CHAPTER 13

APPLICATION OF FACTOR ANALYSIS TO STUDY THE MECHANICAL PROPERTIES OF POLYESTER FABRICS

13.1 INTRODUCTION

This chapter is concerned with the application of factor analysis to analyse the mechanical properties of polyester fabrics.

13.2 MATERIALS AND METHODS

A total of 33 samples has been considered, details of which are given in Chapter 4.

KES-F was used for the determination of mechanical properties.

13.3 FACTOR ANALYSIS TECHNIQUE

Factor analysis is concerned with the identification of structure within a set of observed variables. It attempts to simplify the complex and diverse relationship that exists amongst a set of observed variables by uncovering common factors that link together seemingly unrelated variables. Thus, the confirmatory model of the factor analysis technique used in this investigation is a study of interrelationships among the variables which express what is common among the variables.
13.4 THE USE OF MULTIPLE FACTOR ANALYSIS

Howorth and Oliver (1958) Brown (1969) and recently Vinzanekar et al (1996) have applied this technique to a variety of problems. It is interesting to see that Howorth and Oliver (1958) and Brown (1969) have quoted the example of Thurstone (1947) in their work to demonstrate the principles of this method. Brown (1969) used the factor analysis method since he felt that this was considered to be most suitable. Howorth and Oliver (1958) rejected regression analysis as a method of analysing handle results because of their complexity and they suggested that multiple factor analysis which had previously been used for similar problems involving the testing of cheese, plastics and wire was more appropriate. Factor analysis (FA) has been mainly used in intelligence tests, and there exists some controversial views about this technique. Factor analysis has somewhat similar aims to principal component analysis (PCA) in that it is a variable directed technique which is appropriate when the variables arise 'on an equal footing'. The idea is to derive new variables called factors which will hopefully give us a better understanding of the data. But whereas PCA produces an orthogonal transformation of the variables which depends on no underlying model, FA is leased on a proper statistical model, and is more commenced with explaining the covariance of structure of the variable than with explaining the variances. Pan et al., (1993) have used PCA for obtaining new variables by condensing the original data of the sixteen mechanical properties.

There is a paper by Swarn et al., (1986) on the classification of fabrics on the basis of their mechanical properties by using factors; this work has been preferred by Leaf and Loyd (1993).
13.5 THE FACTOR - ANALYSIS MODEL

Suppose we make observations on P variables, $X_1, X_2, ..., X_p$, which have mean vector $\mu$ and covariance matrix $\Sigma$. As we are interested in explaining the covariances structure of the variables we may without loss of generality assume that $\mu = 0$. It will be also convenient to assume that $\Sigma$ is of full rank $p$.

The FA model assumes that there are $m$ underlying factors (where $m < p$) which are denote by $f_1, f_2, ..., f_m$ and that each observed variable is a linear function of these factors together with a residual variate, so that

$$X_j = \lambda_{j1} f_1 + ... + \lambda_{jm} f_m + e_j \quad j = 1, ..., p. \quad \text{(13.1)}$$

In the above equation, the weights $\{\lambda_{jk}\}$ are usually called the factor loadings, so that $\lambda_{jk}$ is the loading of the $j$th variable on the $k$th factor. The variate $e_j$ describes the residual variation specific to the $j$th variable. For obvious reasons, for factors $\{f_j\}$ are often called the common factors, while the residual variates $\{e_j\}$ are often called the specific factors.

