

Intercriteria Decision Making Approach to EU Member States Competitiveness Analysis

Vassia K. Atanassova¹, Lyubka A. Doukovska¹, Krassimir T. Atanassov^{2,3} and Deyan G. Mavrov³

¹*Institute of Information and Communication Technologies, Bulgarian Academy of Sciences,
Acad. G. Bonchev str., bl. 2, 1113 Sofia, Bulgaria*

²*Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences,
Acad. G. Bonchev str., bl. 105, 1113 Sofia, Bulgaria*

³*Prof. Dr. Asen Zlatarov University, 1 Prof. Yakimov Blvd., 8010 Burgas, Bulgaria
vassia.atanassova@gmail.com, doukovska@iit.bas.bg, krat@bas.bg, dg@mavrov.eu*

Keywords: Global Competitiveness Index, Index Matrix, Intercriteria Decision Making, Intuitionistic Fuzzy Sets, Multicriteria Decision Making.

Abstract: In this paper, we present some interesting results derived from the application of our recently developed decision making approach to data from the World Economic Forum's Global Competitiveness Reports for the years 2008–2009 to 2013–2014. The discussed approach, called 'Intercriteria Decision Making', employs the apparatus of index matrices and intuitionistic fuzzy sets to produce from an existing multiobject multicriteria evaluation table a new table that contains estimations of the pairwise correlations among the set of evaluating criteria, called 'pillars of competitiveness'. Using the described approach over the data about WEF evaluations of the state of competitiveness of the 28 present EU Member States, certain dependences are discovered to connect the 12 'pillars', termed a 'positive' and a 'negative consonance'. The whole research and the conclusions derived are in line with WEF's address to state policy makers to identify and strengthen the transformative forces that will drive future economic growth.

1 INTRODUCTION

The present work contains a novel analysis of the most recent Global Competitiveness Reports (GCRs) of the World Economic Forum (WEF), produced from 2008–2009 to 2013–2014, aiming at the discovery of some hidden patterns and trends in the present Member States of the European Union. We use a recently developed method, based on intuitionistic fuzzy sets and index matrices, two mathematical formalisms proposed and significantly researched by Atanassov in a series of publications from 1980s to present day.

The developed method for multicriteria decision making (Atanassov et al., 2013) is specifically applicable to situations where some of the criteria come at a higher cost than others, for instance are harder, more expensive and/or more time consuming to measure or evaluate. Such criteria are generally considered unfavourable, hence if the method identifies certain level of correlation between such unfavourable criteria and others that are easier, cheaper or quicker to measure or evaluate these

might be disregarded in the further decision making process. In particular, the approach has been so far applied to petrochemical industry, where the aim has been to reduce some of the most costly and time consuming checks of the probes of raw mineral oil, which have proven to correlate with other cheaper and quicker tests, thus reducing production costs and time needed for business decision making.

The present work is the first application of the developed approach in the field of economics. We have considered it appropriate to analyse our selection of data, in order to discover which of the twelve pillars (criteria) in the formation of the Global Competitiveness Index (GCI) tend to correlate. In comparison with related applications of the method, here, we do not conclude that any of the correlating criteria might be skipped, as in the petrochemical case study. We are interested however to discover dependences between the pillars, which could help policy makers, especially in the low performing EU Member States, to focus their efforts in fewer directions and reasonably expect on the basis of this analysis that improved country's

performance against those pillars would positively affect the performance in the respective correlating pillars. Such correlation can be deemed reasonable to expect, as the twelve pillars are based on a multitude of indicators, some of which enter the GCI in two difference pillars each, as explained in the GCR’s Appendix “Computation and structure of the Global Competitiveness Index” (and to avoid double counting, half-weight is being assigned to each instance).

This attempt to identify the correlations between the different pillars of competitiveness reflects WEF addressing the countries’ policy makers with the advice to ‘identify and strengthen the transformative forces that will drive future economic growth’, as formulated in the Preface of the latest Global Competitiveness Report 2013–2014.

