Multidimensional analysis of textiles coated with electroactive polymers for actuators

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ABSTRACT – REZUMAT

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This paper presents a multidimensional analysis of textiles coated with conductive polymers for actuators. The purpose of using multidimensional scaling analysis is to compare similarities and dissimilarities between conductive textiles obtained through conductive polymeric film deposition to observe the optimal value for electrical resistance and to select an adequate method to achieve conductive fabric using different polymers (polyethylene glycol, polyvinyl alcohol or polyvinylidene fluoride) and metal microparticles (copper or nickel). The multidimensional analysis is based on mapping a series of material properties from a proximity matrix (similarities or dissimilarities) between these properties. Multidimensional scaling allows rebuilding the exact map of the values (within approximately a symmetry or rotation). To fit dissimilarity or similarity matrices for multiple variables into one common space estimating the weight parameters for each variable, the INDSCAL model (individual differences multidimensional scaling) was used.

Keywords: *textile, multidimensional scaling, analysis, resistance, conductive, actuators*

Analiza multidimensională a textilelor acoperite cu polimeri electroactivi pentru actuatori

Această lucrare prezintă o analiză multidimensională a textilelor acoperite cu polimeri conductivi pentru actuatori. Scopul utilizării analizei prin scalare multidimensională este de a compara asemănările și deosebirile dintre textilele conductive, obținute prin depunerea filmului polimeric conductiv, de a observa valoarea optimă a rezistenței electrice și a selecta metoda adecvată pentru realizarea țesăturii conductive utilizând diferiți polimeri (polietilenglicol, alcool polivinilic sau fluorură de poliviniliden) și microparticule de metal (cupru sau nichel). Analiza multidimensională se bazează pe maparea unei serii de proprietăți ale materialelor dintr-o matrice de proximitate (asemănări sau deosebiri între aceste proprietăţi). Scalarea multidimensională permite reconstruirea hărții exacte a valorilor (prin simetrie sau rotație). Pentru a stabili matricele de diferențe sau similitudini pentru mai multe variabile într-un spațiu comun estimând ponderea fiecarei variabile, a fost utilizat modelul INDSCAL (scalare multidimensională a diferențelor individuale).

Cuvinte-cheie: *textil, scalare multidimensională, analiză, rezistenţă, conductiv, actuatori*

INTRODUCTION

Conductive textiles are used in numerous applications (medical, technical, fashion) because their flexible surface is easy to wear. To obtain conductive textiles, conductive yarns can be integrated by embroidery, sewing, weaving or knitting, or conductive polymers can be used to obtain a continuous conductive surface for antistatic packaging, microelectronics, rechargeable batteries, photovoltaics, actuators, and flexible electrodes for actuators or sensors [1–4]. In addition, soft actuation technologies are expected to use conductive textiles [5]. The experimental parameters of the conductive textiles can be evaluated by the multidimensional scaling technique. However, this technique is presented in a few articles [6] and is often applied to data clustering in medicine [7]. In general, the multidimensional scaling approach is insufficiently used for conductive textile development [8, 9].

Multidimensional scaling (MDS) is a data analysis technique that examines the structure of dissimilarity or similarity data. MDS consists of point clouds (variables) in a multidimensional space that correspond to similar values that are close together, while those that correspond to dissimilar values are distant [10, 11]. Multidimensional scaling generates a data reduction procedure used on a similarity or dissimilarity matrix. MDS also computes the INDSCAL model (individual differences multidimensional scaling) [12] that fits dissimilarity or similarity matrices for multiple variables into one common space estimating the weight parameters for each variable.

Multidimensional scaling (MDS) is a technique for the analysis of similarity or dissimilarity data on a dataset. A common method for MDS is principal component analysis (PCA) based on a data matrix. The objective of the MDS-based PCA is to explain the k variables by a much smaller set of variables that are linear combinations of the original variables [13]. The diversity of physical phenomena that are the basis of the constructive materialization of actuators opens new horizons in research on their design, realization and use, stimulates the consideration of new physical principles and the search for new materials with special properties through which to respond to actuation requirements [11]. The mechanism of the actuators is based either on the geometric shapes of the component elements to achieve the coupling effect between the two forms of energy – input and output (also called geometric actuators) or on the characteristics of the materials (e.g., piezoelectric actuators, actuators with shape memory, etc.) [12]. To allow the optimal selection of actuators for a given application, specific requirements or performance characteristics are imposed on them: fundamental technical requirements (power output per mass, per volume and actuator efficiency, stress, deformation, deformation rate, lifetime and modulus of elasticity) and general requirements (ease of use, ease of manufacture and maintenance, cost and availability of raw materials, actuation mechanism) [13, 14].

