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IDENTIFYING CONSUMERS'PROFILES CONCERNING RESIDENTIAL LIGHTING

Abstract. *Reducing electricity consumption, by decreasing residential lighting, falls in the range of measures aimed to save 20% of primary energy consumption in European Union, up to 2020, and further to improve energy efficiency after 2020. Public lighting and appliances is about 14 % of total electricity consumption, in Romania. New energy efficient lighting technologies might contribute to a substantial decreasing of household electricity consumption. Data set used to apply the scientific methodology presented in the paper was gathered in a survey research, aiming to investigate Romanians attitude and behavior about lighting consumption in households. The goals of this research paper are both to identify the factors associated with the replacement of old incandescent lamps, with the new energy efficient compact fluorescent lamps and light emitting diodes, and to identify Romanian typologies of consumers and the patterns of their behavior. In order to accomplish the research goals, a model of analysis, based on Cluster Analysis and Multiple Correspondence Analysis methods has been proposed in the paper.*

Key words: *correspondence analysis, classification, clusters, types of consumers, bulbs.*

JEL Classification: **C38, C46, L94, L95**

1. Introduction

At the EU level, the transition to an efficient consumption by using compact fluorescent lamps (CFL) and light-emitting diode(LED) bulbs, has been accelerated in the last 10 years. If in 1995, the weight of the incandescent bulbs was of 85% [17], in 2007 their weight was reduced at 54 %. In the same time, the market of the incandescent bulbs decreased from 61%, in 2006, to 41%, in 2010, while the market of CFLs increased from 15% to 23%. The 244/2009 EU directive of EC imposed a

progressive elimination of incandescent bulbs: in the first stage, up to 2009 year, the replacement of bulbs with a capacity of 100 watts; then, up to 2010, the replacement of bulbs with a capacity of 75 watts, and up to 2011, the replacement of bulbs of 60 watt, and from 2012, the commercialization of incandescent bulbs with capacity of 40 and 25 watts was forbidden [7]. Despite of all these measures, in Romania someone still can buy incandescent bulbs, from online shops, or from small shops that sell electrical accessories. The same situation could be observed also in the other European countries, where people tended to store incandescent or halogen bulbs to prevent their suddenly disappear from market [10, 2]. A more efficient solution may be to adopt non-restrictive measures, but simulative ones, to determine the population to give up to use the inefficient bulbs. Some studies, such as [15, 8, 13], have shown that adoption of the low consumption bulbs is influenced by many factors, as the following: price, life time, the intensity of light, color, the heat, the impact against the environment and so on.
The study done by Kumar et al. (2003) for India [9] showed a strong correlation about adopting low consumption bulbs, between factors such as income and education. Other studies like those made by Scott (1997) [16] and di Maria (2010) [4] for Ireland, have highlighted the influence of impact factors against the environment. Studies carried out after 2009, for instance one done by Mills and Schleich (2013) [10], about Germany, analyses the impact of the restrictions introduced at European level, on the issue of replacing incandescent bulbs. The study conducted by Mills and Schleich (2014) [11] analyses the EU constraints efficiency concerning the incandescent bulbs usage in relation to other factors.

2. Data and Model Specification

2.1 Data Used to Support the Research

The support data used to set-up the analysis is gathered during a face-to-face survey research, conducted between May and June 2013, aiming to investigate Romanians' attitudes and perception about low consumption bulbs and their availability to switch to low consumption bulbs. A multi stratified survey, representative for adult population of Romania has been used. 400 residents from urban and rural localities, from all regions of Romania were surveyed. The theoretical margin of error, at 95% confidence level, is +/- 4.75.
The sample allocation was proportional with estimated population, from each stratum. This approach to sample design, has the advantage of reducing design effects, resulting in estimates of better quality for given sample sizes. Tables 1 to 4 provide details on the distribution of respondents by macro regions, gender, residence and type of dwelling.

Table 1. Sample distribution by macro regions

Macro region	Frequency	Percentage	Population	Percentage
1	100	24.57	4945532	24.79
2	115	28.25	5782461	28.98
3	110	27.03	5368063	26.91
4	82	20.15	3851255	19.31

Table 2. Sample distribution by gender

Gender	Frequency	Percentage	Population	Percentage
woman	215	52.83	10201259	51.14
man	192	47.17	9746052	48.86

Table 3. Sample distribution by residential

Residence	Frequency	Percentage	Population	Percentage
rural	183	44.96	9198308	46.11
urban	224	55.04	10749003	53.89

Table 4. Sample distribution by type of dwelling

Type of dwelling	Frequency	Percentage	Population	Percentage
tenant	49	12.04	487201	6.52
owner	358	87.96	6981884	93.48

The questions from the survey aimed to find answers to the following issues:

- Habit, education level and attitude concerning the domestic lighting consumption;
- Perception concerning the lighting features and the low consumption bulbs;
- Quantitative elements as number of bulbs existing in the households;
- Equipment with ecological bulbs, existing in the households;
- Knowledge and information level about the efficiency of usage of low consumption bulbs;
- Availability to change the consumer habits.