The factor analyst usually makes a number of assumptions about model (13.1). The specific factors are assumed to be independent of one another and of the common factors. It is also usually assumed that the common factors are independent of one another, though this assumption is sometimes relaxed when the factors are later rotated. As we have assumed the $X$'s to have zero mean, it is also convenient to assume that the factors all have zero mean. Looking at equation (13.1) we see that there is an arbitrary scale factor related to each common factor and so it is customary to choose the common factors so that each has unit variance. But the variances of the specific factors may vary, and we denote the variance of $e_j$ by $\psi_j$. 
It is also customary to assume that the common factors and the specific factors each have a multivariate normal distribution. This implies that \( X \) is also multivariate normal, where

\[
X^T = [X_1, X_2, ..., X_p] \quad \text{...(13.2)}
\]

Equation (13.2) describes a relationship between random variables. With actual observations, we write

\[
X_{rj} = \text{rth observation on variable } j
\]

\[
= \sum_{k=1}^{m} \lambda_{jk} f_{rk} + e_{rj} \quad \text{...(13.3)}
\]

Where \( f_{rk} \) is the \( k^{th} \) common factor for the \( r^{th} \) observation and \( e_{rj} \) is the value of the \( j^{th} \) specific factor for the \( r^{th} \) observation.

The model (13.1) is usually written in matrix notation in the form

\[
X = \Lambda f + e \quad \text{...(13.4)}
\]

where \( f^T = [f_1, f_2, ..., f_m] \)

\( e^T = [e_1, e_2, ..., e_p] \)

and \( \Lambda = \begin{bmatrix} 
\lambda_{11} & \lambda_{12} & \cdots & \lambda_{1m} \\
\lambda_{21} & \lambda_{22} & \cdots & \lambda_{2m} \\
\vdots & \vdots & \ddots & \vdots \\
\lambda_{p1} & \cdots & \cdots & \lambda_{pm} 
\end{bmatrix} \)

Here \( \Lambda \) is of order \((p \times m)\) and should not be confused with the diagonal matrix of eigenvalues.

From equation (13.4), using the independence of different factors, we have
\[
\text{Var}(X_j) = \lambda_{j1}^2 + \lambda_{j2}^2 + \ldots + \lambda_{jm}^2 + \text{Var}(e_j)
\]
\[
= \sum_{k=1}^{m} \lambda_{jk}^2 + \psi_j
\]
since the common factors have unit variance. The part of the variance explained by the common factors namely
\[
\left( \sum_{k=1}^{m} \lambda_{jk}^2 \right)
\]
is called the communality of the \(j\)th variable. From equation (13.4) we also find
\[
\text{Cov}(X_i, X_j) = \sum_{k=1}^{m} \lambda_{ik} \lambda_{jk}
\]
Thus the covariance matrix of \(X\), which we denote as usual by \(\Sigma\), is given by
\[
\Sigma = \Lambda \Lambda^T + \Psi
\]
where \(\Psi = \begin{bmatrix}
\psi_1 & 0 & \ldots & 0 \\
0 & \psi_2 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & \psi_p
\end{bmatrix}
\]
Equation \(\Sigma = \Lambda \Lambda^T + \Psi\) is of crucial importance in FA. It demonstrates that the factors 'explain' the off-diagonal terms of \(\Sigma\) (namely the covariances) exactly, since \(\Psi\) is diagonal. It also establishes that finding the factor loadings is essentially equivalent to factorizing the covariance matrix of \(X\) in this particular way, with the added condition that the diagonal elements of \(\Psi\) must be non-negative.

The total number of parameters we have to estimate is the number of factor loading, namely \(pm\), plus the number of communal variances.
namely p. Now there are \( \frac{1}{2}(p(p+1)) \) separate variances, and covariances in \( \Sigma \), so that, equating corresponding elements of the matrices on both sides of equation \( \Sigma = \Lambda \Lambda^T + \Psi \)

\[
\begin{bmatrix}
\Psi_1 & 0 & \cdots & 0 \\
0 & \Psi_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \Psi_p
\end{bmatrix}
\]

we have \( \frac{1}{2}p(p+1) \) equations. We generally require the number of parameters to be less than the number of equations, so that \( (pm+p) < \frac{1}{2}p(p+1) \) or \( m < \frac{1}{2}((p-1) \). In other words, \( m \) should be fairly small compared with \( p \).