Incorporating actuators into textiles is a new approach with incredible development potential for the textile industry, bringing significant improvements in textile performance. Specifically, combining textiles and smart materials has contributed to developing new material capabilities, with smart textiles being considered the next direction of electronics. The challenge was transferring the concept from the laboratory to an industrial scale and integrating these actuators into textiles [13]. However, most actuation technologies rely on rigid actuators with robust, heavy, and noisy operating systems, which make them unsuitable for assembly into smart textiles. In addition, actuators require substantial power supplies that are rarely flexible and lightweight, severely affecting their usability. With the development of wearable devices, the need to develop flexible, light and silent actuators was imposed. In this way, electroactive polymers used in textiles are ideal candidates for making such actuators [15]. Thus, whether we are talking about the fashion industry or the technical fields of the textile industry, textiles with new functions can be made, improving our comfort and ensuring our protection.

EXPERIMENTAL PART

For the classification of the conductive samples, a multidimensional analysis of the research results was used. For this goal, the adequate parameters for textile composites for actuators: mass – M (g/m^2), air permeability – Pa (l/m^2/s), vapour permeability – Pv (%), thickness – δ (mm) and surface resistance – Rs (Ω) obtained in previous experiments were used and are presented in table 1.

The standardized distance takes into account the individual variability that characterizes the observations of the variables that are assumed to be uncorrelated. The Mahalanobis distance is a generalization of the standardized distance that also takes into account the variability of the interaction between the variables [16]. For the construction of the Mahalanobis distance, the variants of the variables are taken into account, and the covariances and correlation coefficients are involved. To analyse data using multidimensional scaling, the proximity matrix (dissimilarities and similarities) was calculated. For the proximity similarity matrix, the Pearson correlation coefficient (equation 1) presented in table 2 was used, and for the dissimilarity matrix, the Mahalanobis distance (equation 2) presented in table 3 and Euclidian distance (equation 3) presented in table 4 were used [17].

$$d_{ij} = \sqrt{\sum_{k=1}^{p}(x_{ik} - x_{jk})^2} \quad (1)$$

$$M^2(x,y) = (x - y)\sum^{-1}(x - y)^T \quad (2)$$

Table 1

ADEQUATE PARAMETERS FOR TEXTILE COMPOSITES FOR ACTUATORS											
Sample	**PEG**	**PVA**	**Cu**	**GO**	**Ni**	**PVDF**	**M (g/m^2)**	**δ (mm)**	**Pv (%)**	**Pa (l/m^2/s)**	**Rs (Ω)**
P1	-	-	-	-	-	-	415	1.060	22.3	33.76	10^{12}
P2	-	-	-	x	-	x	460.4	1.520	28.5	95.2	10^{12}
P3	-	-	-	-	x	x	593.6	1.144	26.7	45.9	1000
P4	-	-	x	-	-	x	748	1.096	30.7	24.42	10^{10}
P5	-	-	x	-	-	x	824.4	1.474	25.3	3.332	10^9
P6	x	x	x	-	-	-	997.6	1.168	23.8	10.86	10^6
P7	x	-	x	-	-	-	1042	1.044	24.7	1.38	10^6
P8	x	-	x	-	-	-	1262	1.060	29.6	2.066	10^7
P9	x	-	-	x	-	-	940.4	1.008	21.6	2.076	10^7
P10	x	-	x	-	-	-	1222	1.006	18.2	2.024	10^7
P11	x	-	-	x	-	-	717.6	1.732	24.1	27.44	10^{10}
P12	x	-	x	-	-	-	608	1.322	24.1	36.74	10^{11}
P13	x	-	x	-	-	-	784.8	1.898	26	19.68	10^{10}
P14	x	-	x	-	-	-	1187.2	1.034	23.5	1.184	10^6
Average							843.0714	1.255	24.93571	21.86157	$2\cdot10^{11}$