2.2 Classification of Model Variables

One main goal of our research is to study the connections between various attitudes and perceptions about low consumption bulbs, investigated through various questions included in the questionnaire.

Each question is modeled by a categorical variable, with a specific set of options given by the possible answers. The proposed solution is to use a hierarchical classification algorithm applied to the model variables. Being categorical variables, the usage distance is derived from the χ^2 distance, the probability threshold value,by rejecting the hypothesis of independence between two variables (*p* value). The χ^2 test of independence shows whether between two categorical variables exists any dependence.

Let $X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & & & \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$, the observations matrix where *n* is the number of observations and *m* is the number of variables (in our case the number of questions from the questionnaire). The array columns of the categorical variables are noted with X^j, $j=\overline{1,m}$. For any two variables, X^k and X^l having *p* and *q* modalities, the crossed frequencies are stored in the *F* table: $F=\begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1q} \\ f_{21} & f_{22} & \cdots & f_{2q} \\ \cdots & & & \\ f_{p1} & f_{p2} & \cdots & f_{pq} \end{bmatrix}$. An element, for instance, f_{ij}, defines the number of instances to which the X^k variable has the *i* modality and the X^l variable has the *j* modality. The cumulated frequencies on lines and columns are defined: $f_{i.}=\sum_{j=1}^{q} f_{ij},\ i=\overline{1,p}$ and $f_{.j}=\sum_{i=1}^{p} f_{ij},\ j=\overline{1,q}$.

The null hypothesis from the independence test χ^2 denotes that between the two variables a connection doesn't exist, it means:

H0: The two variables are independent

H1: The two variables are dependent

The null hypothesis is rejected with a confidence level 1-*α*, if $\chi^2_{Calculated} >$ $\chi^2_{Critical}(\alpha;r)$,

where $\chi^2_{Calculated}=\sum_{i=1}^{p}\sum_{j=1}^{q}\frac{\left(f_{ij}-\frac{f_{i.}f_{.j}}{n}\right)^2}{\frac{f_{i.}f_{.j}}{n}}$, $\chi^2_{Critical}(\alpha;r)$ is the critical value computed for a significance threshold *α* and $r=(p-1)\cdot(q-1)$ degree of freedom.

Using the χ^2 distribution with *r* freedom degree, it is possible to determine the significance threshold, d_{kl}, for which the independence hypothesis is rejected, it means the lowest value α for which $\chi^2_{Calculated} > \chi^2_{Critical}(\alpha;r)$. The distances matrix noted with *D* contains these values.

The proposed hierarchical clustering algorithm is the following:

```
Procedure Hierarchy(D,n;H)
Tree H;
for i=1,n
      call Add(H,{i})
endfor
for i=1,n-1
      call Select(H,D;k,j)
      call Join(H,k,j)
      call UpdateDistances(H,D,k,j)
endfor
return
end
```

Where:
D – is the matrix of distances,
H – is the hierarchical tree,
Select – the procedure that select clusters which join at each step,
Join – the procedure that add a new cluster to the hierarchical tree, and remove the joined clusters;
UpdateDistances – the procedure that updates the distances after join process.

2.3Correspondence Analysis of the Field Survey

Correspondence analysis can be applied for two variables, being named bivariate correspondence analysis, or for many variables named multivariate correspondence analysis. Whatever the type of analysis is, the basic outputs are the same.

The bivariate correspondence analysis studies the relationship between two categorical variables, in terms of the two variables modalities .The standard input is the contingency table. By using the correspondence analysis, the connections between the two variables modalities are highlighted. Let X^k and X^l any two variables having *p* and *q* modalities, with frequencies stored in contingency table, *F*. The modalities of the first variable can be treated as points in a *q*-dimensional space and the modalities of the second one, as points in a *p*-dimensional space.

There are two approaches in the specialized literature depending on the symmetric role [1] or non-symmetric role [3], played by the two variables from the analysis. In the both cases, the main axes of inertia are identified, and the *p* + *q* points are represented and viewed in these axes. Basically, the correspondence analysis is also a matter of informational synthesis performed on the set of modalities.