Consider the case \( m = 1 \). Then is \( \Lambda \) a \( (p \times 1) \) column vector, where \( \Lambda^T = (\lambda_{11}, \lambda_{21}, \ldots, \lambda_{p1}) \). Then equation \( \Lambda \) implies that the off-diagonal terms of \( \Sigma \) must be of the form

\[
\begin{bmatrix}
- & \lambda_{11} & \lambda_{12} & \cdots & \lambda_{11} & \lambda_{p1} \\
\lambda_{21} & - & \lambda_{12} & \cdots & \lambda_{21} & \lambda_{p1} \\
\vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\
\lambda_{p1} & \lambda_{11} & \cdots & - & \lambda_{p1}
\end{bmatrix}
\]

If a solution does exist in the case \( m=1 \), then it will usually, though not always, be unique. But if \( m > 1 \) and a solution exists, then it is easy to show that the solution is not unique.
13.6 ESTIMATING THE FACTOR LOADINGS

The parameters of the FA model, including the factor loadings and
the error variances, are nearly always unknown and need to be estimated
from the sample data. The sample covariance matrix is occasionally used,
but it is much more common to work, with the sample correlation matrix.
Then the X-variables in equations (13.1) and (13.2) refer to scaled variables
having zero mean and unit variance. It then follows from equation (13.5)
that

\[ \Sigma = \sum_{k=1}^{m} \lambda_{jk}^2 + \Psi_j \] ....(13.6)

In the early days of factor analysis, a variety of iterative methods
were used to estimate the factor loadings. These involved subjective
judgement, such as guessing the communalities, with the result that
different researchers could analyse the same data and find entirely different
factors. One popular method was the principal - factor method. This chooses
the first factor so as to account for as much as possible of the communal
variance, the second factor to account for as much as possible of the
remaining communal variance, and so on. The method requires suitable
estimates of the communalities. If they are chosen to be unity, then the
method reduces to principal component analysis. In particular if we choose
to fit a one - factor model by minimizing the total residual sum of squares,
then the first factor turns out to be the first principal component of the
data.

13.7 VARIMAX METHOD

When a set of factors has been derived they are not always easy to
interpret. Since the original loadings may not be readily interpretable, it is
usual practice to rotate them until a "Simpler strucure" is achieved. The
rationale is very much akin to sharpening the focus of a microscope in order to see the detail more clearly.

Various methods have been proposed for rotating the factors to find new ones which may be easier to interpret. The usual aim of rotation methods such as the varimax method is to make the loadings large or small so that most variables have a high loading on a small number of factors. Most rotation methods involve an orthogonal rotation but some rotation methods, like the promax method allow the factors to become correlated rather than independent, although this does not necessarily make interpretation easier.

Principal component analyses are performed separately on the fabrics in order to investigate patterns in the mechanical properties. In this type of analysis, a linear transformation is made of a set of data, the data matrix in terms of a new set of variables, called the principal components, such that these principal components are orthogonal. The principal components or factors are typically ordered in terms of the decreasing proportion of the variability in the data matrix which is accounted for by each principal component. Instead of assigning factors of importance in factor analysis, the factors are generated by the use of principal component analysis (PCA).

The value of this type of analysis is dependent on the majority of the variance in the data being accounted for by a small number of truly 'principal' components. If a small number of principal component factors (in relation to the number of original variables), accounts for a large proportion of the variance in the original variables, these components constitute a valid and much simplified description of the variability in the original data i.e. the original data could be expressed as a smaller number of independent factors. The analysis produces a matrix of weightings, called factor scores of each parameter on each of the principal component factors isolated. These
weightings can be interpreted as correlation coefficients between the parameter and the principal component.

Factor analysis is a generic name given to a class of techniques whose purpose is data reduction and summarisation. Very often market researchers are overwhelmed by the plethora of data. Factor analysis does not entail partitioning the data matrix into criterion and predictor subsets; rather interest is centered on relationships involving the whole set of variables. In factor analysis

1. The analyst is interested in examining the "strength" of the overall examination among variables in the sense that he would like to account for this association in terms of a smaller set of linear composites of the original variables that preserve most of the information in the full data set. Often his interest will emphasize description of the data rather than statistical inference.

