

Nataliia STRELBITSKA

PhD in Economics,
Associate Professor,
Department of International Economic Relations,
Ternopil National Economic University
E-mail: nataliya.strelbitska@gmail.com

Olha KOVALCHUK

PhD in Physics and Mathematics Science,
Associate Professor,
Department of Economic and Mathematical Methods,
Ternopil National Economic University
E-mail: olhakov@gmail.com

ANALYSIS OF DEPENDENCE OF ENERGY INTENSITY LEVEL OF THE ECONOMY ON THE ELECTRICITY PRICE FOR HOUSEHOLDS OF THE EU MEMBER-STATES

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Abstract

In the proposed article, we identified possible dependencies of the price of electricity for households and energy intensity of the economy of the EU Member States. For each of the EU countries we have established limiting values of electricity prices for households in which the energy intensity of the economy is likely to reduce. Association Rules, one of the methods of Data Mining, has been applied, which makes it possible to discover hidden dependencies and relationships between the studied variables at the stage of data exploration. This analysis is based on building Association Rules of relation between the observed processes. The results will be useful in the construction of regression and predictive models and during cluster analysis.

Keywords: electricity prices; energy intensity; infographics; data mining; association rules; EU countries.

JEL classification: Q41, C83

Introduction

Over the past century, energy and electricity have become vital contributors to the quality of our life. Directly or indirectly, energy and electricity use have stimulated improvements in many, if not most, aspects of society, including employment, through the creation of new jobs; health, through improved food preservation and medical technology; education, through better lighting and enhanced learning tools; and culture, through the availability of televisions, radios, and computers. As electricity consumption has continued to grow, electricity's role in these types of quality-of-life improvements has rapidly expanded.

Electricity consumption (energy) and energy intensity are generally influenced by income and prices. Thus rising per capita income and higher energy prices have played an important part in lowering energy intensity [1].

To study the relationship between electricity prices for households and energy intensity we selected EU countries, because energy policy in the region is aimed at more sustainable use of natural resources and the shift towards resource-efficient, low-carbon growth and reducing the dependence on traditional energy sources through the generating electricity from renewable resources. According to projections of EUREL (2013). the power demand in the EU27+ will rise until 2050 to approximately 4300 TWh (in 2008 this number was 3043 TWh). This is an increase of 1,2 % p. a.

There is a great number of researches on synergies between electricity prices and electricity (energy) consumption and energy intensity which are mostly based on classical methods of mathematics. In this article we try to identify possible dependency between electricity prices for households and energy intensity of the

economy of the EU Member States with the help of Association Rules method. We have defined the limiting values of electricity prices for households at which the energy intensity of the economy of each EU country is likely to reduce. The resulting dependencies may be useful for improving the energy policy of the EU, implementation of projections and further research in this area.

The article proceeds as follows. The next section provides a brief overview of previous research, related to the study of relationships between electricity (energy) prices, energy consumption and energy intensity. In the following section, we applied graphical analysis as one of the easiest ways to study the dynamics and the interdependence of economic indicators. In the penultimate section we revealed the main point of Data Mining application methodology to identify association rules. The final section is dedicated to the use of one of the Data Mining methods – Association Rules to determine hidden patterns and relationships between energy intensity and electricity prices for households of each EU country.

1. Literature overview

The relationship between electricity consumption and prices has been widely discussed by many researchers around the world [2; 3]. For instance, the researches held by John Garen, Christopher Jepsen and James Saunoris showed the presence of the sensitivity of electricity consumption to price [4]. Scientists have determined that the industrial sector is the most sensitive to price changes in both the short and long run. In the short run the commercial sector is also sensitive to price changes.

The Granger causality between energy price, energy consumption and economic growth of Turkey was examined by Deniz Aytacı and Mehmet Cahit Güran [5] for the 1987-2007 period using a VAR model and quarterly data. The results indicated that a bidirectional causality relation appears to exist between electricity consumption and GDP, and that there was a causality relation that runs from real GDP to electricity price.

Asafu [6] studied the causality between energy consumption, income and price for a number of Asian developing countries such as India, Indonesia, Philippine and Thailand. He used Granger causality analysis data for 1971 to 1995 period. The results showed that the directions of causality were different for different countries in Asia. He found a unidirectional causality from energy consumption to income in India and Indonesia whereas a bidirectional causality between energy consumption and income was found in Philippine and Thailand.