Where $M^2(x,y)$ is the square of the Mahalanobis distance, x – the vector of the observation (row in a dataset), y – the vector of mean values of independent variables, Σ^{-1} – the inverse of the covariation matrix.

$$d(i,j) = \sqrt{\left(|x_{i1}-x_{j1}|^2 + |x_{i2}-x_{j2}|^2 + \ldots + |x_{ip}-x_{jp}|^2\right)} \quad (3)$$

The stress expression (equation 4) is used to express how well the set of data (thickness, air permeability, vapour permeability and mass) is represented by the model that the analysis imposes [17]. In MDS, the choice for a goodness-of-fit statistic is one based on the differences between the actual distances and their predicted values.

$$stress = \sqrt{\frac{\sum (d_{ij} - \partial_{ij})^2}{\sum d_{ij}}} \quad (4)$$

Kruskal's stress [18] (equation 5) represents the goodness-of-fit statistic that MDS tries to minimize, consisting of the square root of the normalized squared discrepancies between interpoint distances in the MDS plot and the smoothed distances predicted from the dissimilarities. The stress value is 0.001 (figure 1) and is very close to 0, indicating a better fit.

$$\sigma_1 = \sqrt{\left(\sum_{i<j} w_{ij}(d'_{ij} - d_{ij}(X))^2 / \sum_{i<j} w_{ij} d_{ij}^2(X)\right)^{1/2}} \quad (5)$$

The Shepard diagram (figure 1) compares the disparities and the distances to the dissimilarities. The MDS configuration (figure 2) shows the coordinates of objects in the representation space.

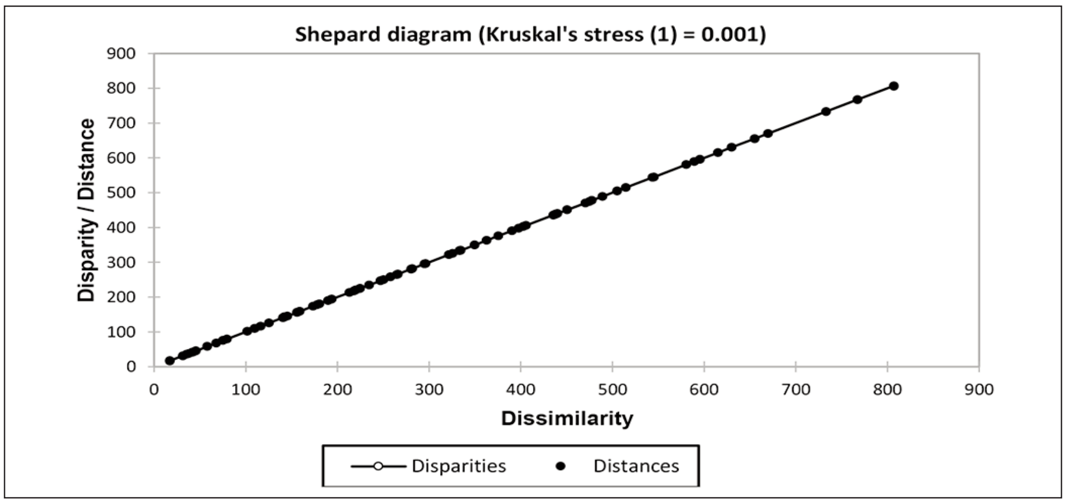

Fig. 1. Shepard diagram of MDS analysis of four variables: mass, thickness, vapour permeability and air permeability

