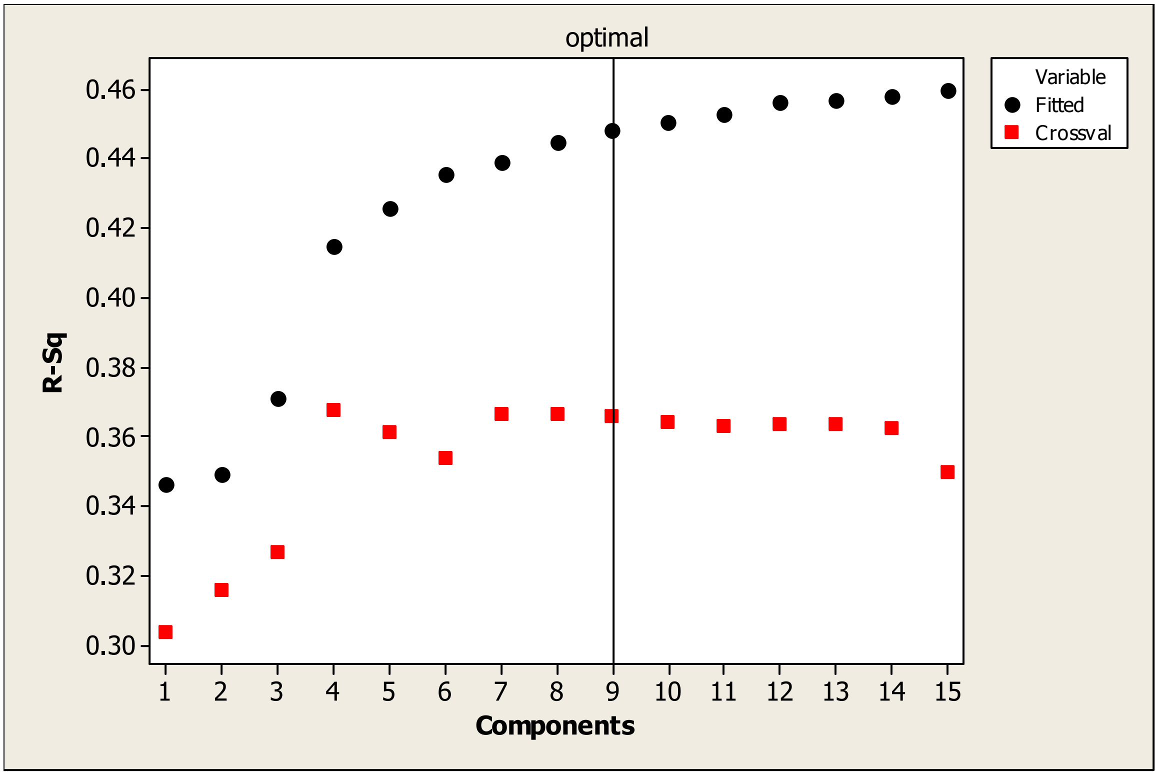

Figure 7. PLS model selection plot (response is long thin).