Asit Mohanty & Devtosh Chaturvedi examined whether electricity energy consumption drives economic growth or vice versa in the Indian context using the annual data covering the period from 1970-1971 to 2011-2012 [7].

A. Ciarreta and A. Zarraga used a panel data from 1970 to 2007 to analyze the causality of electricity consumption, prices and real GDP for a set of 12 European countries [8]. The results show evidence of a long-run equilibrium relationship between the three series and a negative short-run and strong causality from electricity consumption to GDP. Also, they found bidirectional causality between energy prices and GDP and weaker evidence between electricity consumption and energy prices.

Various researchers have studied the relationship between energy (electricity) consumption, prices, employment, real GDP, income etc. and they used different methodology for this. However, they usually used only methods of classical mathematics.

Whereas we offer to analyze the relationships between energy intensity of the economy and electricity prices for households and along with traditional graphic techniques of studying the relationship between economic indicators, use one of the methods of Data Mining – Association Rules. Such analysis makes it possible to detect the hidden non-obvious dependencies of the studied variables at the stage of initial analysis (intelligence data) and formulate association rules of their interference.

2. Graphic methods of investigation

One of the easiest ways to study the dynamics and the interdependence of economic indicators is a graphical analysis. It is used as a preliminary stage in the research of any complexity. The choice of further methods depends on the results of the graphical analysis.

Infographic tools were used for a comprehensive analysis of the dependence of energy intensity (variable EIE) of the economy on electricity prices for households (variable Price) (Figures 1-7). The study was conducted according to the figures of energy intensity of the economy (gross inland consumption of energy divided by GDP, kg of oil equivalent per 1, 000 EUR) in the EU Member States for 2005-2014, and the corresponding price of electricity for households of these countries over the years [9-14].

In most EU countries over the period there was a steady trend to the rising cost of electricity prices. Since 2008, the electricity prices in the EU have risen by 33%. However, in the Netherlands, Cyprus and Malta, the price of this strategic resource was not so stable. For instance, Cyprus experienced a price increase of electricity from 2005 to 2006, from 2007 to 2008 and from 2009 to 2012 and the reduction in other periods of monitoring. In Malta there was a significant leap in electricity prices in 2009 (Figure 1). Cyprus and Malta as island Member States are highly dependent on liquid hydrocarbons and because of isolation faced by these countries, they have to manage the island's cyclic demand by relying solely on their own power systems.

The average electricity price for households for a period from 2005 to 2014 was the highest in Denmark and Germany, and the lowest in Bulgaria and Estonia (Figure 2). The highest average electricity prices for households in Denmark and Germany can be explained by considerable share of taxes and levies in total household electricity prices in these countries, whereas the low average electricity price for households in Bulgaria can be explained by the lowest share of taxes and levies. Generally, taxes & levies for household consumers in the EU increased from €51/MWh to €67/MWh, a rise of 31%. The share of this component in the total price increased from 29% to 34% in the period 2008-2012 (5 p. p.).

As was mentioned above, energy intensity is the ratio between the gross inland consumption of energy and Gross Domestic Product (GDP) calculated for a calendar year. The Gross Inland Energy Consumption (GIEC) is calculated as the sum of the gross inland consumption of the five sources of energy: solid fuels, oil, gas, nuclear and renewable sources.

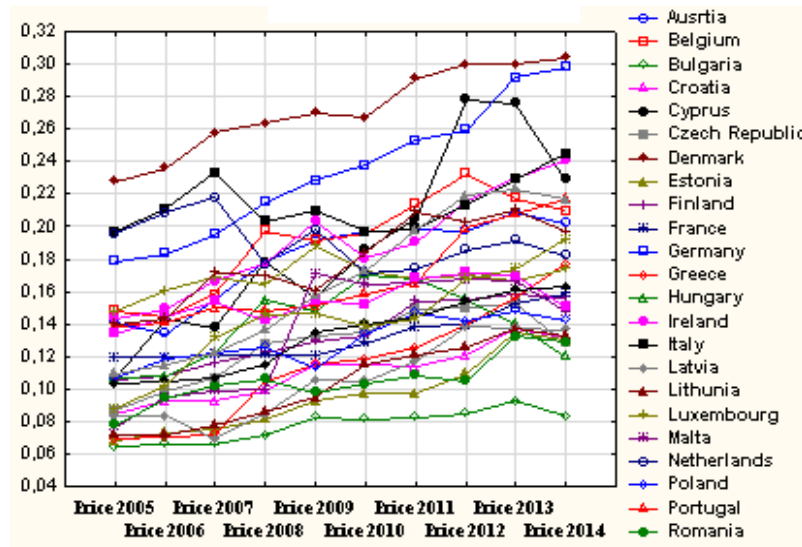


Figure 1. Changes in electricity prices for households in the EU for 2005-

Source: Self compiled.

