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THE STUDY OF THE CHARACTERIZATION INDICES OF FABRICS BY PRINCIPAL COMPONENT ANALYSIS METHOD

HRISTIAN Liliana[1], OSTAFE Maria Magdalena[1], BORDEIANU Demetra Lacramioara[1] and APOSTOL Laura Liliana[1]

[1]"Gheorghe Asachi" Technical University of Iasi, Faculty of Textile, Leather & Industrial Management, Department of Engineering and Design of Textile Products, Blvd. Mangeron, No.28, Iasi, Romania

Corresponding author: Hristian Liliana, e-mail: hristian@tex.tuiasi.ro

Abstract: *The paper was pursued to prioritize the worsted fabrics type, for the manufacture of outerwear products by characterization indeces of fabrics, using the mathematical model of Principal Component Analysis (PCA). There are a number of variables with a certain influence on the quality of fabrics, but some of these variables are more important than others, so it is useful to identify those variables to a better understanding the factors which can lead the improving of the fabrics quality.*
A solution to this problem can be the application of a method of factorial analysis, the so-called Principal Component Analysis, with the final goal of establishing and analyzing those variables which influence in a significant manner the internal structure of combed wool fabrics according to armire type. By applying PCA it is obtained a small number of the linear combinations (principal components) from a set of variables, describing the internal structure of the fabrics, which can hold as much information as possible from the original variables. Data analysis is an important initial step in decision making, allowing identification of the causes that lead to a decision- making situations. Thus it is the action of transforming the initial data in order to extract useful information and to facilitate reaching the conclusions. The process of data analysis can be defined as a sequence of steps aimed at formulating hypotheses, collecting primary information and validation, the construction of the mathematical model describing this phenomenon and reaching these conclusions about the behavior of this model.

Key words: *Principal Component Analysis, degree of compactness, fabric, porosity, factorial axis.*

1. INTRODUCTION

Principal components analysis (PCA) is a descriptive method for multivariate analysis/ multi-dimensional of data, which aims at decreasing the size of the matrix in which are shown the data to be analyzed. This technique aims to reduce the number of controlled variables (columns) of the matrix data, as far as possible two or three. Thus based on information about each group/types of fabrics, it is desirable that instead of interrelated variables to have only two or three new variables, called components. The PCA goal is to extract the smallest number of components to recover as much of the total information contained in the initial data [1]. The objectives of PCA are: synthesizing initial information contained in a large table; highlighting similarities or differences between data (individuals); highlighting the correlations between variables; explaining the similarities or differences between data (individuals); in terms of the considered variables [2;3]. At the beginning ,the methods of multivariate analysis of data were applied in fields of humanities:

biology, psychology, sociology [4-6]. Later, they were applied in numerous areas such as psychometry, genetics, medicine, economic industry [7;8]. Outstanding contributions to theoretical and practical development of these methods had,in particular, Galton and K. F. Pearson, by the studies in the field of regression and correlation analysis, Spearman and H. C. Hotteling by factor analysis and research of the principal components analysis. Nowadays, more specialized softwares allow the use of a variety of the methods for multivariate analysis of data for statistical processing of the research results: SPSS, STATISTICA, SAS, ADDAD [8-10].

2. EXPERIMENTAL PART

2.1. Materials and methods

In this study, there were analyzed four articles from five groups of worsted type fabric, made of different compositions, representing the number of individuals so:

Group A (100% Wool) - encoded items: A1; A2; A3; A4;
Group B (45% Wool + 55% Pes) - encoded items : B1; B2; B3; B4;
Group C (45% Pes + 55%Wool) - encoded items: C1; C2; C3; C4;
Group D (44%Pes + 52% Wool +4%Dorlastan) - encoded items: D1; D2; D3; D4;
Group E (60% Pes + 40% Celo) - encoded items: E1; E2; E3; E4

In making the fabrics from groups **A, B, C** and **E** , they were used Sirospun yarns which are twisted appearance yarns, called Jasper or yarn from double roving fibers. At group **D** fabrics, the weft threads are elastomeric yarns with core made of filament and their sheaths are made of fibers obtained also by the Siorospun process, through simultaneous supplying of the drawing frame with the roving and the filament core.

The joining of the two components takes place in front of the delivery rollers so that by simultaneous twisting of them it is made the yarn structure with the filament core covered by the fibers. Using two rovings which will be rolled separately and a filament core at one of the sides, it is obtained a twisted yarn from a spun yarn and a core yarn. Most polymers and elastomers used for industrial or commercial applications are composites, which contain solid fillers.

Analysis of fabrics structure and the manner of calculation of these indicators reflect the real state of the internal structure of the fabric in accordance with the armure. The values of the characterization indices of the combed wool-type fabrics were processed in SPSS using PCA. The variables used in the analysis are: volumetric filling coefficient, **Cvu**; the degree of compactness, **Kt** (%); the texture coefficient, **Ct**; the coverage percentage, **Et** and porosity, **Pz** (%).

