Application of a Multivariate Analysis (Biplot) Method to a Comparative Study of Fabric Characteristics

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Abstract: **A wide range of fabric groups were subjected to different treatments viz., heat setting, alkaline oxidation, alkaline hydrolysis etc., The fabrics were tested for KES.F data. Biplot clearly distinguished the group of fabrics (in clusters) based on their low stress mechanical properties. Complex data related to aesthetic and functional property can be well analysed by Biplot.**

I. INTRODUCTION

In the field of research, there exist no occasion in which the results are analysed without the use of statistics. Specially the case studies undertaken in various corners of the world in the field of Textile manufacture, application of Advanced Statistical techniques has acclaimed popularity. Most of the statistical techniques analyse the effect of variables in the process considered. The statistical technique which simultaneously analyse more than two variables on a sample of observations can be categorized as multivariate techniques. Multivariate analysis is a collection of methods for analyzing the data in which a number of observations are available for each object.Multivariate techniques are largely emperical and deal with reality; they possess the ability to analyse complex data.The basic objective underlying in multivariate techniques is to represent a collection of massive data in a simplified way. In other words these technique transform a mass of observations into a smaller number of composite scores in such a way that they reflect as much information as possible contained in the new data. Mathematically, multivariate techniques involves “forming a linear composite vector in a vector sub space which can be represented in terms of projection of a vector to certain specified sub spaces”. Many variables (viz., Explanatory variables, criterion variables; latent variable, pseudo variable etc.,) are used in multivariate analysis. Multiple regression, multiple discriminant analysis, multi variate analysis of variance, canonical correlation analysis, factor analysis and principle components method of factors analysis are the various techniques grouped under multivariate analysis. This paper deals with application of Biplot a group of mechanical properties of 37 fabrics which were subjected to surface modification by alkaline hydrolysis.

II. EXPERIMENTAL

Materials:

The details of the materials selected for the study are given in the Tables(1-4). All the chemicals used were of reagent grade and were used without further purification.

Methods:

Spinfinish removal

In all the cases polyester substracts were immersed in fresh iso propylene alcohol at room temperature for about 15 minutes and then washed with soap solution at 80^{o}C for 20 minutes, to remove the spinfinish. After the final hot and cold wash with water, the specimens were dried and conditioned for the experimental use.

Table 5 show the particulars of the treatment given to the set of 37 fabrics considered for the study.

Testing:

Low stress mechanical properties of the treated samples were measured on KES-F system. Table 6 shows the mechanical properties (KES-F data) of fabrics considered for multivariate analysis study (BIPLOT).

III. APPLICATION OF BIPLOT TO KES-F DATA

About Biplot:

A Biplot [Gabriel (1971) and 1980)] is a graphical representation of the rows and columns of a data set X. The prefix “bi” in “Biplot” refers to the joint representation of the rows and columns of the matrix X, and not to the fact that the visual representation is of a two dimensional nature. The columns of such a data set X, represent variables and the rows represent cases (e.g. individuals). A data set or data matrix can be written symbolically as follows:

Variables

$$\begin{array}{ccccc} & \mathbf{X_1} & \mathbf{X_2} & \mathbf{X_p} & \textbf{Cases} \\ X = & \begin{vmatrix} X_{11} & X_{12} & X_{1p} \\ X_{21} & X_{22} & X_{2p} \\ . & . & . \\ X_{n1} & X_{n2} & X_{np} \end{vmatrix} & & \ldots\ldots\ldots & \begin{matrix} 1 \\ 2 \\ . \\ n \end{matrix} \end{array}$$

In the above notation, X_{21} for instance indicates the outcome of variable in respect of the second case.

Assume that $l_1, l_2, \ldots\ldots l_p$ are the eigen values (eigen roots) of X and that $l_1 \geq l_2 \ldots \geq l_p$. assume further that $U_1, U_2 .. U_n$ and V_1, V_2, V_p are respectively the left and right eigen vectors of X. By means of the so called singular value factorization of a rectangular matrix, it now approximately holds that

$$X = X_{(2)} \begin{vmatrix} U_{11} & l_1^k & U_{12} & l^k{}_2 \\ U_{21} & l_1^k & U_{22} & l^k{}_2 \\ . & . & . & . \\ U_{n1} & l_1^k & U_{n2} & l^k{}_2 \end{vmatrix} \ldots\ldots\ldots \begin{bmatrix} V_{11} l_1^{1-K}, V_{21} l_1^{1-k} \ldots V_{p1} l_1^{1-k} \\ V_{12} l_2^{1-k}, V_{22} l_2^{1-k} \ldots V_{p2} l_2^{1-k} \end{bmatrix}$$

$= AB^1$ where by $0 \leq K \leq 1$.