In this paper we propose an analysis of a non-symmetric type based on the decomposition of the inertia matrix. In fact, this is a principal component analysis of the inertia matrix. The modalities contribution to the $\chi^2$are: $CC_{ij} = \frac{n \cdot \left(f_{ij} - f_{i.} f_{.j}\right)^2}{f_{i.} f_{.j}}$, $i = \overline{1,p}$, $j = \overline{1,q}$. As such of value is higher as the couple of the both modalities, it is more important in the connection. The contribution to the contingence inertia matrix is: $CI_{ij} = \frac{\left(f_{ij} - f_{i.} f_{.j}\right)^2}{f_{i.} f_{.j}}$. The f_{ij} values are effective frequencies, reals, empirics while the $f_{i.} \cdot f_{.j}$ are theoretical frequencies, it means those expected frequencies to have confirmed the independence hypothesis, for the two variables. The deviations among these values can be interpreted as deviations from the independence hypothesis, and they are calculated in this way: $R_{ij} = \frac{f_{ij} - f_{i.} f_{.j}}{\sqrt{f_{i.} f_{.j}}}$.

These deviations can be grouped in a matrix R ,having the general element R_{ij}, $i = \overline{1, p}$, $j = \overline{1, q}$. This is the inertia matrix. The sum of the elements square represents the total inertia of the contingence table.

The correspondence analysis can be realized by using the principal components analysis of the R table. This thing is equivalent with the inertia decomposition in the principal space or principal components. The first principal component gathers the maximum inertia, the second one takes maximum from the rest of inertia and so on, components being absolutely uncorrelated two by two [3].

The inertia axis will be obtained by the R matrix diagonalization using singular value decomposition or the $R^t \cdot R$ matrix by eigen value decomposition.

Multiple correspondence analysis is an extension of the simple correspondence analysis algorithm, to multivariate categorical data coded in the form of a Burt matrix. In fact, the Burt table is a generalized contingence table for many categorical variables. If it is denoted by q_1, q_2, ...,q_m the number of modalities for each categorical variable, the Burt table will have a number of $p = \sum_{i=1}^{m} q_i$ rows and columns representing the cross frequencies of the modalities of the m variables.

$$B = \begin{array}{rc} \begin{array}{r} q_1 \left\{ \begin{array}{c} \\ \\ \end{array} \right. \\ \dots \\ q_i \left\{ \begin{array}{c} \dots \\ k \\ \dots \end{array} \right. \\ \dots \\ q_m \left\{ \begin{array}{c} \\ \\ \end{array} \right. \end{array} & \left(\begin{array}{ccc} & & \\ & & \\ & b_{ik,jl} & \\ & & \\ & \dots\ l \dots & \end{array} \right) \\ & \underbrace{\qquad}_{q_1} \quad \underbrace{\qquad}_{q_j} \quad \underbrace{\qquad}_{q_m} \end{array}$$

The general element, $b_{ik,jl}$represents the number of instance for which the i variable has the k modality and the j variable has the l modality.

Similar, with the bivariate analysis case, the analysis purpose is to identify the main inertia axis and to make a representation of the modalities profiles, in this space.

Analysis stages:

1. The matrix of relative frequencies is determined by reporting the absolute frequencies, from the Burt table, to the sum of frequencies from the same table:

$$S= \frac{1}{N} \cdot B ,$$

where $N = n \cdot m^2$

2. The row and column masses of the P matrix are determined by relation:

$$s_i = \sum_{j=1}^{p} S_{ij} ,\ i = \overline{1, p}$$

The row masses are equal with the column masses because of the P matrix is symmetric.

3. The R standard deviation matrix is determined by:

$$R_{ij} = \frac{S_{ij} - s_i s_j}{\sqrt{s_i s_j}} ,\ i=\overline{1, p} ,\ j= \overline{1, p} .$$

4. The Eigen Decomposition algorithm is applied to matrix R, in order to determine the inertia axis and their importance. According to the Eigen Decomposition algorithm, the R matrix, which is square and symmetric can be written:

$R = U \cdot S \cdot U^{t}$,

where U will contain on columns the orthogonal Eigen vectors of the R matrix (inertia axis) and S will contain the Eigen values on the main diagonal.

5. Determining the standardized row/column coordinates:

$$L_{ij} = \frac{U_{ij} \cdot \sqrt{\lambda_j}}{\sqrt{s_i}} ,\ i=\overline{1, p} ,\ j= \overline{1, p} .$$

6. Determining the percentage of inertia associated with each axis:

$$I_k = \frac{\lambda_k}{\sum_{i=1}^{m} \lambda_i} ,\ k= \overline{1, p} .$$

3. Research Results

3.1 Grouping the Variables by Using the χ2Distance

Figure 1 presents the dendrogram of hierarchy built on complete linkage method. The partition with five clusters is assumed as optimal partition. The optimal partition is achieved based on subjective criterion that concern the purpose of the analysis, or by considering a particular criterion as being the criterion of maximal differences among the joining distances.