2.2. Results and discussions

After processing the data in SPSS programme, applying PCA, the following results were obtained on statistical variables: descriptive statistics indicators (Descriptive Statistics); the correlation matrix; calculated values for both $\chi 2$ test statistics and **KMO** statistics; the variance of the variables; eigenvalues and variance explained by each factorial axis; variable coordinates on factorial axes; contributions of the variables at the inertia of factorial axes and graphics.

1. Descriptive Statistics Indices

The statistical parameters calculated for each variable are presented in Table 1 (output Descriptive Statistics).

Analyzing the data from Table 1, which contains information about each independent analyzed variable it can be seen that:

- the variable "Cvu, volumetric filling coefficient" is characterized by (39.33) average and (160,36) variance; the maximum volumetric filling coefficient was obtained to Article **D4**, made of

44% Pes + 52% Wool +4% Dorlastan, **Cvu=65,32**, and the minimum value was obtained to Article **A1** made of 100% wool , **Cvu=21,34;**

- the variable "**Kt** (%), degree of compaction" is characterized by the average (87.53) and the variance (41.895); the maximum value of the degree of compaction was obtained for Article **B4** made of **45% Wool + 55% Pes, Kt = 98,29%** and the minimum value for Article **A1** made of **100% Wool, Kt = 75,23%;**

Table 1: *Descriptive Statistics*

Variables	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Cvu	20	21,34	65,32	39,3340	12,66344	160,363
Kt(%)	20	75,23	98,29	87,5275	6,47263	41,895
Pz(%)	20	58,50	79,21	67,4185	5,17203	26,750
Ct	20	92,10	114,20	97,5000	4,85191	23,541
Et	20	85,40	106,30	94,0150	6,56973	43,161
Valid N (listwise)	20					

Analogous to this, the other variables are analyzed. Following this independent analysis of every variable it is observed that the homogeneous variable is that related to the coefficient of density. The same trend is observed for the variable "coverage percentage".

2. Correlation Matrix (output of Correlation Matrix)

The correlation matrix shows the correlation coefficient values of the variables considered in pairs. It is a square matrix symmetrical about the main diagonal (equal to one, because a variable is perfectly correlated with itself). The shape of the correlation matrix is shown in Table 2, after the data have been standardized

Table 2: *Correlation Matrix*

		Cvu	Kt(%)	Pz(%)	Ct	Et
Correlation	Cvu	1,000	0,508	0,222	-0,371	0,063
	Kt(%)	0,508	1,000	0,252	-0,360	-0,423
	Pz(%)	0,222	0,252	1,000	-0,307	-0,420
	Ct	-0,371	-0,360	-0,307	1,000	-0,093
	Et	0,063	-0,423	-0,420	-0,093	1,000
Sig. (1-tailed)	Cvu		0,037	0,174	0,054	0,396
	Kt(%)	0,037		0,142	0,060	0,032
	Pz(%)	0,174	0,142		0,094	0,033
	Ct	0,054	0,060	0,094		0,348
	Et	0,396	0,032	0,033	0,348	

a. Determinant = 0,321

The analysis of the correlation coefficients of the matrix allows the assessment of the application of the PCA. High values of coefficients (greater than +0.5 and less than -0.5) shows that there are significant statistically links between the considered variables (direct connection if the coefficient values are positive, the reverse link if the coefficient values are negative). For example, from Table 2 it is observed that there are:

- significant statistical connections (direct link) between: Cvu and Kt (%); Kt(%) and Cvu;
- significant statistical connections (indirect link) between: Cvu and Ct; Kt (%) and Ct, Et; Pz (%) and Ct, Et; Ct and Cvu, Kt (%), Pz (%), Et; Et and Kt (%), Pz (%), Ct.

In this case, PCA can be applied. A feature of the correlation matrix is that the number of correlation coefficients increases greatly when the number of variables (k) included in the analysis increases, regardless of the volume of statistics community. The number of the correlation coefficients is: k (k-1)/2. For the experimental data which are showing values for five variables, the number of the correlation coefficients is 10 (Table 2).

3. The Eigenvalues λ_k associated with each factorial axis and the total variance explained by each factorial axle (output of Total Variance Explained)

The eigenvalues of the correlation matrix are shown in the Total Variance Explained output, initial Eigenvalues column (Table 3).

Table 3: *Total Variance Explained*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,082	41,640	41,640	2,082	41,640	41,640
2	1,289	25,786	67,426	1,289	25,786	67,426
3	0,774	15,470	82,897			
4	0,596	11,910	94,807			
5	0,260	5,193	100,000			

Extraction Method: Principal Component Analysis.

Table 4 shows that the eigenvalues of the correlation matrix are: $\lambda_1 = 2{,}082$; $\lambda_2 = 1{,}289$; $\lambda_3 = 0{,}774$; $\lambda_4 = 0.596$; $\lambda_5 = 0{,}260$

The eigenvalues correspond to inertia explained by the factorial axes. Their sum is the total inertia of the cloud of points equal to the number of statistical variables of the original data table or the amount of elements from the main diagonal of the correlation matrix. Based on the values from Table 6 it may result:

$$\sum_{k=1}^{k} \lambda_k = 2{,}082 + 1{,}289 + 0{,}774 + 0{,}596 + 0{,}260 = 5 \tag{1}$$

The first factorial axis explains 2,082/5 = 41,64% of the total variance of the cloud points.