2. No attempt is made to divide the variables into criterion versus prediction sets.

3. The models are primarily based on linear relationships.

Factor analysis is a "search" technique. The research - decision maker does not typically have a clear prior structure of the number of factors to be identified. Cut off points with respect to stopping rules for the analysis are often adhoc as the output becomes available. Even where the procedures and rules are stipulated in advance, the results are more descriptive than inferential.

The procedure involved in computation of factor analysis is extremely complicated, and cannot be carried out effectively without the help of computer. Packages like SPSS, SAS and Bio-medical programs
(BMD) can be used to analyse various combinations leading to factor reduction.

The term "factor analysis" embraces a variety of techniques. Our discussion focusses on one procedure principal component analysis and the factors derived, from the analysis are expressed as linear equations. These linear equations are of the form

\[ F_i = a_{i1}X_1 + a_{i2}X_2 + a_{i3}X_3 + \ldots + a_{im}X_m \] \hspace{1cm} (13.7)

The \( i \) factors are derived, and each variable appears in each equation. The \( a_k \) coefficient indicate the importance of each variable with respect to a particular factor. Coefficient of zero indicating the variable is of no significance for the factor. In principal component analysis, the factors are derived sequentially, using criteria of maximum reduction in variance and non-correlation among actors. The correlation coefficient between the mechanical properties of the fabrics used are given in the table 13.1.

13.8 ESTIMATED FACTOR LOADING

The coefficients in the factor equations are called "factor loadings"; they appear in each variable. The equations are:

\[
F_1 = 0.9227X_1 + 0.8867X_2 + 0.9640X_3 + 0.9469X_4 \\
- 0.6131X_5 + 0.6540X_6 - 0.0116X_7 + 0.2641X_8 \\
- 0.5728X_9 + 0.2934X_{10} - 0.5196X_{11} + 0.7572X_{12} \\
+ 0.4650X_{13} - 0.0938X_{14} - 0.1773X_{15} + 0.8015X_{16} \quad \ldots \text{ (13.8)}
\]

\[
F_2 = 0.2141X_1 + 0.1452X_2 + 0.1145X_3 + 0.1587X_4 \\
+ 0.4749X_5 + 0.2996X_6 - 0.6537X_7 - 0.1411X_8 \\
+ 0.6646X_9 + 0.4198X_{10} + 0.2503X_{11} - 0.3385X_{12} \\
- 0.3301X_{13} - 0.7401X_{14} - 0.3662X_{15} + 0.4284X_{16} \quad \ldots \text{ (13.9)}
\]
\[ F_3 = 0.1093 X_1 - 0.1683 X_2 + 0.0793 X_3 + 0.0922 X_4 \\
+ 0.2795 X_5 + 0.3674 X_6 - 0.5585 X_7 - 0.3853 X_8 \\
+ 0.1551 X_9 + 0.0263 X_{10} - 0.512 X_{11} + 0.0537 X_{12} \\
+ 0.7351 X_{13} + 0.1164 X_{14} + 0.8470 X_{15} - 0.3013 X_{16} \]  \[ (13.10) \]

\[ F_4 = 0.1305 X_1 - 0.2900 X_2 + 0.1088 X_3 + 0.1511 X_4 \\
+ 0.0517 X_5 - 0.1336 X_6 + 0.2814 X_7 - 0.0698 X_8 \\
+ 0.1531 X_9 + 0.8249 X_{10} - 0.2217 X_{11} - 0.0137 X_{12} \\
- 0.1120 X_{13} + 0.4003 X_{14} + 0.1349 X_{15} + 0.1838 X_{16} \]  \[ (13.11) \]