The above approximation is known as the rank two approximation of X and usually is satisfactory if $l_3, l_4, \ldots l_p$ are small in relation to l_1 and l_2. Similarly higher rank approximations can be obtained by including additional columns and rows for the matrices A and B respectively.

The corresponding elements of the first and second columns of the matrix A are the co-ordinates for plotting the n cases. Similarly the corresponding elements of the first and second rows of B^1 are the co-ordinates for plotting the p variables. The values l^{1-k} and $l^{1-k}{}_2$ determine the length of the axes.A measure of how satisfactorily $X_{(2)}$ approximates the original matrix X is given by the following goodness of fit criterion.

$$\frac{l_1 + l_2}{l_1 + l_2 + \ldots\ldots\ldots + l_p} \quad \ldots\ldots\ldots (1)$$

From the expression of $X_{(2)}$ and the above formula it follows that

$X_{(2)} = X$ if $l_3 = l_4 = \ldots\ldots = l_p = 0$

A biplot is usally obtained from the matrix Y with the elements of Y equalling the deviations of the original observations from the corresponding means.

$$Y = \begin{matrix} X_{11} - \hat{X}_1 & X_{12} - \hat{X}_2 & \ldots & X_{lp} - X_p \\ X_{21} - \hat{X}_1 & X_{22} - \hat{X}_2 & \ldots & X_{2p} - X_p \\ .. & .. & \ldots & .. \\ X_{n1} - \hat{X}_1 & X_{n2} - \hat{X}_2 & \ldots & X_{np} - X_p \end{matrix}$$

If a Biplot is made of rows and columns jointly, k = ½ is chosen, whereas k=0 is usually chosen if only the columns (variables) are represented Fig.1 illustrates a Biplot in respect of four imaginary variables.If k=0, the lengths OX_1, OX_2 etc., represent the standard deviations of the corresponding variables. The correlation between any two variables X_1 and X_j is the cosine of the angle between the lines OX_1 & OX_j. From the fig.1, for instance, it follows that the standard deviation of X_4 is considerably smaller than that of X_1 or X_3. The correlation between X_1 and X_2 is approximately the cosine of 90^o ie., 0. On the same basis it follows that $r_{x1.x3}$ = Cos 30^o = 0.87 and

$r_{x2.x4}$= Cos 190^o = -0.99

Therefore, the variables X_1 and X_2 are uncorrelated but there is a high degree of correlation between X_1 and X_3 and between X_2 and X_4. Bishop and Cox(1994) have utilized the data provided by Gong and Mukhopadhyay (1993), and by means of a Biplot, have made a comparative study of the various fabric groups and fabrics. Earlier this analysis was used by Mackay (1992) for investigating the effect of laundering on the sensory, and mechanical properties of 1x1 Rib knit weaker fabrics; this technique it is claimed, gives an overview of a very large and complex data set without discarding any of the data, and is a powerful means of communicating complex relationships between the mechanical and sensory properties of fabrics and is particularly appropriate for visualising audiences in the fashion and retail industries. There is some resemblance between Biplot and snake diagram suggested by Kawabata as, in both the cases, the normalised values are used.

IV. BIPLOT MODEL (APPLICATION)

In Biplot (Figure. 1), the samples are represented by points, and the properties by vectors by way of row column plottings. The distance of the samples from the vectors (extrapolated) will determine the nature of impact of the sample on the property.In order to produce this model, the data were normalised to a near of zero and a standard deviation of one so that the full ranges of all measured properties are represented by vectors of equal length. The normalized data were then processed using a Biplot (1971) macro given in the SAS system for statistical graphics (1991).

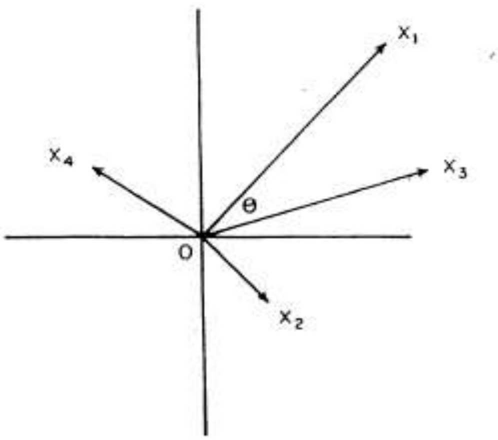

Fig. 1 Principle of Biplot

Materials

The materials selected for the study is shown in Table 1.