The first two factorial axes together explain 42.929% of total variance.

The number of factorial axes which are to be interpreted in the PCA was chosen according to the Kaiser criterion (1960) which implies the choice of that number of factorial axes for which the corresponding own values are higher than one. According to this criterion, two factorial axes are chosen, corresponding to their own values ($\lambda_1 = 2{,}082$; $\lambda_2 = 1{,}289$) >1.

These axes explain the biggest differences between statistical units in terms of the considered variables.

4.The coordinate of X_j variable on k factorial axis (output of the Component Matrix)

The values of the coordinate variables on the two-factorial axis are shown in Table 5.

The values in Table 4 shows the position of the variables on the factorial axes. For example, the variable "Cvu" has a coordinated position on the first factorial axis (0.622) and a positive coordinated on the second factorial axis (0.516); the variable will be plotted in the positive values quadrant of the first factorial axis and in the positive values quadrant of the second factorial axis.

The high values of the coordinate of variables on the factorial axes listed that are strongly correlated with that factorial axis.

For example, the variables "Kt (%)" and "Pz (%)" are correlated with the first factorial axis indicating that these variables explain significantly the differences between the statistical units (it means,there are significant differences between statistical units in terms of the recorded values for these variables). The coordinates of the variables on the factorial axes represent the coefficients of the linear equation of the relationship/links between variables.

Table 4: *Component Matrix*

Variables	Component	
	1	**2**
Cvu	0,622	0,516
Kt(%)	0,787	-0,072
Pz(%)	0,675	-0,295
Ct	-0,625	-0,520
Et	-0,480	0,813

Extraction Method: P.C.A

For example, for the data from Table 5, the first axis is a new variable defined by the linear combination of the initial variables, having the form:

F_1= 0,622 Cvu + 0,787 Kt + 0,67Pz – 0,625 Ct - 0,480 Et **(2)**

In order to identify the variables that explain the second factorial axis, those variables are selected from Table 4 (Component 2 column) that have higher coordinate values. It is noted that the realization of the second factorial axis is explained, only by the variables "Cvu" and "Et".

5. Graphical representation

The representation of the variable points in the first two factorial axes is shown in Figure 1. The first factorial axis represented on the horizontal indicates that between the "Kt (%)", "Pz (%)" and "Cvu" variables there is a strong direct connection and between the variable "Kt (%)"and the variable"Et "there is a reverse link.

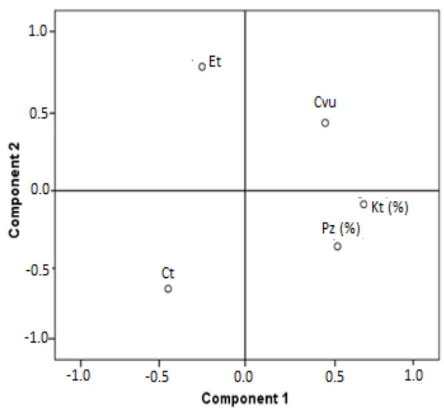

Fig.1:*Position of variables on the first two factorial axes*

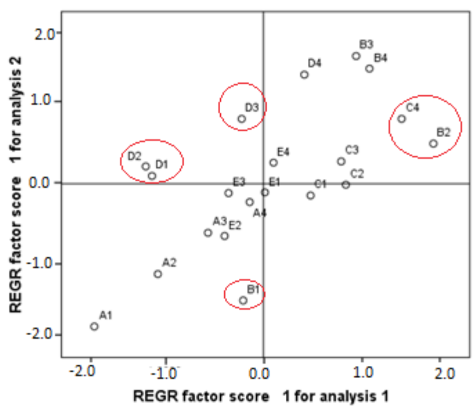

Fig.2:*Position of varieties of fabrics on the first two factorial axes*

The variables representative for the second factorial axis, represented on the vertical, are "Et" and "Pz (%)" between which there is a reverse link. The graphical representation of the variety of fabrics, from the five groups, on the first two factorial axes is shown in Figure 2.

3. CONCLUSIONS

The first axis factorial highlights two groups of types of fabrics: the first group is made up of articles **B2** and **C4** (with an extreme position to the right of the graph in Figure 2), and the second group of items **D1** and **D2** (with an extreme position to the left of the same graph).

The articles from the first group is characterized by higher values than average, of the following characteristics: volumetric filling coefficient, degree of compactness and porosity of woven fabrics, because the percentage of polyester fibers in the composition of the threads, as opposed to items in the second group, items **D1** and **D2**, in which the yarns have in their composition 4% Dorlastan.

The second factorial axis highlights the **B1** item, which is characterized by high values of compactness, volumetric filling factor and porosity of the fabric, unlike the **D3** item where the degree of compaction and porosity of fabrics are below the average.

By using **PCA** on indices for characterizing the worsted type fabrics it may be noted that the number of data matrix variables was reduced to two components, namely the degree of compactness, Kt (%) and the porosity, Pz (%), whose values reflect the real state of the internal structure of the fabric, in accordance with its armure.

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