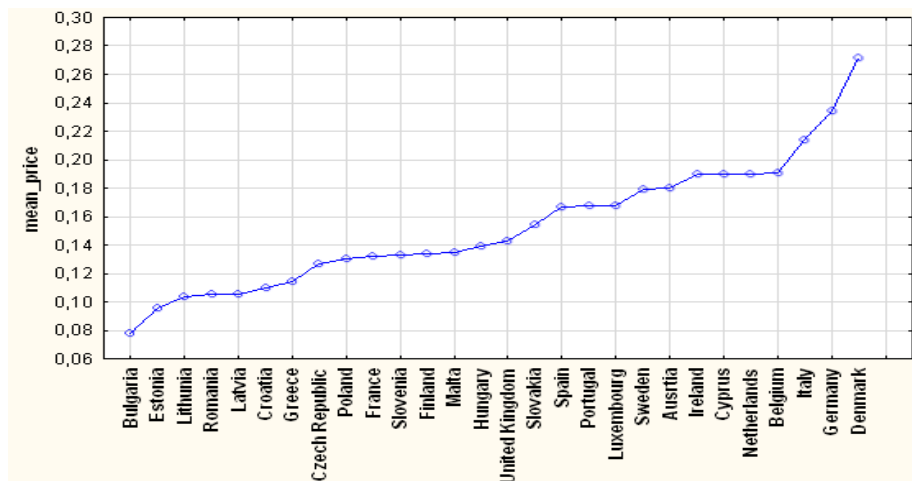


Figure 2. Line graph of average electricity price for households

Source: Self compiled.

Dynamics of energy intensity of the economies of the EU Member States for the observed period was characterized by a trend to decrease for most countries in the union. However, the steady reduction of energy use is not peculiar to Estonia, Slovenia, Croatia, Malta and Greece. (Figure 3). It should be noted that the economic structure of an economy plays an important role in determining energy intensity, as service based economies will, a priori, display relatively low energy intensities, while economies with heavy industries (such as

iron and steel production) may have a considerable proportion of their economic activity within industrial sectors, thus leading to higher energy intensity.

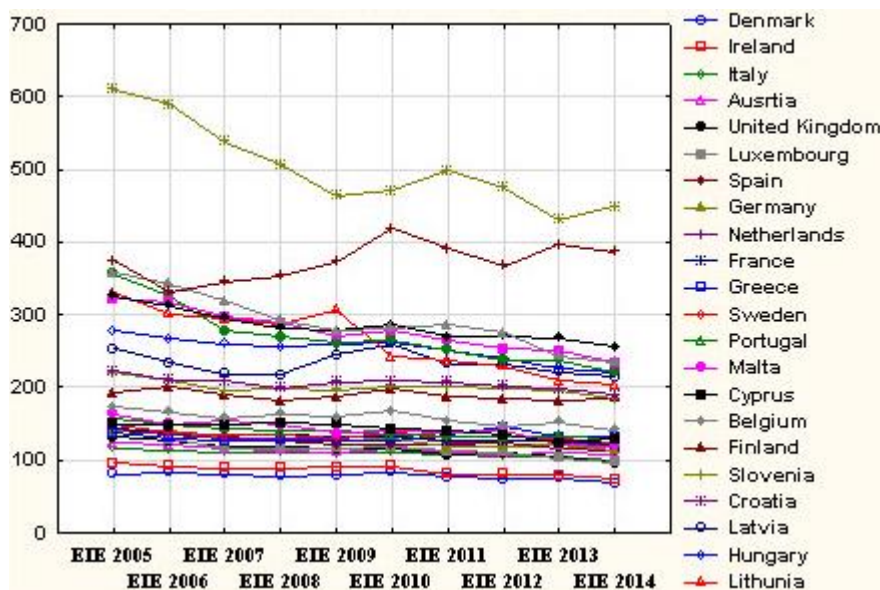


Figure 3. Dynamics of energy intensity in EU countries for 2005–2014

Source: Self compiled.