This paper is organized as follows. In Section 2 are briefly presented the two basic mathematical concepts that we use, namely, intuitionistic fuzzy sets and index matrices. On this basis, the proposed method is outlined. Section 3 contains our results from applying the method to analysis of a selection of data about the performance of the currently 28 Member States of the EU during the last six years against the twelve pillars of competitiveness. We report of the findings, produced by the algorithm and formulate our conclusions in the last Section 4.

2 BASIC CONCEPTS AND METHOD

The presented multicriteria decision making method is based on two fundamental concepts: intuitionistic fuzzy sets and index matrices. It bears the specific name ‘intercriteria decision making’.

Intuitionistic fuzzy sets defined by Atanassov (Atanassov, 1983; Atanassov, 1986; Atanassov, 1999; Atanassov, 2012) represent an extension of the concept of fuzzy sets, as defined by Zadeh (Zadeh, 1965), exhibiting function $\mu_A(x)$ defining the membership of an element x to the set A , evaluated in the $[0; 1]$ -interval. The difference between fuzzy sets and intuitionistic fuzzy sets (IFSs) is in the presence of a second function $\nu_A(x)$ defining the non-membership of the element x to the set A , where:

$$\begin{aligned} 0 \leq \mu_A(x) &\leq 1, \\ 0 \leq \nu_A(x) &\leq 1, \\ 0 \leq \mu_A(x) + \nu_A(x) &\leq 1. \end{aligned}$$

The IFS itself is formally denoted by:

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in E \}.$$

Comparison between elements of any two IFSs, say A and B , involves pairwise comparisons between their respective elements’ degrees of membership and non-membership to both sets.

The second concept on which the proposed method relies is the concept of index matrix, a matrix which features two index sets. The theory behind the index matrices is described in (Atanassov, 1991). Here we will start with the index matrix M with index sets with m rows $\{C_1, \dots, C_m\}$ and n columns $\{O_1, \dots, O_n\}$:

$$M = \begin{array}{c|cccccc} & O_1 & \dots & O_k & \dots & O_l & \dots & O_n \\ \hline C_1 & a_{C_1,O_1} & \dots & a_{C_1,O_k} & \dots & a_{C_1,O_l} & \dots & a_{C_1,O_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ C_i & a_{C_i,O_1} & \dots & a_{C_i,O_k} & \dots & a_{C_i,O_l} & \dots & a_{C_i,O_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ C_j & a_{C_j,O_1} & \dots & a_{C_j,O_k} & \dots & a_{C_j,O_l} & \dots & a_{C_j,O_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ C_m & a_{C_m,O_1} & \dots & a_{C_m,O_j} & \dots & a_{C_m,O_l} & \dots & a_{C_m,O_n} \end{array},$$

where for every p, q ($1 \leq p \leq m, 1 \leq q \leq n$), C_p is a criterion (in our case, one of the twelve pillars), O_q in an evaluated object (in our case, one of the 28 EU Member states), a_{C_p,O_q} is the evaluation of the q -th object against the p -th criterion, and it is defined as a real number or another object that is comparable according to relation R with all the rest elements of the index matrix M , so that for each i, j, k it holds the relation $R(a_{C_k,O_p}, a_{C_i,O_j})$. The relation R has dual relation \bar{R} , which is true in the cases when relation R is false, and vice versa.

For the needs of our decision making method, pairwise comparisons between every two different criteria are made along all evaluated objects. During the comparison, it is maintained one counter of the number of times when the relation R holds, and another counter for the dual relation.