It can be observed that partition with five clusters is the optimal one, taking into consideration the last criterion. If we analyses the components of clusters, we can say that this partition is "satisfactory" both in term of significance and considering the role played by the questions, from the questionnaire, corresponding to the variables from the clusters. Thus, it can be observed that the first cluster of the partition groups the variables that denote the general information; the second cluster of partition groups the variables derived from the target questions of the questionnaire, namely the questions concerning the adoption of the low consumption bulbs; the third cluster contains variables related to information about replacing bulbs and variables like age of professional profile. This is a heterogeneous cluster. The fourth cluster contains variables related to understanding of economic advantages of using economic bulbs, except the variable gender. The fifth cluster groups variables that capture the attitude and education towards consumption.

Figure 1. Optimal partition. Dendrogram

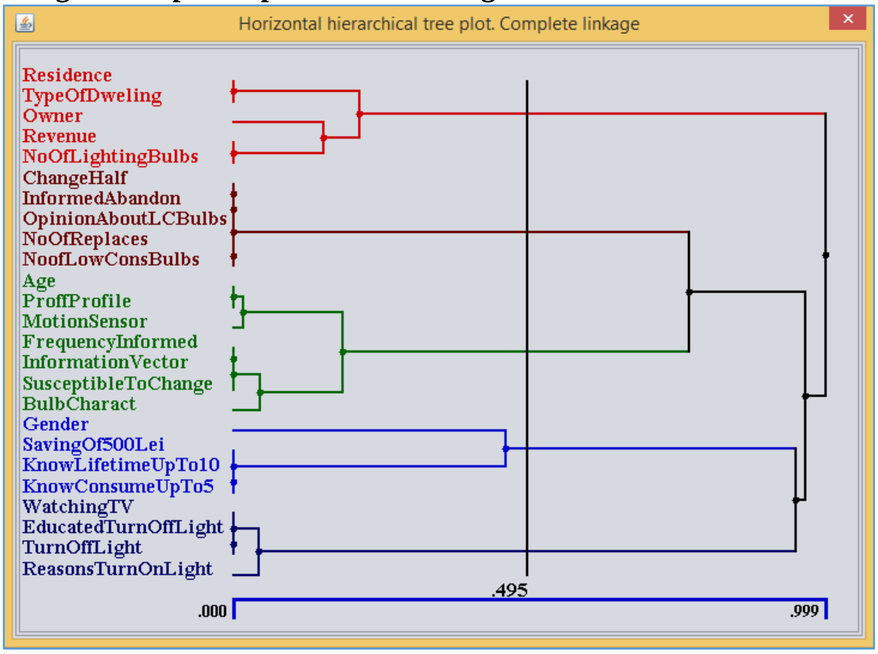


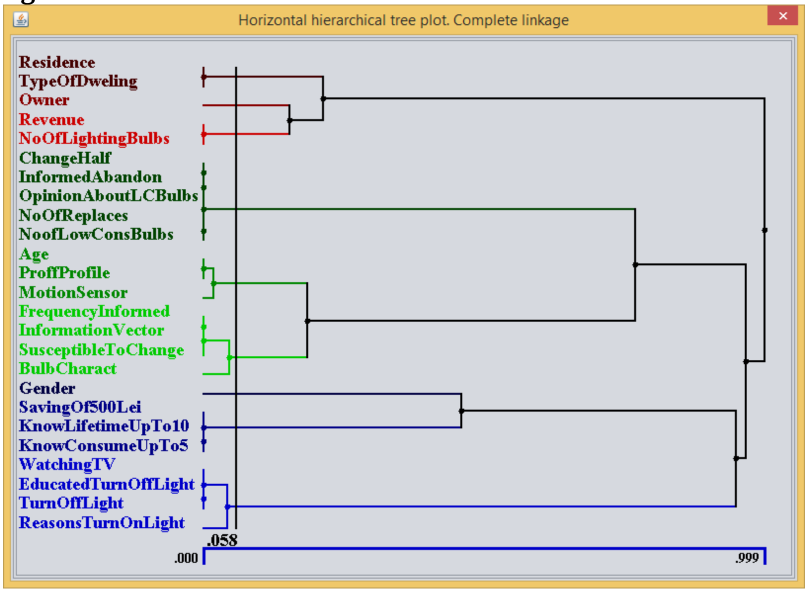
Table 5 includes the joining and average distances among objects from the five clusters of the partition. Can be observed that for the fourth cluster, the average distances are greater than a maximum acceptable value (0.1), for the significant threshold, in the $\chi 2$ independence test. Thus, in this cluster exist pairs of variables for which the independence test is not rejected with a confidence greater than 90%.