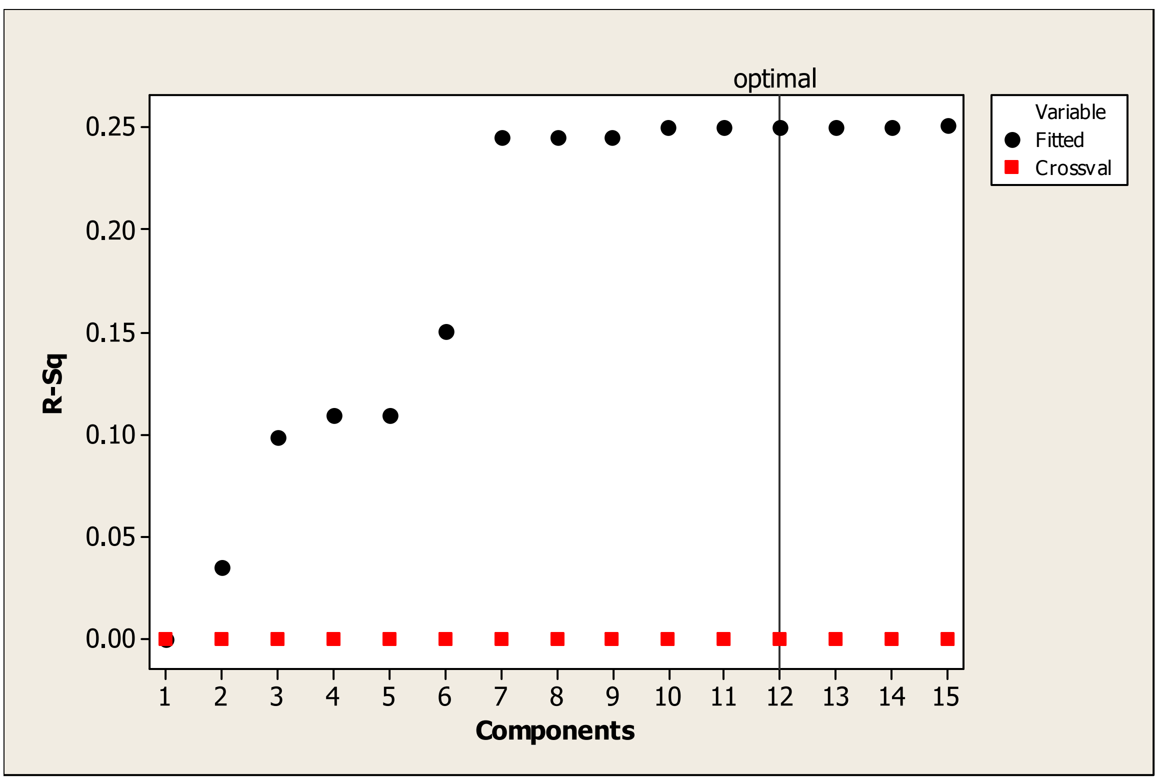

Figure 8. PLS Model selection plot (response is long thick).

