# Exploratory data analysis of energy security in the EU member countries in the period 2000-2010

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## 1  Introduction

Fossil fuels form the foundation of energy balance in the European Union member countries. Their share in the total primary energy supply in 2010 amounted to respectively: oil (33.3%), gas (25.5%) and coal (16.2%). Net import constituted 55.5% of the total primary energy supply in 2010 and increased in comparison with 2000, when it constituted 49%. A growing dependence of the EU on imported energy and diminishing deposits of its own resources make the issues connected with energy security and energy policy of the EU one of the most important topics of debates. Additionally, energy balance of the EU does not correspond to energy balance of its particular member countries due to their diversification, which results in difficulties with developing a single energy policy. The EU member countries differ in their energy balance structure, the level of dependence on import and the level of diversification of energy suppliers. Those aspects, Papiez (2013), make the issue of energy security of the EU and the EU member countries worth considering.

There are numerous definitions of energy security developed by countries and international organizations (e.g. the International Energy Agency (IEA, 2009), the Asia Pacic Energy Research Centre (APREC, 2009) or the World Energy Council (WEC, 2009), since energy security depends on national priorities and their national concerns. Thus, it is difficult to define the term energy security precisely. Generally, most definitions of energy security make reference to its three aspects (energy, economy and ecology) and describe it as the availability of 'uninterrupted energy supplies at acceptable prices with respect to the natural environment'. Energy security is not directly measurable, although it can be approximated by multivariate set of variables. That is why in order to evaluate energy security in

quantitative terms the authors have developed indicators describing the relations between energy consumption and economic development, natural environment and social issues. The aim of the paper is to analyse energy security in the EU member countries in the period 2000 - 2010.

## 2   Empirical results

Taking into account a great variety of objects analysed with regard to the indicators describing energy security, which results in high volatility and the occurrence of outliers, partitioning among medoids (PAM) procedure developed by Kaufman and Rousseeuw (1990) was used. Similarly to a traditional k-means method, it assumes partitioning n observations into k clusters. PAM operates on the dissimilarity matrix, is less sensitive to outliers because it is based on the most centrally located object in a cluster (i.e. medoids), provides the silhouette which allows to determine which objects lie well within their clusters and which do not, and also shows how good is the quality of the clustering obtained. They suggested that silhouettes, i.e. average silhouette width, can be used for the selection of the best number of clusters in PAM (or in k-means methods).

In the second part of the analysis the authors focused on interpretations of the differences between the countries and clusters of countries. The classical principal components (PC) analysis is the most popular extraction and dimension reduction tool. It seeks the linear combinations of the original variables which capture maximal variance. Each PC is a linear combination of all variables and the loadings are usually non zero, which makes the interpretation difficult. Zou et al. (2004) proposed a new method called a sparse principal component analysis (sPCA). They used the lasso (elastic net) to generate modified principal component with sparse loadings. The idea is to formulate PCA as a regression-type optimization problem and obtain sparse loadings by imposing the lasso constraint on the regression coefficients.

The analysis of the level of energy security in EU member countries in the period 2000 - 2010 was conducted on the basis of variables used to obtain the Aggregated Energy Security Performance Indicator (AESPI) in (Martchamadol, Kumar 2013). As not all the values of the variables were accessible, only 15 out of 25 were selected for the analysis. The first stage of the analysis focused on the assessment of the quality of clustering based on average silhouette width. The value of average silhouette width (0.27) indicates a poor quality of clustering, which may indicate an artificial division of countries into clusters. The poor quality of clustering may also result from geographic, political and economic factors significantly differentiating the EU member countries.

The application of sPCA indicated four main components of energy security, which explained 78% of total variance. The components were named
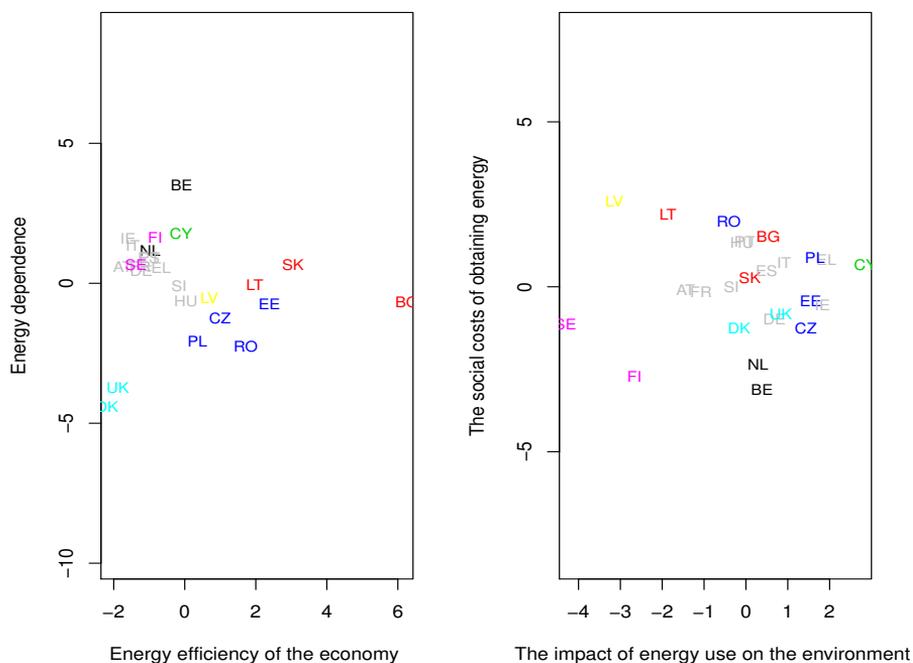
FIGURE 1. The situation in EU countries with respect to the new dimensions of energy security

according to their economic interpretation. The first sPCA component represents energy efficiency of the economy. The higher its value, the worse the economic situation of a given country with regards to energy efficiency. The highest energy efficiency in 2000 was found in Denmark and the United Kingdom, and the lowest in Bulgaria. It can be noticed that 'old' EU countries are characterised by higher energy efficiency and 'new' ones - by lower energy efficiency.

The second sPCA component represents energy dependence, i.e. dependence on energy source and type. The higher the component is, the more energy dependent a country is. In 2000 Belgium was the country with the highest dependence, and Denmark and the United Kingdom were the countries with the lowest energy dependence.

The third sPCA component represents the impact of energy use on the environment. The higher the component is, the more negative impact of energy use on the environment in a given country can be noticed. The lowest negative impact was observed in 2000 in Sweden, Finland, Lithuania and

Latvia, and the highest in Cyprus.

The fourth sPCA component represents the social costs of obtaining energy. The higher the component is, the less it costs a society of a given country to obtain energy. The lowest value of this component in 2000 was noticed in Belgium, Finland and the Netherlands and the highest in Lithuania, Latvia and Romania.

## 3    Conclusion

The results obtained indicate that the greatest improvement of energy efficiency took place in Romania, Bulgaria and Slovakia, and deterioration in Lithuania, Belgium and Estonia. The highest increase of energy dependency was noted in the United Kingdom and Lithuania, and the greatest decrease of energy dependency in Estonia. The negative impact of energy use on the environment decreased in Denmark and Portugal, and increased in Finland and Estonia. The social costs of obtaining energy decreased most in the United Kingdom and Ireland, and increased in Estonia.

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