\[ F_5 = 0.0122 X_1 - 0.1144 X_2 + 0.0206 X_3 + 0.0016 X_4 \\
+ 0.1335 X_5 - 0.1707 X_6 - 0.0119 X_7 + 0.7215 X_8 \\
+ 0.0432 X_9 + 0.0416 X_{10} - 0.4210 X_{11} - 0.3033 X_{12} \\
+ 0.1978 X_{13} - 0.2641 X_{14} + 0.1618 X_{15} - 0.0869 X_{16} \]  \[ (13.12) \]

\[ F_6 = -0.0443 X_1 - 0.0114 X_2 - 0.0252 X_3 - 0.0274 X_4 \\
+ 0.0138 X_5 + 0.2278 X_6 - 0.0118 X_7 + 0.4595 X_8 \\
- 0.0537 X_9 + 0.1965 X_{10} + 0.5582 X_{11} + 0.1985 X_{12} \\
+ 0.0002 X_{13} + 0.0921 X_{14} + 0.1107 X_{15} - 0.0233 X_{16} \]  \[ (13.13) \]

\[ F_7 = 0.1613 X_1 + 0.1056 X_2 + 0.1171 X_3 + 0.1379 X_4 \\
+ 0.4836 X_5 - 0.2321 X_6 + 0.1657 X_7 + 0.0635 X_8 \\
+ 0.2469 X_9 - 0.2878 X_{10} + 0.1264 X_{11} + 0.0822 X_{12} \\
+ 0.0796 X_{13} + 0.2743 X_{14} - 0.0604 X_{15} + 0.0749 X_{16} \]  \[ (13.14) \]

\[ F_8 = 0.1334 X_1 + 0.0076 X_2 + 0.0307 X_3 + 0.1357 X_4 \\
- 0.1102 X_5 - 0.3282 X_6 + 0.1316 X_7 - 0.1220 X_8 \\
- 0.1720 X_9 + 0.0587 X_{10} + 0.3306 X_{11} - 0.2664 X_{12} \\
- 0.2099 X_{13} - 0.2120 X_{14} + 0.1223 X_{15} + 0.0902 X_{16} \]  \[ (13.15) \]

The factor loadings depict the relative importance of each variable with respect to a particular factor. In above first, third and fourth equations, G,
2HG, 2HG5 and W have got positive loading factor indicating that they are variable of importance in determining the mechanical properties.

13.9 VARIANCE SUMMARISED

Factor analysis employs the criterion of maximum reduction of variance found in the initial set of variables. Each factor contributes to reduction. Factor 1 accounts for 40.1% of the total variance. Factor 2 for 16.5% and factor 3 for 13.3%. Factor 4 accounts for 7.6% and factor 5 for 6.2, factor 6 for 4.3%, factor 7 accounts for 4.0% and factor 8 for 3.2% respectively. All the eight factors explain almost 95% of the variance.

In factor loading 1, G, HB, 2HG, 2HG5, LT, MMD, T and B play a dominant role. RC, LC, LT and B play a vital role in factor 2, W, WT and T are the variables which are found to play a key role in factor 3, RT and WC in factor 4, MMD in factor 5, SMD in factor 6, LC in factor 7 and SMD in factor 8. In the equations (13.8, 13.10, 13.11) G, 2HG and 2HG5 have positive loading factor indicating that they are variables of importance in determining the handle of fabrics.

The three factors derived from the 16 mechanical properties by a principal component analysis (SAS programs) are presented.

The factor loadings depict the relative importance of each variable with respect to a particular factor. In all the three equations, variable G, 2HG, 2HG5 have positive loading factor indicating that they are variables of importance in determining fabric handle. This demonstrates that shear properties are the most important. For the 33 fabrics used in this work, the results indicate that that bending has almost nothing to do with the evaluation of handle. The mechanism of this needs further research.
13.10 COMMUNALITY

In the ideal solution the factors derived will explain 100% of the variance in each of the original variables that is captured by the combination of factors in the solution. Thus a communality is computed for each of the original variables. Each variable's communality might be thought of as showing the extent to which it is revealed by the system of factors. In this case, the communality is 100% for every variable. Thus the factors seem to capture the underlying dimensions are involved in these variables.