The maximum value of energy intensity of the economy, in average for the observed period, was characteristic of Bulgaria and Estonia. Denmark and Ireland proved to be the leanest in this respect (Figure 4).

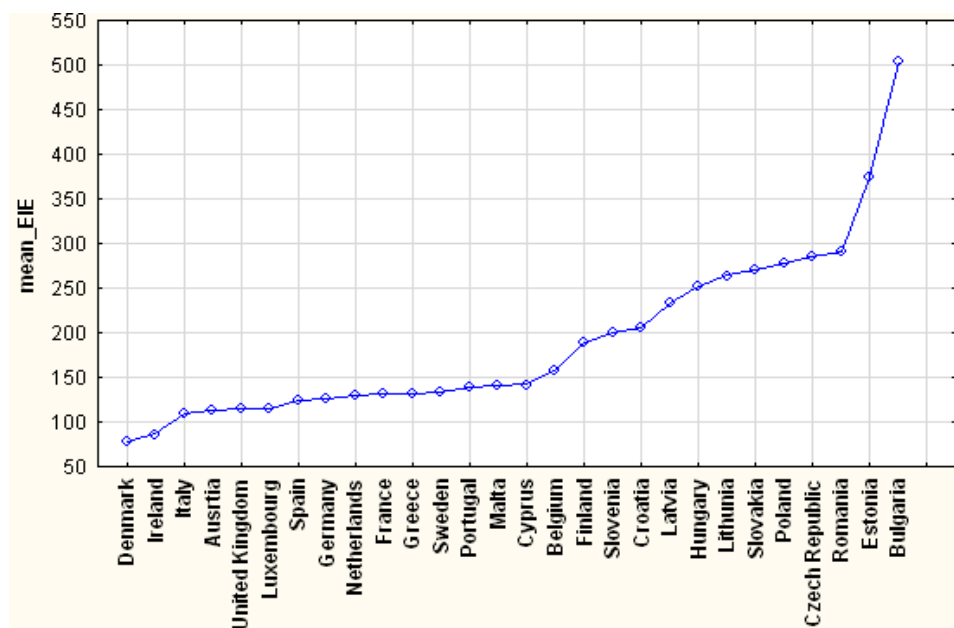


Figure 4. Line graph of average values of energy intensity of the economies for 2005-2014 in EU countries

Source: Self compiled.

Factors that influence on energy intensity are: energy prices; composition of an economic sector’s output (e. g., the mix or type of industrial or commercial activities); capacity utilization; capital investment and new construction; population and demographics; climate; technological innovation; energy policies and actions of national, state, and local governments. The price of energy (including electricity) is one of the key factors affecting the level of energy intensity of the economy. Electricity prices depend on the energy requirements of

fixed capital (e. g., commercial buildings), the types of technologies in use, fuel availability, the ability to move electricity across large areas (prior to recent innovations in electricity markets), and regulatory requirements etc.

In our study, we detected associative links in terms of empirical data on the energy intensity of the economy and electricity prices for households in EU Member States. For each of the EU countries we have identified limiting values of electricity prices for households at which the energy intensity of the economy is very likely to decrease.

Generally, over the period there was an inverse relation between energy intensity and electricity prices for households in EU Member States (Figure 5).