Let $S_{k,l}^\mu$ be the number of cases in which the relations $R(a_{C_k,O_i}, a_{C_l,O_j})$ and $R(a_{C_l,O_i}, a_{C_k,O_j})$ are simultaneously satisfied. Let also $S_{k,l}^\nu$ be the number of cases in which the relations $R(a_{C_k,O_i}, a_{C_l,O_j})$ and its dual $\bar{R}(a_{C_l,O_i}, a_{C_k,O_j})$ are simultaneously satisfied. As the total number of pairwise comparisons between the object is $n(n-1)/2$, it is seen that there hold the inequalities:

$$0 \leq S_{k,l}^\mu + S_{k,l}^\nu \leq \frac{n(n-1)}{2}.$$

For every k, l , such that $1 \leq k \leq l \leq m$, and for $n \geq 2$ two numbers are defined:

$$\mu_{C_k, C_l} = 2 \frac{S_{k,l}^\mu}{n(n-1)}, \quad \nu_{C_k, C_l} = 2 \frac{S_{k,l}^\nu}{n(n-1)}.$$

The pair constructed from these two numbers plays the role of the intuitionistic fuzzy evaluation of the relations that can be established between any two criteria C_k and C_l . In this way the index matrix M that relates evaluated objects with evaluating criteria can be transformed to another index matrix M^* that gives the relations among the criteria:

$$M^* = \begin{array}{c|ccc} & C_1 & \dots & C_m \\ \hline C_1 & \langle \mu_{C_1, C_1}, \nu_{C_1, C_1} \rangle & \dots & \langle \mu_{C_1, C_m}, \nu_{C_1, C_m} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ C_m & \langle \mu_{C_m, C_1}, \nu_{C_m, C_1} \rangle & \dots & \langle \mu_{C_m, C_m}, \nu_{C_m, C_m} \rangle \end{array}.$$

The final step of the algorithm is to determine the degrees of correlation between the criteria, depending on the user's choice of μ and ν . We call these correlations between the criteria: 'positive consonance', 'negative consonance' or 'dissonance'.

Let $\alpha, \beta \in [0; 1]$ be given, so that $\alpha + \beta \leq 1$. We call that criteria C_k and C_l are in:

- (α, β) -positive consonance, if $\mu_{C_k, C_l} > \alpha$ and $\nu_{C_k, C_l} < \beta$;
- (α, β) -negative consonance, if $\mu_{C_k, C_l} < \beta$ and $\nu_{C_k, C_l} > \alpha$;
- (α, β) -dissonance, otherwise.

Obviously, the larger α and/or the smaller β , the less number of criteria may be simultaneously

connected with the relation of (α, β) -positive consonance. For practical purposes, it carries the most information when either the positive or the negative consonance is as large as possible, while the cases of dissonance are less informative and can be skipped.

3 MAIN RESULTS

We ran the described algorithm over collected data from six WEF GCRs for the 28 (current) EU Member States. Here, we present only the results from the two extreme periods: years 2008–2009 and year 2013–2014, comparing them for μ_{C_i, C_j} and ν_{C_i, C_j} in Tables 1–2. Despite having the results with precision of 9 digits after the decimal point, we will use precision of 3 digits after the decimal point.

In Tables 1 and 2, all cells are coloured in the greyscale, with the highest values coloured in the darkest shade of grey, while the lowest ones are coloured in white. Of course, every criteria perfectly correlates with itself, so for any i the value μ_{C_i, C_i} is always 1, and $\nu_{C_i, C_i} = \pi_{C_i, C_i} = 0$. Also, the matrices are obviously symmetrical according to the main diagonal. The twelve pillars are: 1. Institutions; 2. Infrastructure; 3. Macroeconomic stability; 4. Health and primary education; 5. Higher education and training; 6. Goods market efficiency; 7. Labour market efficiency; 8. Financial market sophistication; 9. Technological readiness; 10. Market size; 11. Business sophistication; 12. Innovation.

In the beginning, let us present in Table 3 some findings from the analysis of the six periods.

Table 1: Comparison of the calculated values of μ_{C_i, C_j} for years 2008–2009 and 2013–2014.