Table 5. Optimal partition. Summary

No of cluster	Joining distance	Average distance
1	0.21295	0.07509
2	0.00021	0.00002
3	0.18592	0.03244
4	0.46053	0.14592
5	0.04317	0.01379

In this situation, it is recommended to continue the searching of partition with clusters that contain variables connected among them. We can establish as target the partition that contains only clusters having the average distance lower than 0.1. In our case, this is the partition with nine clusters. The dendrogram graphic corresponding to this partition is presented in the figure 2 and the joining and the average distances are in the table 6.

Figure 2. Partition with 9 clusters



In the partition, with nine clusters, the variables taken from the questionnaire were grouped in this way:

- Cluster 1 is formed at the distance of 0 from the variables {*Residence*,*TypeOfDweling*}, that reflects issues concerning the type of residence and the type of dwelling. Generally speaking the Romanian's households from rural areas are houses as type, while from urban areas are flats.
- The clusters 2 and 7 are formed from single variable: *Owner* and respectively *Gender*. These variables are relatively independent from the others.
- Cluster 3 is logically composed from two dependent variables: *Revenue*and *NoOfLightingBulbs*. People who have high incomes have also many bulbs in the household.
- Cluster 4 contains the key question of the questionnaire. The variables from this cluster are the following: {*ChangeHalf*, *InformedAbandon*, *OpinionAboutLCBulbs*, *NoOfReplaces*, *NoofLowConsBulbs*} and they are in relation with the process of replacing of the incandescent bulbs with the low consumption bulbs.
- Cluster 5 underlines the connection between age, professional profile and the option, for motion sensors.

- Cluster 6 reflects the relationship between the informing issue and the variable regarding susceptibility to change the consumption.
- Cluster 8 is formed from the variables *SavingOf500Lei*, *KnowLifetimeUpTo10*, and *KnowConsumeUpTo5* that reflects the knowledge about advantages of usage low consumption bulbs.
- Cluster 9, {*WatchingTV*, *EducatedTurnOffLight*, *TurnOffLight*, *ReasonsTurnOnLight*} is defined of the variables that reflect education, behavior, caring for saving.

Table 6. Partition with 9 clusters. Summary

No of cluster	Joining distance	Average distance
1	0.00	0.00
2	0	0
3	0.00001	0.00001
4	0.00021	0.00002
5	0.01807	0.00611
6	0.04586	0.01313
7	0	0
8	0.00001	0.00001
9	0.04317	0.01379

3.2 Correspondence Analysis in Clusters and Among Clusters

As already presented, the variables of analysis can be grouped in the large categories that highlight some issues of behaviors concerning the lighting consumption, in the households. In order to identify the types of consumers, it is necessary to analyze the connections among clusters by selecting of a representative variable for each cluster. The analyzed clusters are those clusters having more than three variables. In the cluster 4, the cluster of variables that reflect the incandescent bulbs replacing with the economic ones, the distribution of modalities on the first two axes of inertia is presented in figure 3.Three agglomerations of profiles are visible in the chart. An agglomeration (rectangle 1) contains the answers of people who reject the economic bulbs; they have no economic bulbs and they don’t intend to buy such bulbs even they have or not information about the advantages of usage the economic bulbs. Another group of profile (rectangle 2) groups the answers of the people who already changed the incandescent bulbs. A third group (rectangle 3) contains the answers of persons who partially replaced the incandescent bulbs and are predisposed to change more incandescent bulbs, in the future. It can be also observed that the *ChangeHalf* variable are representative for the three types of behavior. The correspondence analysis for the sixth cluster of variables doesn’t show the patterns behavior. The first three dimensions cover only 18% from inertia. The profiles distribution to the first two axes (figure 4) shows a marginal position of the people who are disinterested by the problem, not wishing to be informed and unwilling to change the behavior (*SusceptibleToChange*).