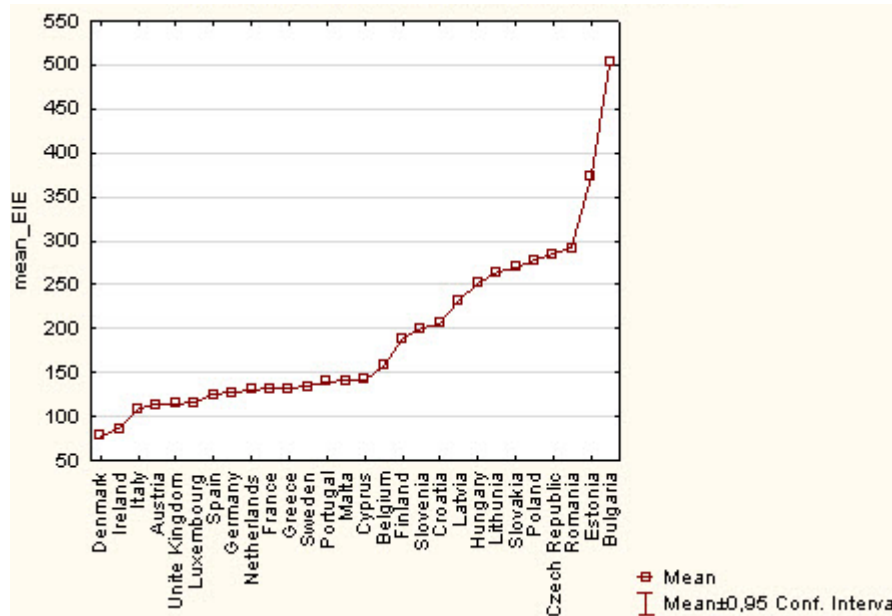


Figure 5. Graph of dependency of average values of energy intensity of the economies (for 2005-2014) on average electricity price for households (for 2005-2014) in EU countries

Source: Self compiled.

In the whole, from 2005 to 2014 there was a growth in electricity prices for households in EU countries, and only in 2013 a slight decline began (Figure 6).

At the same time from 2005 to 2009 the energy intensity in the EU was characterized by steady decline. From 2009 to 2010 there was a significant increase in energy intensity by members of the association. Since 2010 there has been a steady decline (Figure 7).

3. Data Mining application methodology for association rule mining

Data mining, or data intelligence is a process aimed to find new correlations, trends, patterns, relations and categories by sorting large volumes of data using sample recognition techniques as well as statistical and mathematical methods [15].

While data mining, the operations and transformations of "raw" data (feature selection, stratification – placement by layers, clustering, visualization and regression) are performed repeatedly and are intended to find:

- self-explanatory structures, better revealing the essence of the processes;
- models of predicting results or characterizing the real-world situations based on the analysis of historical and subjective evidence.

The essence and the aim of data mining are to find non-obvious, objective, useful in practice patterns within large information arrays.

Classical statistics operates averaged characteristics of retrieval, which are often fictitious variables. Therefore, its methods are effective primarily to test developed hypotheses, while formulating a hypothesis in some cases turns out to be a difficult and time consuming task. Modern data mining technologies analyze the information for the purpose of automatic search of patterns typical of separate pieces of non-homogeneous multivariable data.

The following data mining tasks are aimed to detect hidden patterns and relationships between

chronological events:

- Associations – search for patterns among related events in the data set;
- Sequential Association – detecting patterns of chronological events;
- Link Analysis – finding dependencies in the data set;
- Visualization, Graph Mining – use of graphical methods demonstrating the patterns within the data sets.

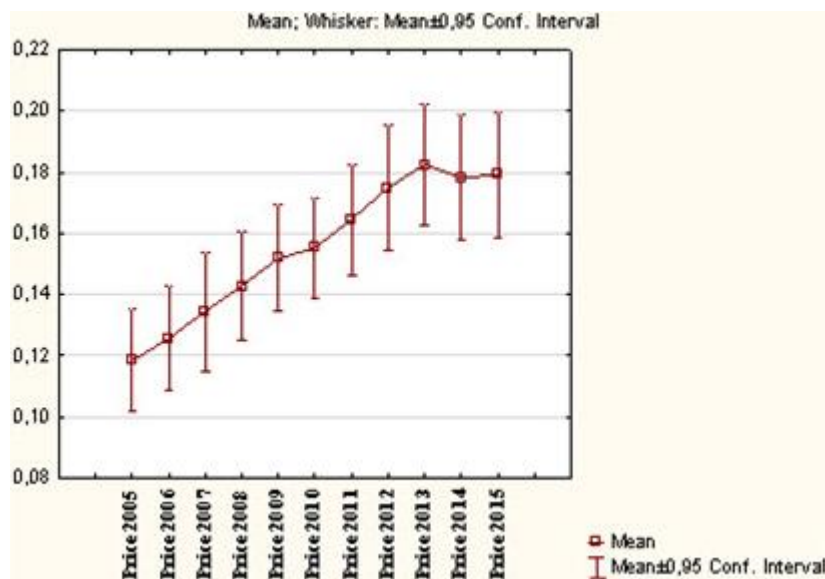


Figure. 6. Graph line of average electricity prices for households arranged by years

Source: Self compiled.