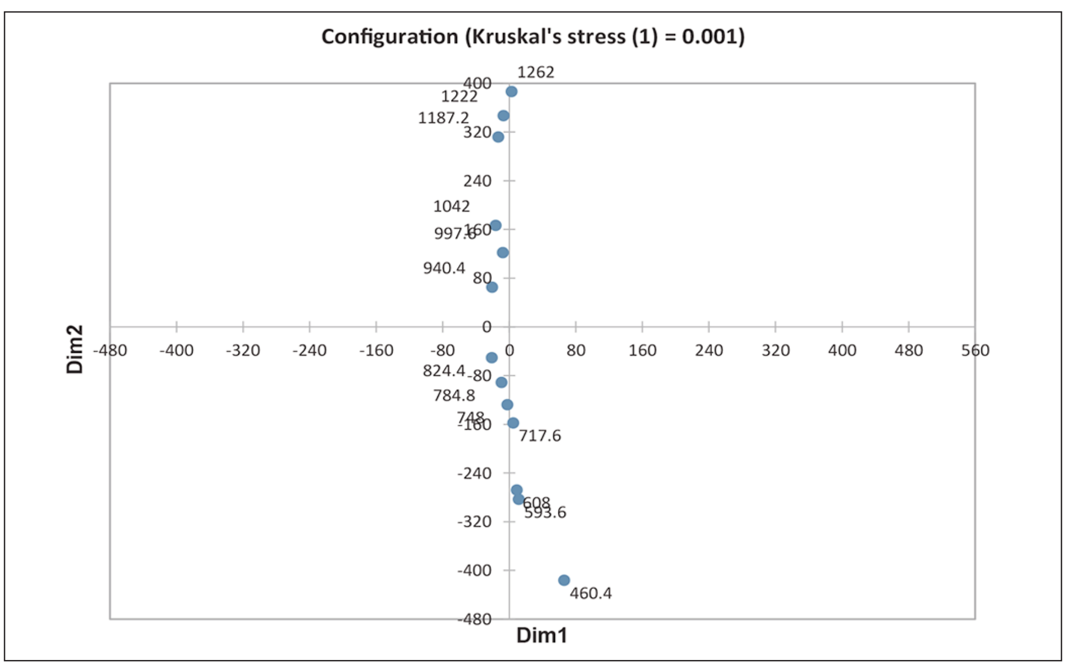

Fig. 2. MDS configuration of four variables of conductive materials for actuators

Table 2

PROXIMITY MATRIX (PEARSON CORRELATION COEFFICIENT)													
Sample	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**
P2	1	0.992	0.986	0.982	0.983	0.982	0.982	0.982	0.982	0.987	0.990	0.985	0.982
P3	0.992	1	0.999	0.998	0.998	0.998	0.998	0.998	0.998	0.999	1.000	0.999	0.998
P4	0.986	0.999	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
P5	0.982	0.998	1.000	1	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
P6	0.983	0.998	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
P7	0.982	0.998	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	0.999	1.000	1.000
P8	0.982	0.998	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	0.999	1.000	1.000
P9	0.982	0.998	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	0.999	1.000	1.000
P10	0.982	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	0.999	1.000	1.000
P11	0.987	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000
P12	0.990	1.000	1.000	0.999	0.999	0.999	0.999	0.999	0.999	1.000	1	0.999	0.999
P13	0.985	0.999	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1	1.000
P14	0.982	0.998	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1

Table 3

PROXIMITY MATRIX (MAHALANOBIS DISTANCE)													
Sample	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**
P2	0	2.961	3.942	4.228	3.272	3.740	4.020	4.155	3.924	3.374	3.219	3.920	3.509
P3	2.961	0	1.876	2.486	1.989	1.940	3.684	1.894	3.419	2.815	1.132	3.660	2.648
P4	3.942	1.876	0	2.394	2.497	2.017	2.862	2.758	4.380	3.368	2.534	3.676	2.912
P5	4.228	2.486	2.394	0	1.808	1.736	3.370	2.058	3.486	1.593	1.925	1.952	2.487
P6	3.272	1.989	2.497	1.808	0	0.747	2.595	1.465	1.984	1.934	1.728	2.618	0.869
P7	3.740	1.940	2.017	1.736	0.747	0	2.459	1.363	2.487	2.415	1.909	2.970	1.140
P8	4.020	3.684	2.862	3.370	2.595	2.459	0	3.808	3.826	3.672	4.002	3.506	2.154
P9	4.155	1.894	2.758	2.058	1.465	1.363	3.808	0	2.383	2.644	1.443	3.544	2.051
P10	3.924	3.419	4.380	3.486	1.984	2.487	3.826	2.383	0	3.071	2.988	3.840	1.777
P11	3.374	2.815	3.368	1.593	1.934	2.415	3.672	2.644	3.071	0	2.032	1.181	2.560
P12	3.219	1.132	2.534	1.925	1.728	1.909	4.002	1.443	2.988	2.032	0	3.063	2.561
P13	3.920	3.660	3.676	1.952	2.618	2.970	3.506	3.544	3.840	1.181	3.063	0	3.031
P14	3.509	2.648	2.912	2.487	0.869	1.140	2.154	2.051	1.777	2.560	2.561	3.031	0