TABLE 1DETAILS OF FABRIC SAMPLE (NUMBER AND CODE) USED FOR THE STUDY

Sample No.	Code	Material	Treatment detail
1	a	100% PET dress material	Control WR (unset)
2	a_1	100% PET dress material	Heat set at 160°C and WR
3	a_2	100% PET dress material	Heat set at 170°C and WR
4	a_3	100% PET dress material	Heat set at 180°C and WR
5	a_4	100% PET dress material	Heat set at 190°C and WR
6	a_5	100% PET dress material	WR with Bath ratio 1:3
7	a_6	100% PET dress material	WR with Bath ratio 1:10
8	a_7	100% PET dress material	WR with Bath ratio 1:20
9	a_8	100% PET dress material	WR with Bath ratio 1:30
10	a_9	100% PET dress material	WR with Bath ratio 1:40
11	b	100% PET micro-chiffon	Control WR (unset)
12	b_1	100% PET micro-chiffon	Heat set at 160°C and WR
13	b_2	100% PET micro-chiffon	Heat set at 170°C and WR
14	b_3	100% PET micro-chiffon	Heat set at 180°C and WR
15	b_4	100% PET micro-chiffon	Heat set at 190°C and WR
16	b_5	100% PET micro-chiffon	WR with Bath ratio 1:3
17	b_6	100% PET micro-chiffon	WR with Bath ratio 1:10
18	b_7	100% PET micro-chiffon	WR with Bath ratio 1:20
19	b_8	100% PET micro-chiffon	WR with Bath ratio 1:30
20	b_9	100% PET micro-chiffon	WR with Bath ratio 1:40
21	c_1	100% PET control sample b	Boiling water shrinkage and WR
22	c_2	100% PET control sample b	Only boiling water shrinkage
23	d_1	100% PET control sample a	Control (unset) RH
24	d_2	100% PET control sample a	Heat set at 180°C and RH
25	d_3	100% PET control sample a	Heat set at 190°C and RH
26	d_4	67/33 (P/C W_p X P/C W_f)	Control untreated
27	e	67/33(P/C W_p X P/C W_f)	Treated (AO)
28	f	67/33 (P/C W_p X Fil.W_f)	Control
29	g	67/33 (P/C W_p X Fil.W_f)	Treated (AO)
30	h	100% PET control sample a	WR with 5% EDA
31	i	100% PET control sample a	WR with 10% EDA
32	j	100% PET control sample b	WR with 5% EDA
33	k	100% PET control sample b	WR with 10% EDA
34	l	Jute/Polyester	Control (13 picks/cm)
35	m	Jute/Polyester	WR
36	n	Jute/Polyester	Control (16 picks/cm)
37	o	Jute/Polyester	WR

- WR - Weight Reduction ,AO - Alkaline Oxidation ,RH - Repeated Hydrolysis

All the materials were in grey state and were treated with NaoH for finishing .

In Figure.3 the fabrics are identified by individual numbers from 1 to 37 corresponding to their order (Table 6 to 9).The first and third dimensions indicated in Fig.2 & 3 account for a total of 40% of the variance of the data, and the second and fourth dimensions cover 60% of the variance of the data; this provides an adequate overview of the data. The disposition of the vectors is characteristic of these data. The correlation between any two vectors is represented by the cosine of the angle between them Table 10 gives the correlation co-efficients. For example, there exists a high and positive correlation between G, 2HG, 2HG5, B and 2HB. The correlation between MIU and WC is very poor as the value of cos θ is low θ. Where as RC & LC are highly correlated. Thickness (T_o) and Weight (W) are highly correlated, and this is a phenomenon which has been noticed by Gong and Mukhopadhyay (1993). In fact

they have divided SMD by thickness in order to compare the different fabrics. B and W are also well correlated, and this again is well known.LC & RT are also well correlated as is evident from the Biplot. B is uncorrelated with RC & WC. Fabric properties such as WC, RC, LT & RT are found to be poorly correlated among themselves.The positions of individual fabrics on the model are determined by their KES values. The relative sizes of these values for individual fabrics may be estimated by the positions of the perpendicular drawn from the fabric points onto the appropriate vector or its extrapolation. Fabric samples which are included in quadrant 1 generally have higher values compared to quadrant 2. In fact this is found to be the case in fabric samples 21,22,34,35,36 and 37. Samples 3,4,5,6,7,8,9,10, 12,13, 15,16,17,18,19,20,24,25,26,30,32 and 33 are found in the fourth quadrant. Fabric sample 27 has a higher G value whereas fabrics 23,2829 have a lower value.

V. FABRIC COMPARISONS

Using the above guidelines, it will be apparent that fabrics appearing close together in the model will have similar mechanical and hand profiles. Viewing the model in two dimensions may, however, slightly distort their true positions in space. It is interesting to note that fabric sample 23,27,28 and 29 are spread over and have not formed into a particular group; the same observation is made for fabric samples woven with Jute and polyester yarns. Fabric samples of a,b,d,j,i and k are characterised by higher RC,LC & RT values. Similarly e,g,f are showing higher shear and bending rigidity values.

VI. CONCLUSIONS

The foregoing discussion illustrates the value of this multivariate analysis method in giving an overview of a large and complex data set without discarding and averaging any of the data. Looking at a glance, many conclusions can be drawn on fabric samples, and it is possible to categorise them on the basis of their low stress mechanical properties.