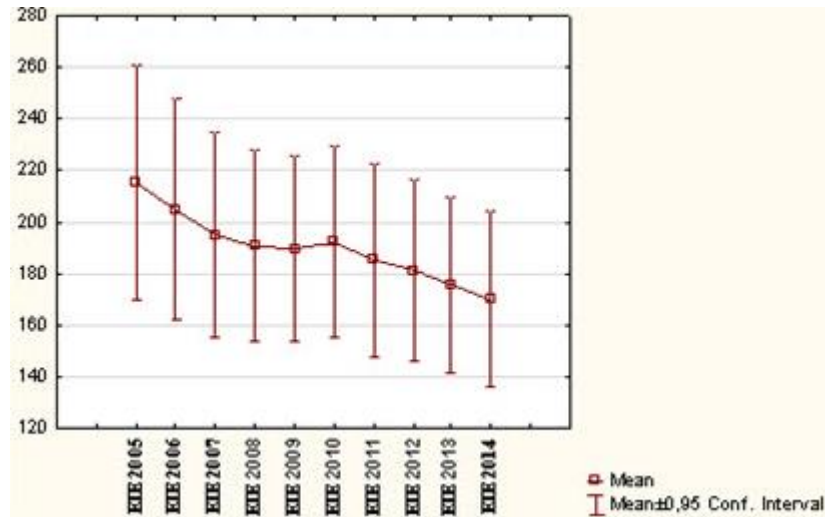


Figure. 7. Graph line of average values of energy intensity in EU countries arranged by years

Source: Self compiled.

Data mining is a set of a large number of different methods of knowledge discovery. The choice of a method often depends on the type of data available and the nature of the source information.

Association rules are applied in order to detect hidden patterns and relationships in large datasets. The association rules analysis is based on establishing the association rules of links between the observed processes. Association rules allow finding patterns among related events [16].

Association links – dependencies of “if the event *A* took place, correspondingly the event *B* is likely to

take place" type. Association rules allow finding patterns among related events. For the first time the problem of finding association rules was proposed for detecting typical patterns of purchases, made in supermarkets, that is why it is sometimes called market basket analysis [17].

The information base for analysis is a set of transactions. A set goods paid in one check can be an example of transaction. Such a transaction is called market basket.

A generalized mathematical description of the problem of determining the sets of items, which are often found, in a large set of elements.

Let us denote the items, which make the itemsets being investigated, a set [15]

$$I = \{i_1, i_2, \dots, i_j, \dots, i_n\},$$

in which i_j – items, that belong to analyzed itemsets, n – total number of items.

Itemsets from set I , which undergo the analysis, are called transactions. The transaction can be described as a subset of the set I :

$$T = \{i_j | i_j \in I\}.$$

Let us describe the set of transactions, information about which is available for analysis, as a set

$$D = \{T_1, T_2, \dots, T_r, \dots, T_m\},$$

in which m – the number of transactions available for analysis.

Let us denote the set of transactions, which includes item i_j , as

$$D_{i_j} = \{T_r | i_j \in T_r; j = \overline{1, n} \ r = \overline{1, m}\} \subseteq D.$$

Let us denote the undefined itemset as

$$F = \{i_j | i_j \in I; j = \overline{1, n}\}.$$

The itemset, which consists of k items, is called k -term itemset.

The set of transactions, which includes a set F , is set down as

$$D_F = \{T_r | F \subseteq T_r; r = \overline{1, m}\} \subseteq D.$$

The ratio of the number of transactions, which includes a set F , to the total number of transactions is called the itemset support:

$$Supp(F) = \frac{|D_F|}{D}.$$

While performing the mine the analyst can define minimum values of the support of the analyzed itemsets $Supp_{min}$. The itemset is called a large itemset if the value of its support is bigger than the defined minimum value of the support:

During association rules mining it is necessary to find the set of all large itemsets:

$$L = \{F | Supp(F) > Supp_{min}\}.$$

Association rules analysis is aimed to define dependencies of "if in the transaction there is a separate set of X elements, then on the basis of this we can conclude that another set of Y elements should also appear in this transaction" type. Defining such dependencies allows finding very simple and self-explanatory rules.