Table 4

PROXIMITY MATRIX (EUCLIDEAN DISTANCE)													
Sample	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**
P2	0	142.043	296.190	375.428	543.801	589.131	806.993	488.999	767.348	266.013	158.817	333.084	732.873
P3	142.043	0	155.938	234.697	405.527	450.609	669.842	349.595	629.987	125.395	17.264	192.992	595.290
P4	296.190	155.938	0	79.442	250.063	294.962	514.487	193.907	474.693	31.261	140.696	37.409	439.873
P5	375.428	234.697	79.442	0	173.370	217.610	437.623	116.067	397.666	109.494	218.967	42.850	362.811
P6	543.801	405.527	250.063	173.370	0	45.410	264.610	57.913	224.644	280.491	390.459	212.995	189.847
P7	589.131	450.609	294.962	217.610	45.410	0	220.056	101.650	180.118	325.446	435.439	257.855	145.205
P8	806.993	669.842	514.487	437.623	264.610	220.056	0	321.699	41.593	545.019	654.942	477.539	75.054
P9	488.999	349.595	193.907	116.067	57.913	101.650	321.699	0	281.621	224.254	334.212	156.657	246.809
P10	767.348	629.987	474.693	397.666	224.644	180.118	41.593	281.621	0	505.075	615.009	437.627	35.211
P11	266.013	125.395	31.261	109.494	280.491	325.446	545.019	224.254	505.075	0	109.995	67.673	470.334
P12	158.817	17.264	140.696	218.967	390.459	435.439	654.942	334.212	615.009	109.995	0	177.632	580.291
P13	333.084	192.992	37.409	42.850	212.995	257.855	477.539	156.657	437.627	67.673	177.632	0	402.834
P14	732.873	595.290	439.873	362.811	189.847	145.205	75.054	246.809	35.211	470.334	580.291	402.834	0

DISCUSSION

Using a Shepard diagram (figure 1), the performance of the model was evaluated by observing if the (dissimilarity/distance) points were near the (dissimilarity/disparity) points.

Multidimensional tests were used to compare the samples based on several variables (*Pa, M*, δ, *Pv*). The proximity matrix (table 2) shows that the Pearson correlation coefficient is between 0.998 and 1, which indicates a good correlation between samples with 5 parameters (*M*, δ, *Pa, Pv* and *Rs*). Considering that we have different records with 5 objects (vectors of parameters), such as mass (*M*), thickness (δ), air permeability (*Pa*), vapour permeability (*Pv*) and surface resistance (*Rs*), having different scales, the Euclidian distance is not suitable to handle these aspects, and we used a generalization of the Euclidian distance, the Mahalanobis distance (quadratic distance). The Mahalanobis distance is useful when the values of parameters are partially correlated or have different scaling values. Moreover, the Mahalanobis distance is used in classification to observe whether a sample is an outlier, whether the coating process is in control or whether a sample is a member of a group (conductive samples). The high values in Euclidean distance observed in the proximity matrix (table 2) show a low similarity between individual values measured. The low values for the Mahalanobis distance, such as 1 or lower than 1, indicate that the points are right among the benchmark points. For example, in table 3, we observed between P7, P6 and P14 that $M(x,y)<1$, which indicates that points P6, P7 and P14 have similarities, such as an *Rs* value equal to 10^6 Ω. Table 5 presents the correlation matrix.

Analysing the predictors using the following procedure, it was observed that the mass has a relevant contribution in the prediction of the surface resistance *Rs* values, being in an inverse correlation with *Rs* (figure 3):

```
Predictor Screening(
    Y(:Rs),
    X(:Mass, :G, :Pv, :Pa),
    SendToReport(Dispatch({}, "", TableBox, {Sort By
    Column(1, 1)}))
)
```

Predictor	Contribution (Rs)	Portion (Rs)	Rank
Mass	6.528e+23	0.6570	1
G	1.286e+22	0.0129	4
Pv	4.348e+22	0.0438	3
Pa	2.845e+23	0.2863	2