μ	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000	0.844	0.685	0.757	0.788	0.833	0.603	0.828	0.823	0.497	0.794	0.802
2	0.844	1.000	0.627	0.751	0.749	0.743	0.529	0.741	0.775	0.582	0.831	0.807
3	0.685	0.627	1.000	0.616	0.638	0.664	0.653	0.648	0.693	0.434	0.651	0.667
4	0.757	0.751	0.616	1.000	0.780	0.720	0.550	0.704	0.725	0.524	0.765	0.772
5	0.788	0.749	0.638	0.780	1.000	0.746	0.622	0.728	0.757	0.558	0.767	0.796
6	0.833	0.743	0.664	0.720	0.746	1.000	0.627	0.817	0.802	0.505	0.786	0.765
7	0.603	0.529	0.653	0.550	0.622	0.627	1.000	0.664	0.611	0.389	0.563	0.590
8	0.828	0.741	0.648	0.704	0.728	0.817	0.664	1.000	0.820	0.476	0.733	0.751
9	0.823	0.775	0.693	0.725	0.757	0.802	0.611	0.820	1.000	0.548	0.817	0.815
10	0.497	0.582	0.434	0.524	0.558	0.505	0.389	0.476	0.548	1.000	0.648	0.601
11	0.794	0.831	0.651	0.765	0.767	0.786	0.563	0.733	0.817	0.648	1.000	0.860
12	0.802	0.807	0.667	0.772	0.796	0.765	0.590	0.751	0.815	0.601	0.860	1.000

μ	1	2	3	4	5	6	7	8	9	10	11	12
1	1.000	0.735	0.577	0.720	0.807	0.836	0.733	0.749	0.854	0.503	0.804	0.844
2	0.735	1.000	0.479	0.661	0.749	0.677	0.537	0.590	0.786	0.661	0.804	0.799
3	0.577	0.479	1.000	0.421	0.519	0.558	0.627	0.675	0.550	0.413	0.548	0.556
4	0.720	0.661	0.421	1.000	0.730	0.683	0.590	0.563	0.677	0.497	0.712	0.690
5	0.807	0.749	0.519	0.730	1.000	0.735	0.622	0.632	0.775	0.579	0.815	0.847
6	0.836	0.677	0.558	0.683	0.735	1.000	0.749	0.712	0.788	0.466	0.759	0.751
7	0.733	0.537	0.627	0.590	0.622	0.749	1.000	0.741	0.685	0.399	0.624	0.624
8	0.749	0.590	0.675	0.563	0.632	0.712	0.741	1.000	0.712	0.497	0.688	0.680
9	0.854	0.786	0.550	0.677	0.775	0.788	0.685	0.712	1.000	0.526	0.810	0.831
10	0.503	0.661	0.413	0.497	0.579	0.466	0.399	0.497	0.526	1.000	0.611	0.598
11	0.804	0.804	0.548	0.712	0.815	0.759	0.624	0.688	0.810	0.611	1.000	0.873
12	0.844	0.799	0.556	0.690	0.847	0.751	0.624	0.680	0.831	0.598	0.873	1.000

Table 2: Comparison of the calculated values of $v_{C_i C_j}$ for years 2008–2009 and 2013–2014.

v	1	2	3	4	5	6	7	8	9	10	11	12
1	0.000	0.114	0.241	0.140	0.140	0.077	0.275	0.116	0.116	0.458	0.148	0.127
2	0.114	0.000	0.304	0.156	0.190	0.167	0.365	0.220	0.180	0.384	0.127	0.138
3	0.241	0.304	0.000	0.265	0.265	0.209	0.204	0.270	0.225	0.495	0.270	0.241
4	0.140	0.156	0.265	0.000	0.108	0.140	0.294	0.201	0.169	0.381	0.138	0.111
5	0.140	0.190	0.265	0.108	0.000	0.135	0.233	0.198	0.164	0.378	0.156	0.130
6	0.077	0.167	0.209	0.140	0.135	0.000	0.209	0.090	0.095	0.397	0.114	0.127
7	0.275	0.365	0.204	0.294	0.233	0.209	0.000	0.212	0.259	0.497	0.315	0.265
8	0.116	0.220	0.270	0.201	0.198	0.090	0.212	0.000	0.132	0.476	0.217	0.196
9	0.116	0.180	0.225	0.169	0.164	0.095	0.259	0.132	0.000	0.399	0.122	0.116
10	0.458	0.384	0.495	0.381	0.378	0.397	0.497	0.476	0.399	0.000	0.307	0.336
11	0.148	0.127	0.270	0.138	0.156	0.114	0.315	0.217	0.122	0.307	0.000	0.079
12	0.127	0.138	0.241	0.111	0.130	0.127	0.265	0.196	0.116	0.336	0.079	0.000