Figure 3. Plot of profiles for cluster 4

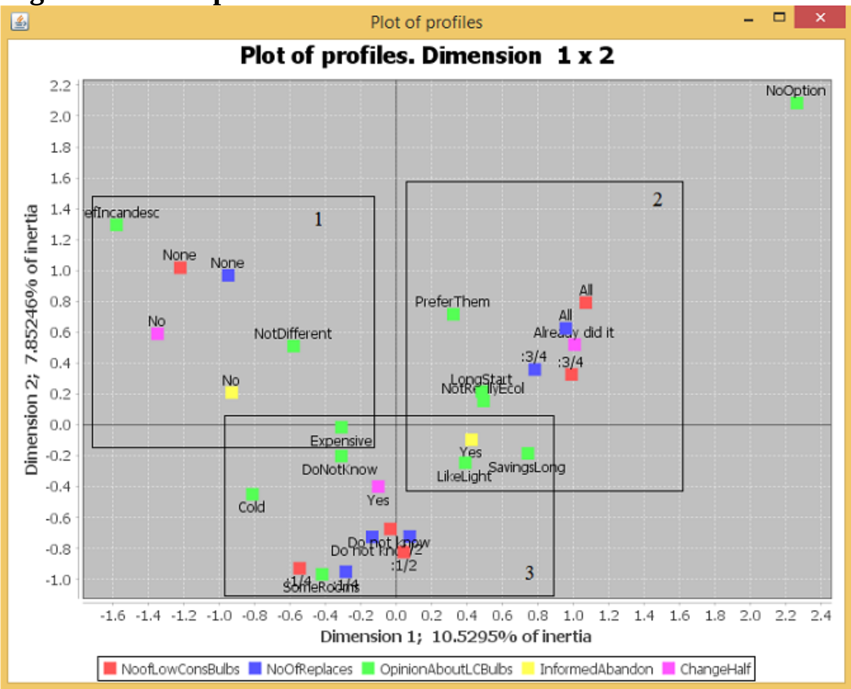
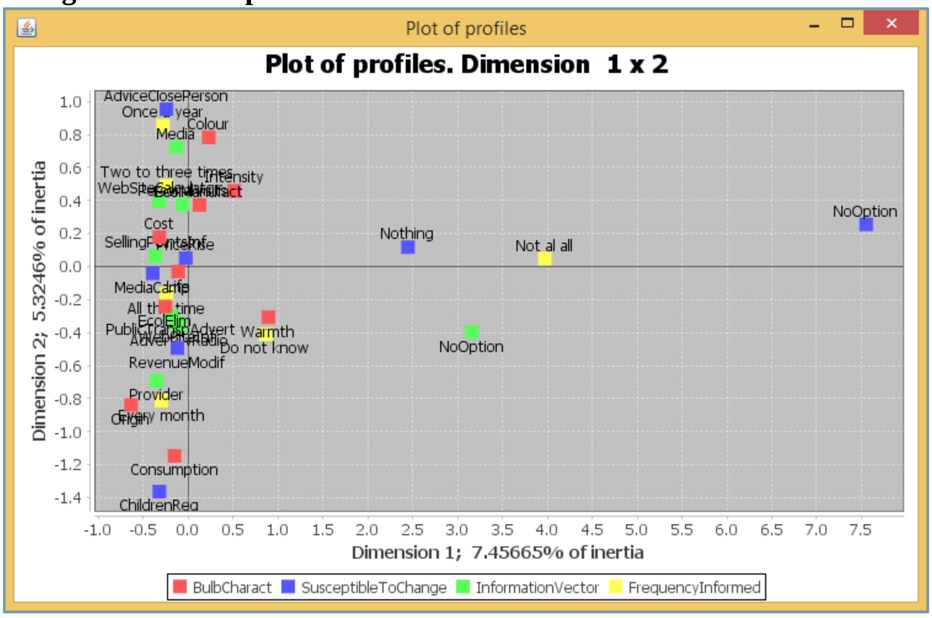
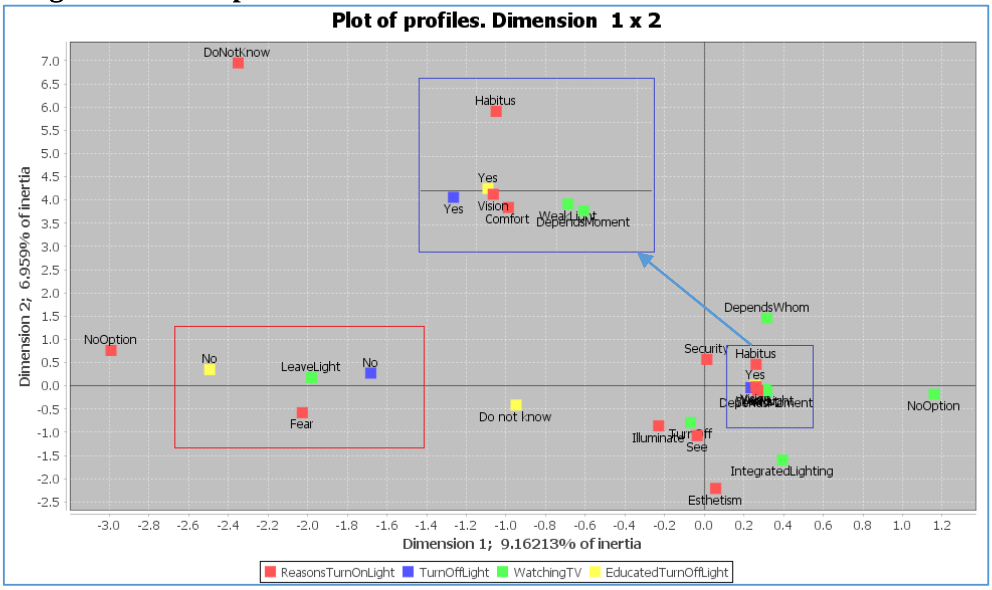