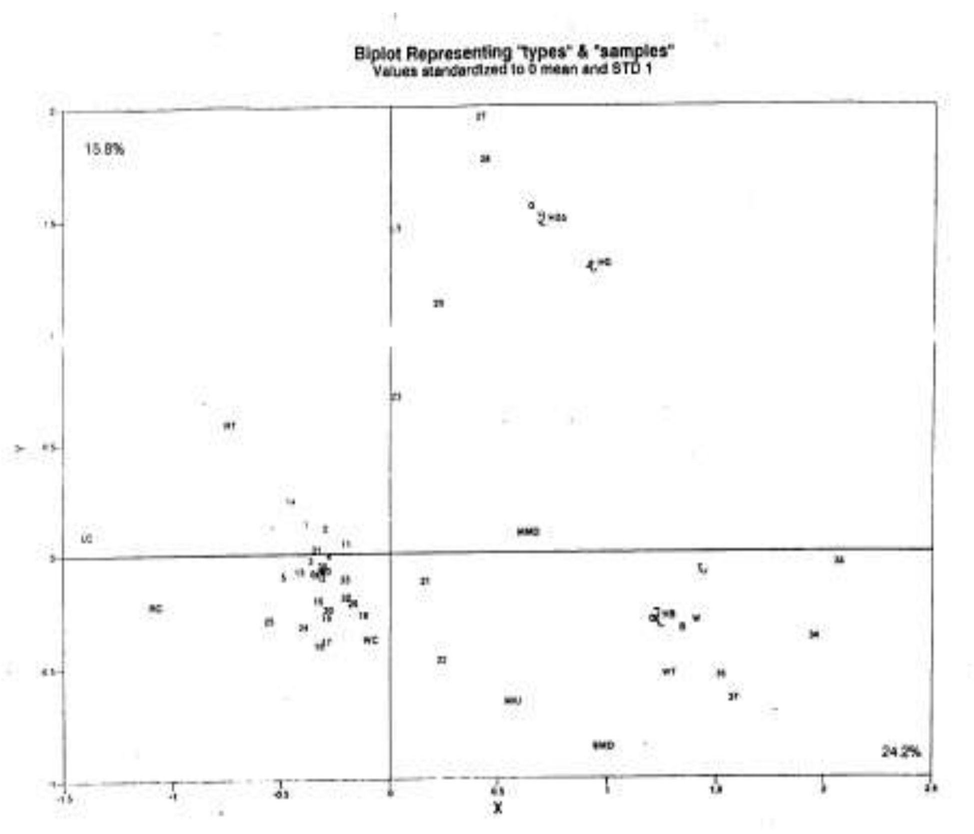

Figure 2. Biplot with individual fabric number and samples

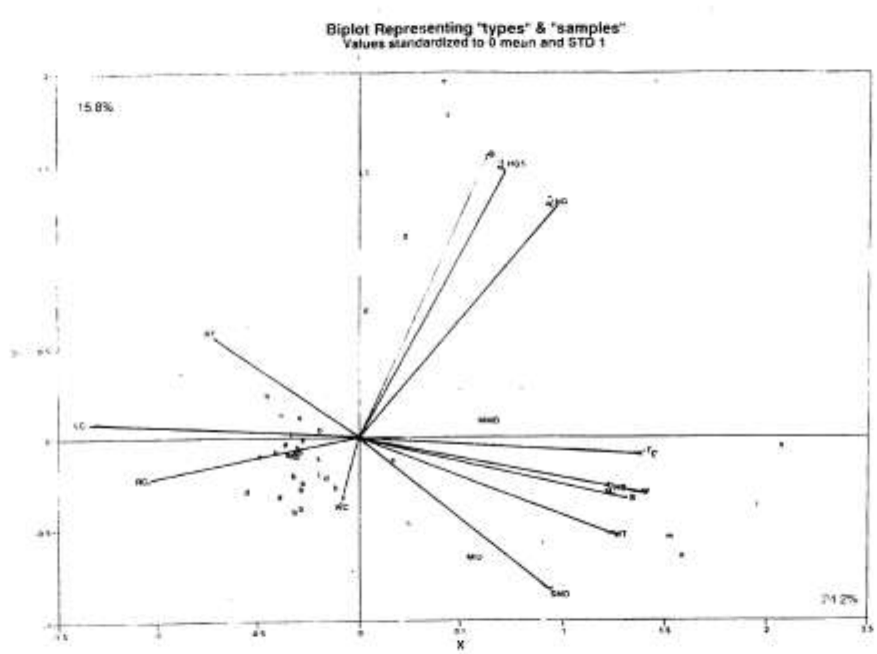

Figure 3 . Biplot with KES-F data for fabric samples