Table 3: Maximal and minimal values of positive and negative consonance between the twelve pillars of competitiveness for years 2008–2009 to 2013–2014.

Year	μ		v	
	$\max(\mu_{C_i C_j})$	$\min(\mu_{C_i C_j})$	$\max(v_{C_i C_j})$	$\min(v_{C_i C_j})$
2008–2009	0.860	0.389	0.497	0.077
2009–2010	0.865	0.410	0.505	0.071
2010–2011	0.852	0.447	0.468	0.087
2011–2012	0.870	0.405	0.534	0.074
2012–2013	0.870	0.421	0.519	0.071
2013–2014	0.873	0.399	0.537	0.071

From Table 3, we can make certain conclusions about the range of values of the parameters α and β , which are used to measure the consonance between the criteria. Obviously, depending on how the values of α and β have been chosen, different sets of correlating criteria will form; and this can be done over the data for each year. For the purposes of illustration, let us only take the data for the latest period (2013–2014), and check how the relations between the criteria change by selecting different values of α and β . Obviously, in this case putting $\alpha > 0.873$ or $\beta < 0.071$ would yield no results.

In general, the question how to select the values of α and β , with respect to our various needs and purposes, is important and challenging, but is beyond the scope of the present research. Hence, we will conduct our analysis by taking the following exemplary pairs of $(\alpha; \beta)$: (0.85; 0.15), (0.80; 0.20), (0.75; 0.25), (0.70; 0.30), (0.65; 0.35), and will see which pillars are in positive consonance (Table 4, those in negative consonance follow by analogy).

Obviously, values $\alpha = 0.85$; $\beta = 0.15$ are rather discriminative, since only two consonance pairs are discovered to hold between four different criteria: ‘Institutions – Technological readiness’ and ‘Business sophistication – Innovation’, the second one being quite natural, since these two pillars take

part in the formation of the ‘Innovation and sophistication factors’ defining the difference between the efficiency driven countries (2nd stage of development) and innovation driven countries (3rd stage of development). The rest two criteria are of more heterogeneous nature, where ‘Institutions’ belongs to the set of ‘Basic requirements’ and ‘Technological readiness’ belongs to the set of ‘Efficiency enhancers’.

Table 4: List of pillars in positive consonance for the year 2013–2014, per different α, β . Highlighted in grey on each row are those consonances, which have been reported on previous (upper) rows, the white ones appearing for first.

(α, β)	List of positive consonances $C_i - C_j$	No. of μ -pairs	No. of v -pairs	No. of consonances	No. of involved criteria
(0.85; 0.15)	1–9; 11–12	2	19	2	4
(0.80; 0.20)	1–5; 1–6; 1–9; 1–11; 1–12; 2–11; 5–11; 5–12; 9–11; 9–12; 11–12	11	29	11	7
(0.75; 0.25)	1–5; 1–6; 1–9; 1–11; 1–12; 2–9; 2–11; 2–12; 5–9; 5–11; 5–12; 6–9 6–11; 6–12; 9–11; 9–12; 11–12	17	37	17	7
(0.70; 0.30)	1–2; 1–4; 1–5; 1–6; 1–7; 1–8; 1–9; 1–11; 1–12; 2–5; 2–9; 2–11; 2–12; 4–5; 4–11; 5–6; 5–9; 5–11; 5–12; 6–7; 6–8; 6–9; 6–11; 6–12; 7–8; 8–9; 9–11; 9–12; 11–12	29	45	29	10
(0.65; 0.35)	1–2; 1–4; 1–5; 1–6; 1–7; 1–8; 1–9; 1–11; 1–12; 2–4; 2–5; 2–6; 2–9; 2–10; 2–11; 2–12; 3–8; 4–5; 4–6; 4–9; 4–11; 4–12; 5–6; 5–9; 5–11; 5–12; 6–7; 6–8; 6–9; 6–11; 6–12; 7–8; 7–9; 8–9; 8–11; 8–12; 9–11; 9–12; 11–12	39	51	39	12