Figure 4. Plot of profiles for the sixth cluster



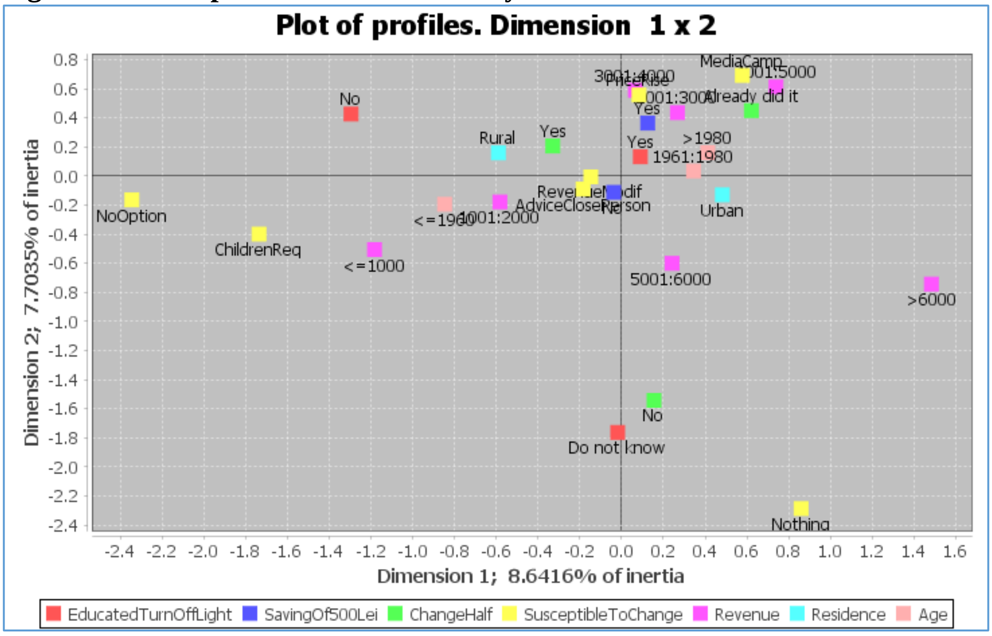
The association among response variants is very clear in the cluster of the *KnowConsumeUpTo5*, *KnowLifetimeUpTo10* and *SavingOf500lei* variables that reflects the knowledge about the advantages of usage the economic bulbs. There are one group of *Yes* answers and another group of *No* answers.
In the cluster of *TurnOffLight*, *EducatedTurnOffLight*, *ReasonTurnOnLight* and *WatchingTV* variables are highlighted the associations between the answers that reflect the education for saving. It can be observed one group (figure 5 – left rectangle) of the people which don’t turn the light off, when they leave the room, don’t turn the light off when they watch to the TV set, in general they weren’t educated to turn the light off and they are afraid of the dark. In the right rectangle are highlighted the opposite answers,namelythe people who turn the light off, in general persons educated to turn the light off.

Figure 5. Plot of profiles for the ninth cluster



A correspondence analysis which include all variables from the questionnaire is difficult to explain because of the large number of modalities. As it has been showed already, the variables can be grouped in clusters of variables with strongly connections between them. In order to perform an overall analysis, from each cluster can be selected only one variable, for instance: age, revenue or type of residence, such that to better identify associations among various categories of consumers. The selected variables are: *EducatedTurnOffLight*,*SavingOf500Lei*, *ChangeHalf*, *SusceptibleToChange*, *Revenue*, *Residence* and *Age*. The profiles distribution on to the first two inertia axes is presented in figure 6. In the complementary way, and in order to underline more clearly the connections among profiles, it can be used the cluster analysis on the inertia matrix. This brings a plus of information because of takes into consideration all inertia axes. The dendrogram (figure 7) not only complete, in terms of information, the profiles plot but permits to identify more clearly the groups of appropriate profiles.

Figure 6. Plot of profiles for overall analysis



Each category of consumers is identified by a cluster of profiles. Cluster analysis provides information about each category of consumers. A first information is related to the support level of the clusters, namely the number of individuals to which two profiles from cluster are simultaneously identified. Another useful information is linked to the percentage of inertia covered by clusters. When inertia is at a high level, the amount of information that can be extracted and interpreted at cluster level is high, too. Based on the standard deviation matrix the total inertia can be calculated as follows:

$$I = \sum_{i=1}^{p} \sum_{j=1}^{p} R_{ij}^{2} \quad ,$$

where p is the number of profiles and R is the standard deviation matrix.