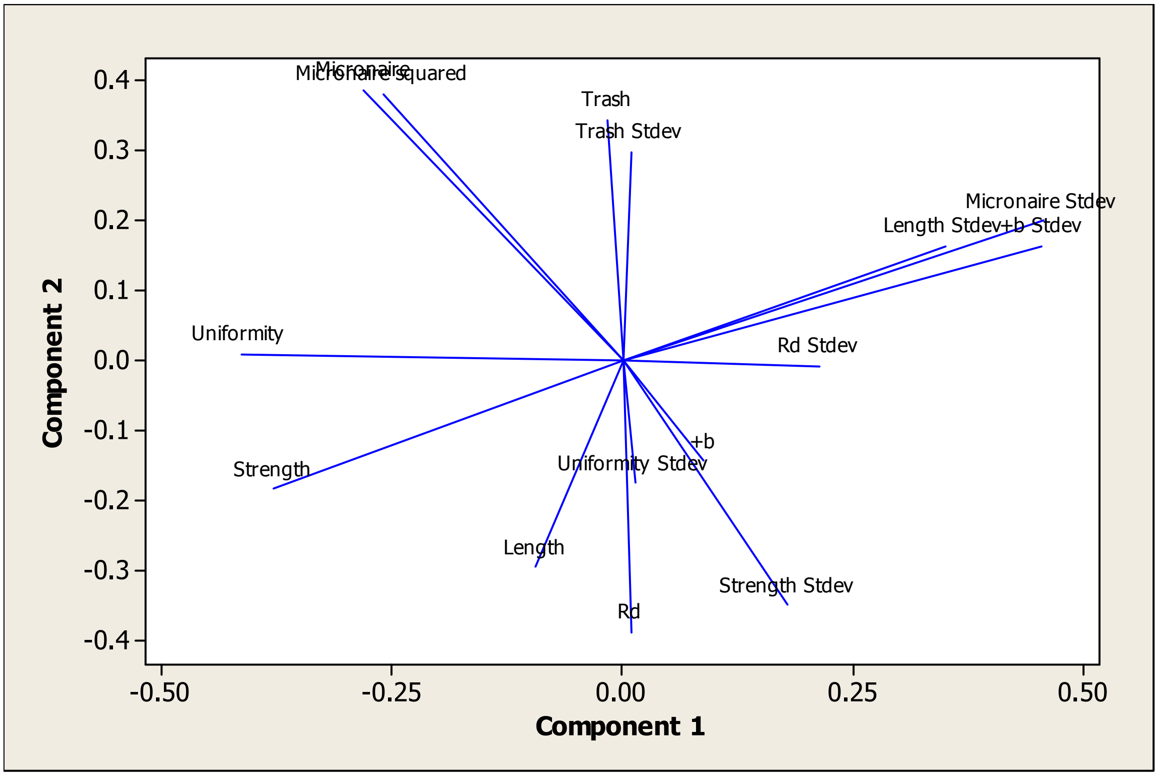

Figure 9. PLS loading plot using HVI variables.

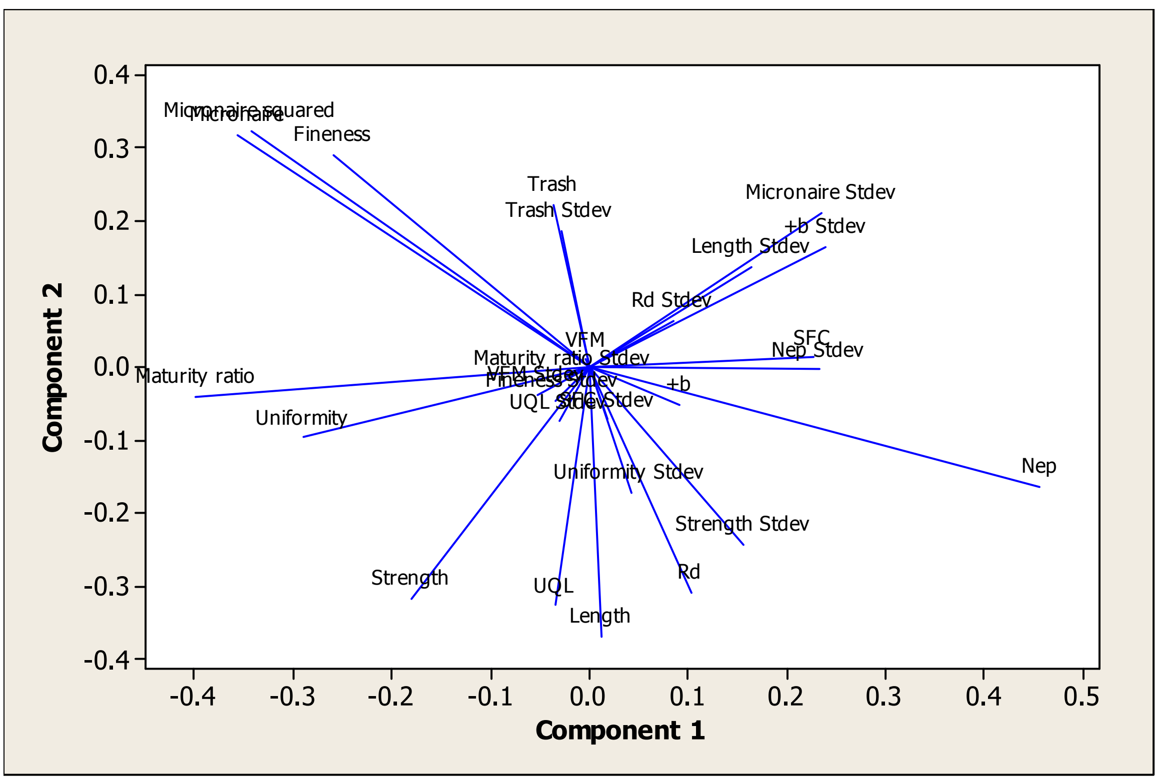

Figure 10. PLS loading plot using HVI and AFIS variables.