13.11 VARIMAX ROTATION TECHNIQUE

The effective dimension of the matrix can be determined by extracting the first eight principal components, ranked according to their eigenvalues = 6.41, 2.64, 2.12, 1.21, 0.98; 0.68, 0.65 and 0.51 totally accounting for 95.1% of the variance. Accounting for 85% of the variance is considered satisfactory. (Kendall 1975). In other words, the first eight components, represent nearly all the information. It is thus possible to reduce the effective dimension of the variables from sixteen to eight by discarding the other eight principal components with smaller eigenvalues. Then according to the method proposed by Kendall (1975) the parameters, having the largest correlation coefficients with respect to these discarded components, are considered unimportant and can be dropped. In other words, the importance of all sixteen parameters can be determined by their correlation with the ranked principal components.

There is yet another analysis known as variance rotation which has been employed. In this case, the equations are

\[
F_1 = 0.9621 X_1 + 0.8026 X_2 + 0.9193 X_3 + 0.9604 X_4 - 0.2727 X_5 + 0.4915 X_6 - 0.0851 X_7 + 0.1155 X_8
\]
\[
F_2 = -0.1076X_1 - 0.2430X_2 - 0.1615X_3 - 0.1587X_4
+ 0.9072X_5 - 0.0900X_6 - 0.2752X_7 - 0.1063X_8
+ 0.8198X_9 + 0.1372X_{10} + 0.1719X_{11} - 0.3574X_{12}
- 0.1310X_{13} - 0.1281X_{14} - 0.0460X_{15} - 0.1124X_{16}
\quad \ldots \quad (13.17)
\]

\[
F_3 = 0.1032X_1 - 0.1259X_2 + 0.1000X_3 + 0.1122X_4
+ 0.0397X_5 + 0.1230X_6 - 0.1503X_7 - 0.0597X_8
- 0.1317X_9 - 0.0469X_{10} - 0.1102X_{11} + 0.0938X_{12}
+ 0.8618X_{13} + 0.1882X_{14} + 0.9265X_{15} - 0.3430X_{16}
\quad \ldots \quad (13.18)
\]

In all the above two equations, parameters $2HB$, $G$, $2HG$, $LC$, $RC$, $2HG5$, $RT$, $B$, $W$, $WC$ and $WT$ have a positive loading factor indicating that they are variables of importance in determining the mechanical properties. This it may be noted, is greater than that of the earlier case where only $G$, $2HG$ and $2HG5$ were found to have positive loading.

\[
F_4 = 0.0418X_1 - 0.2736X_2 + 0.167X_3 + 0.564X_4
+ 0.0455X_5 + 0.0326X_6 - 0.0297X_7 - 0.0223X_8
+ 0.2169X_9 + 0.9828X_{10} + 0.0025X_{11} - 0.1348X_{12}
- 0.2001X_{13} - 0.0100X_{14} + 0.0956X_{15} + 0.1864X_{16}
\quad \ldots \quad (13.19)
\]

\[
F_5 = -0.0237X_1 - 0.1863X_2 + 0.0314X_3 - 0.0075X_4
- 0.0328X_5 - 0.1000X_6 + 0.2729X_7 - 0.0444X_8
- 0.1693X_9 - 0.0117X_{10} - 0.0510X_{11} + 0.2719X_{12}
+ 0.0321X_{13} + 0.92402X_{14} + 0.1804X_{15} - 0.1260X_{16}
\quad \ldots \quad (13.20)
\]

\[
F_6 = 0.0331X_1 + 0.1454X_2 + 0.0690X_3 + 0.0397X_4
- 0.0505X_5 - 0.0329X_6 + 0.1372X_7 + 0.9759X_8
- 0.1424X_9 - 0.0202X_{10} - 0.0941X_{11} + 0.0329X_{12}
+ 0.0038X_{13} - 0.05526X_{14} - 0.0806X_{15} + 0.0499X_{16}
\quad \ldots \quad (13.21)
\]
The data in Table 13.1 have been analysed and the eight factor solution obtained is shown in table. In an orthogonal matrix the communality = (Factor 1)$^2$ + (Factor 2)$^2$ + (Factor 3)$^2$ + (Factor 4)$^2$ + ... for each test.