Inertia due profiles is: $IP_i = \sum_{j=1}^{p} I_{ij}$, i=1,p. The inertia of the profiles cluster is the sum of the profiles inertias belonging to the cluster: $CI_k = \sum_{i \in k} \sum_{j \in k} R_{ij}^{2}$, where k is the cluster number. The inertias are presented by percentage as histograms (figure 8), for the clusters corresponding to the five categories of consumers. The degree of support of the cluster can be calculated as:

$$CS_k = \sum_{i \in k} \sum_{j \in k} b_{ij} ,$$

where k is the cluster number and b_{ij} are the cross frequencies from the Burt table corresponding to the i and j profiles.

Figure 7. Classification profiles by inertia

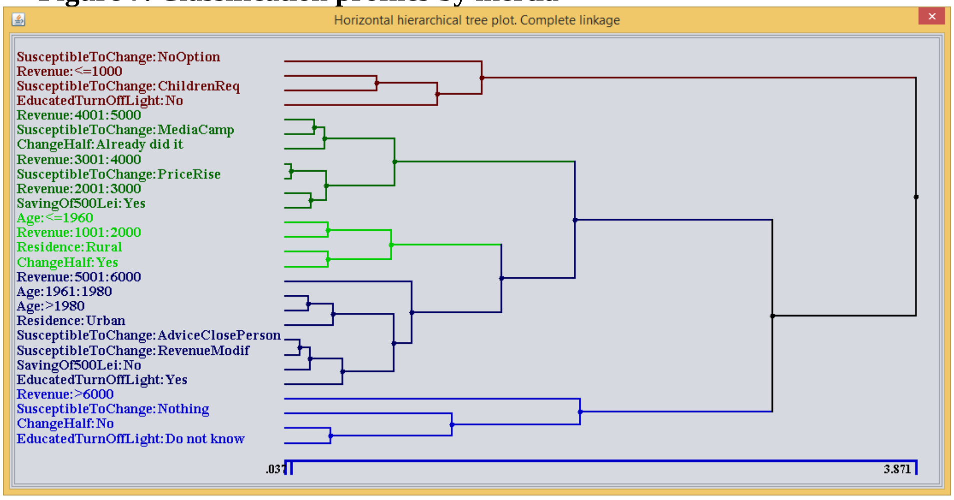
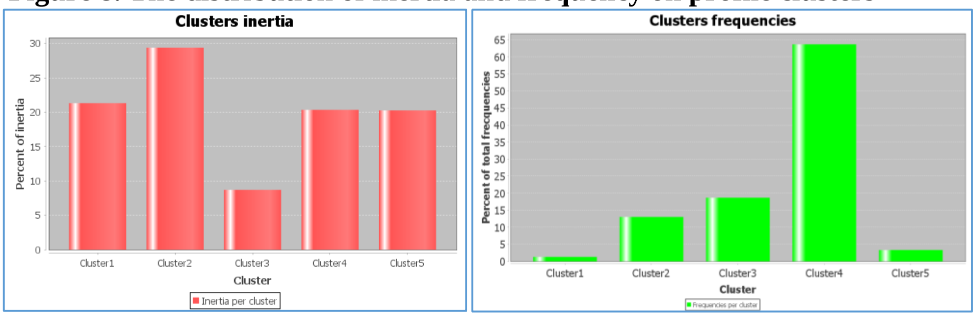


Figure 8. The distribution of inertia and frequency on profile clusters



A software analysis application was designed and used for data processing, in order to get the results, and to display them in tabular and graphical forms. The software application was developed based on Java technologies. *Apache Commons Mathematics* library was used as support for statistical and numerical methods implementation. *JFreeChart* library was the base support for graphical processing development.

4. Conclusions

The paper proposes a methodology to identify the profiles of respondents, based on answers gathered from a survey research. The particular task of our scientific approach is to identify consumers' profiles, based on domestic lighting behavior, habitand attitude to change incandescent bulbs exiting in households with low consumption bulbs.

By applying proposed methodology and summarizing the results of both analyzes performed, the following categories of consumers were identified:

1. Consumers with very low revenues who are available to modify their own consume behavior at their sons' or daughters' request;
2. Consumers with average revenues, who are informed, having knowledge about the advantages of the usage of the low consumption bulbs and who already replaced at least a half of bulbs;
3. Consumers with low revenues, elderly people, from rural areas, willing to replace the incandescent bulbs from their households;
4. Consumers with relatively high revenues, being young or of middle-aged, from urban areas, who didn't exactly realize the financial benefits of the low consumption bulbs usage, but they are willing to change their consumption behavior. They are consumers which give importance to the financial aspects of consumption, and they have been educated for savings;
5. Consumers with high level revenues, being indifferent about the consumption. They don't want to change their consume behavior.

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