Fig. 3. *Surface resistance predictor screening*

Table 5

CORRELATION MATRIX					
Parameter	**Mass**	**G**	**Pv**	**Pa**	**Rs**
Mass	1.0000	–0.4067	–0.2237	–0.7894	–0.6492
G	–0.4067	1.0000	0.2183	0.3623	0.0639
Pv	–0.2237	0.2183	1.0000	0.3727	0.0589
Pa	–0.7894	0.3623	0.3727	1.0000	0.7103
Rs	–0.6492	0.0639	0.0589	0.7103	1.0000

Figure 4 presents a multidimensional scaling plot of the correlation between different vectors (*Rs, Pa, Pv,*

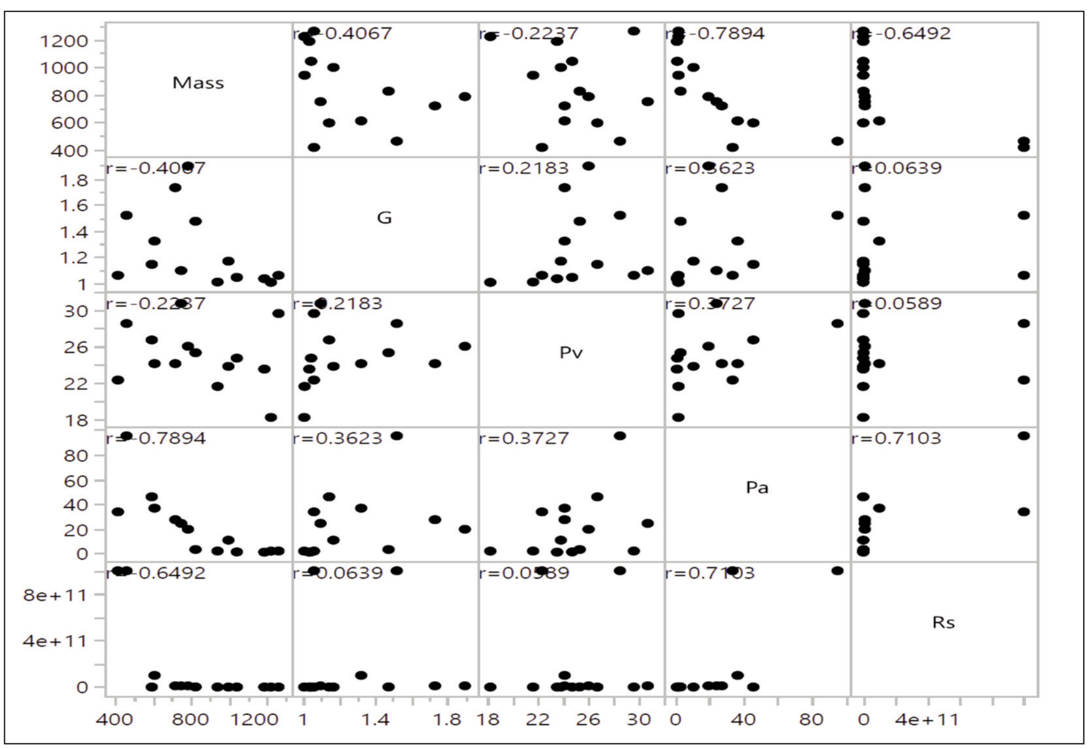

Fig. 4. Multidimensional scaling plot correlation (*Rs, Pa, Pv, G, Mass*)

G, Mass). The correlation coefficients between mass and *Pa* ($r_{M,Pa}$ = –0.7894) and between mass and *Rs* ($r_{M,Rs}$ = –0.6492) have negative values, indicating an inverse correlation between the analysed vectors. In the mean time between *Rs* and *Pa* there is a positive correlation coefficient ($r_{Rs,Pa}$ = 0.7103), indicating a direct correlation between *Rs* and *Pa*.

CONCLUSIONS

In conclusion, analysing the experimental data using multidimensional scaling can classify the conductive samples having different scales on different classes by *Rs* values. In addition, the negative correlation between the mass and *Pa* and the *Rs* of the conductive sample is credible because increasing the quantity of the conductive paste can obtain a surface that is continuously perfectly conductive with low values of *Rs* and *Pa*. *Rs* and *Pa* are directly correlated because by reducing the *Pa* value, the spaces between the yarns are filled with the applied polymer layer and generate a reduction in permeability and implicitly the electrical resistance of the surface. The optimal values of the electrical resistance, based on similarities, are for P6, P7 and P14, where *Rs* is 10^6 Ω.

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