Algorithms of association rules mining are designed to find all the XY rules, what is more, the support and the confidence of these rules should be higher than pre-determined thresholds, which are called minsupport and minconfidence accordingly.

The task of association rules mining consists of two sub-tasks:

- finding all the sets of items that meet the threshold of minsupport;

- generating the rules from the found sets of items that correspond to minsupport with certainty, which meets the threshold of minconfidence.

The values for such parameters as minsupport and minconfidence are selected to limit the number of found rules. Association rules mining is not a trivial task. One of the problems is algorithmic complexity in finding the set of items that are often found. As the number of items in the set I increases, the number of potential sets of items increases exponentially.

During association rules mining the task becomes significantly easier – it is checked if there is an element in the transaction or not.

With the help of data mining it is possible to build a model that will lead to a radical improvement in the financial and market position of the company or even a position of the state on the international arena.

The scope of data mining is not limited.

4. Finding hidden dependencies among total gross of domestic consumption of energy and its price by means of Association Rules

Association Rules analysis is based on building association rules of links between the observed processes. Association Rules allow finding patterns among related events.

The main advantage of association rules is that it is easily perceptible by a human and simply interpretable by programming languages.

Finding insights between energy intensity of the economy and electricity prices for households in EU countries for 2005-2014 was performed within software environment of Statistica 10 Statistical Package by means of association rules.

As a result of the applied analysis the association rules that satisfy the restriction on the minimum value of 0.90% of support, 99% of reliability and tight correlation of 0.99 (Figure 8) were found:

“If in one of the EU countries the electricity price for households during the current year is higher than average electricity price for households in this country for 2005-2014, with probability of 99 % energy intensity of the economy in this country this year will be lower than average energy intensity of the economy in this country for the same period. And vice versa”.

Summary of association rules (article_association_Rules_binar)						
Min. support = 99,0%, Min. confidence = 99,0%, Min. correlation = 99,0%						
Max. size of body = 10, Max. size of head = 10						
	Body	==>	Head	Support(%)	Confidence(%)	Correlation(%)
1	0,	==>	1,	100,0000	100,0000	100,0000
2	1,	==>	0,	100,0000	100,0000	100,0000

Figure 8. The results of the Association Rules analysis

Utility evaluation of the found association rules

Support shows what percentage of transactions is generally supported by the found rule. In our case the maximum support is reached, i. e. the associations rule with can be extended to all EU countries with high reliability:

1. If in Denmark electricity price for households was higher than 0.2717 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 78.1 kg of oil equivalent per 1000 euros.
2. If in Ireland electricity price for households was higher than 0.1895 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 86.3 kg of oil equivalent per 1000 euros.
3. If in Italy electricity price for households was higher than 0.2136 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 108.8 kg of oil equivalent per 1000 euros.
4. If in Austria electricity price for households was higher than 0.1802 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 113.6 kg of oil equivalent per 1000 euros.
5. If in United Kingdom electricity price for households was higher than 0.1430 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 114.6 kg of oil equivalent per 1000 euros.
6. If in Luxembourg electricity price for households was higher than 0.1680 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 115.7 kg of oil equivalent per 1000 euros.
7. If in Spain electricity price for households was higher than 0.1670 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 124.8 kg of oil equivalent per 1000 euros.
8. If in Germany electricity price for households was higher than 0.2339 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 126.7 kg of oil equivalent per 1000 euros.
9. If in Greece electricity price for households was higher than 0.1146 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 132 kg of oil equivalent per 1000 euros.