It is evident that by considering the eigen values which are $\geq 0.5$, eight factors which account for 95% have been identified. The factor loadings depict the relative importance of each variable with respect to a particular factor. In all the eight equations, 2HG (hysteresis, during shear) has positive loading factor indicating that this variable is of importance in the mechanical properties.

Varimax rotation can also be employed if needed. In this case it is noticed that 2HB, G, 2HG, LC, RC, 2HG5, RT, B, WT and WC have a positive loading factor indicating that they are variables of importance in determining the handle.

In factor loading 1, 2HB, G, 2HG, 2HG5 and B assume a dominant role, LC and RC play a dominant role in factor 2, W and WT in factor 3, RT in factor 4, WC in factor 5, MMD in factor 6, SMD in factor 7 and MIU in factor 8 respectively. It is interesting to note that in factor loading 1, bending, surface and shear properties assume importance showing thereby
mechanical properties LC, RC and RT play an important role in deciding the mechanical properties of fabrics. A single factor plays a dominant role in factors 3, 4, 5, 6, 7 and 8. On the basis of the loading coefficients, the above conclusions were drawn from the data. The variance technique seeks rotated loadings that maximise the variance of the squared loadings in each column of $\hat{A}$. It is available in virtually all factor analysis software programs.

Since the variables, B, 2HB, G, 2HG, 2HG5 and RC affect the handle of fabrics, they may be considered as important.

13.12 COMPARISON BETWEEN ESTIMATED FACTOR LOADING AND ROTATED ESTIMATED FACTOR LOADING

The original factor loadings (obtained by the principal component method) the communalities and the (varimax) rotated factor loadings are shown in Table 13.4.

It is clear that variables B, G, 2HB, 2HG, 2HG5 and T define factor 1, (high loadings on factor 1, small or negligible loadings on factor 2 while variable T defines factor 2(high loading on factor 2, small or negligible loading on factor 1. Variable LT defines factor 3 adequately.

13.13 CONCLUSION

It has been found that by factor analysis, G, 2HG, 2HG5 and W have positive loadings indicating that they are variables of importance in determining the mechanical properties.

According to varimax rotation method, the variables B, G, 2HG5, WC and WT have a significant role in that they affect the mechanical properties. It is enough if these mechanical properties are measured in order to have a complete characterisation of fabrics considered in the study.
### TABLE 13.1  CORRELATION MATRIX

<table>
<thead>
<tr>
<th></th>
<th>G</th>
<th>2HB</th>
<th>2HG</th>
<th>2HG5</th>
<th>LC</th>
<th>LT</th>
<th>MIU</th>
</tr>
</thead>
<tbody>
<tr>
<td>G</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2HB</td>
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<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2HG</td>
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<td>0.82</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2HG5</td>
<td>0.98</td>
<td>0.80</td>
<td>0.98</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LC</td>
<td>-0.37</td>
<td>-0.48</td>
<td>-0.44</td>
<td>-0.42</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LT</td>
<td>0.00</td>
<td>0.55</td>
<td>0.64</td>
<td>0.60</td>
<td>-0.24</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>MIU</td>
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<td>-0.06</td>
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Determined of Correlation Matrix = 0.000000
TABLE 13.2 THREE FACTORS RESULTS WITH 16 VARIABLES

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TABLE 13.3 ROTATED FACTOR MATRIX (Varimax)

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