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10. If in Netherlands electricity price for households was higher than 0. 1902 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 130. 3 kg of oil equivalent per 1000 euros.
 11. If in France electricity price for households was higher than 0. 1318 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 131. 5 kg of oil equivalent per 1000 euros.
 12. If in Sweden electricity price for households was higher than 0. 1787 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 133. 9 kg of oil equivalent per 1000 euros.
 13. If in Portugal electricity price for households was higher than 0. 1677 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 139. 5 kg of oil equivalent per 1000 euros.
 14. If in Malta electricity price for households was higher than 0. 1351 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 141. 3 kg of oil equivalent per 1000 euros.
 15. If in Cyprus electricity price for households was higher than 0. 1896 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 141. 8 kg of oil equivalent per 1000 euros.
 16. If in Belgium electricity price for households was higher than 0. 1908 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 158. 1 kg of oil equivalent per 1000 euros.
 17. If in Finland electricity price for households was higher than 0. 13379 EUR per kWh, to with probability of 99 % energy intensity of the economy was lower than 188. 8 kg of oil equivalent per 1000 euros.
 18. If in Slovenia electricity price for households was higher than 0. 1326 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 200. 3 kg of oil equivalent per 1000 euros.
 19. If in Croatia electricity price for households was higher than 0. 1101 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 295. 6 kg of oil equivalent per 1000 euros.
 20. If in Latvia electricity price for households was higher than 0. 1058 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 232. 6 kg of oil equivalent per 1000 euros.
 21. If in Hungary electricity price for households was higher than 0. 1392 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 251. 4 kg of oil equivalent per 1000 euros.
 22. If in Lithuania electricity price for households was higher than 0. 1035 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 264 kg of oil equivalent per 1000 euros.
 23. If in Poland electricity price for households was higher than 0. 1299 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 277. 7 kg of oil equivalent per 1000 euros.
 24. If in Slovakia electricity price for households was higher than 0. 1541 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 270. 4 kg of oil equivalent per 1000 euros.
 25. If in Czech Republic electricity price for households was higher than 0. 1266 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 284. 4 kg of oil equivalent per 1000 euros.
 26. If in Romania electricity price for households was higher than 0. 1055 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 291 kg of oil equivalent per 1000 euros.
 27. If in Estonia electricity price for households was higher than 0. 0959 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 373. 5 kg of oil equivalent per 1000 euros.
 28. If in Bulgaria electricity price for households was higher than 0. 0774 EUR per kWh, with probability of 99 % energy intensity of the economy was lower than 503. 1 kg of oil equivalent per 1000 euros.

The confidence indicates the probability of the fact that if in a transaction there is X set there is also the Y set. While detecting hidden dependencies of energy intensity of the economy on the electricity price for households the 99% authenticity is applied, indicating the high utility of the resulting rules. It contains reliable information that was not previously known, but has a logical explanation. Such rules can be used to make decisions that bring benefit, for example, regulation of pricing policy in the individual EU countries.

Conclusions

The formal record of the detected Association Rule is as follows:

“IF $Prise_i > Mine_Prise_i$, THEN $EIE_i < Mine_EIE_i$ ”.

where Mean is the function of average computation in the Statistics program. $Prise$, $mean_Prise$, EIE and $mean_EIE$ denote the variables. $Mean_Prise$, and $mean_EIE$ are the average values of electricity prices and energy intensity for the whole period of observation correspondingly.

In our article, we detected associative links in terms of empirical data on the energy intensity of the economy and electricity prices for households in EU Member States. For each of the EU countries we have identified limiting values of electricity prices for households at which the energy intensity of the economy is very likely to decrease (Table 1).

Table 1. Limiting values of electricity prices for households and the energy intensity of the economy for EU Member States

<i>i</i>	Country	<i>Mean_Prise_i</i> , EUR per kWh	<i>Mean_EIE_i</i> , kg of oil equivalent per 1000 euros
1	Denmark	0,2717	78,1
2	Ireland	0,1895	86,3
3	Italy	0,2136	108,8
4	Ausrtia	0,1802	113,6
5	United Kingdom	0,1430	114,6
6	Luxembourg	0,1680	115,7
7	Spain	0,1670	124,8
8	Germany	0,2339	126,7
9	Greece	0,1146	132
10	Netherlands	0,1902	130,3
11	France	0,1318	131,5
12	Sweden	0,1787	133,9
13	Portugal	0,1677	139,5
14	Malta	0,1351	141,3
15	Cyprus	0,1896	141,8
16	Belgium	0,1908	158,1
17	Finland	0,13379	188,8
18	Slovenia	0,1326	200,3
19	Croatia	0,1101	295,6
20	Latvia	0,1058	232,6
21	Hungary	0,1392	251,4
22	Lithunia	0,1035	264
23	Poland	0,1299	277,7
24	Slovakia	0,1541	270,4
25	Czech Republic	0,1266	284,4
26	Romania	0,1055	291
27	Estonia	0,0959	373,5
28	Latvia	0,1058	232,6

The use of association rules makes it possible to find possible hidden dependencies and relationships at the analysis stage of exploration. The results can be used for developing regressive and predictive models, clustering, and so on.

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