The rest investigated values of α and β are looser, thus yielding greater number of consonance pairs between larger sets of criteria. We make the detailed analysis only for the second pair, (0.8; 0.2).

Putting $\alpha > 0.8$, we obtain 11 pairs of criteria which have their $\mu > 0.8$; and putting $\beta < 0.2$, we obtain 29 pairs of criteria which have their $\nu < 0.2$. The first set of 11 pairs is completely a subset of the second set of 29 pairs, meaning that we will discuss only these 11 pairs, which are in positive consonance; they connect 7 out of 12 pillars, as shown in Table 5.

Table 5: List of pillars in positive consonance for the year 2013–2014, when $\alpha > 0.8, \beta < 0.2$.

C_i-C_j	Full titles of criteria C_i-C_j	$\mu_{C_i C_j}$	$\nu_{C_i C_j}$
1–5	Institutions – Higher education and training	0.807	0.132
1–6	Institutions – Goods market efficiency	0.836	0.077
1–9	Institutions – Technological readiness	0.854	0.090
1–11	Institutions – Business sophistication	0.804	0.138
1–12	Institutions – Innovation	0.844	0.111
2–11	Infrastructure – Business sophistication	0.804	0.135
5–11	Higher education and training – Business sophistication	0.815	0.098
5–12	Higher education and training – Innovation	0.847	0.079
9–11	Technological readiness – Business sophistication	0.810	0.119
9–12	Technological readiness – Innovation	0.831	0.101
11–12	Business sophistication – Innovation	0.873	0.071

Putting $\alpha = 0.75; \beta = 0.25$, we obtain 17 pairs w.r.t. α and 37 pairs w.r.t. β , giving a total of 17 pairs of consonance w.r.t. both parameters at a time. In these 17 pairs take part again the same 7 criteria, as in the previous case (0.80; 0.20), but 6 more correlations between them are now discovered, namely, ‘Infrastructure – Technological readiness’, ‘Infrastructure – Innovation’, ‘Higher education and training – Technological readiness’, ‘Goods market efficiency – Technological readiness’, ‘Goods market efficiency – Business sophistication’ and ‘Goods market efficiency – Innovation’.

The pairs (0.70; 0.30) and (0.65; 0.35) are rather inclusive and non-discriminative values, since they involve, respectively, 10 and 12 out of 12 pillars of competitiveness and yield, respectively, 29 and 39 correlations between them.

We can visually illustrate the findings in Table 4 by constructing graphs for each run of α and β , depicting the outlined dependences. We will do it

here only for the described case when $\alpha > 0.8, \beta < 0.2$, see Figure 1.

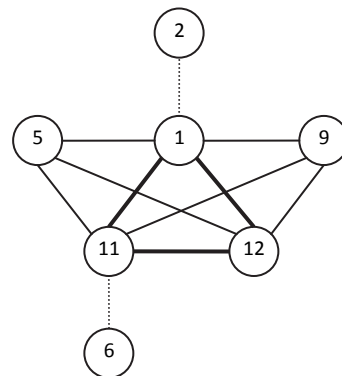


Figure 1: Graph structure of the pillars forming positive consonance for the year 2013–2014 when $\alpha > 0.8, \beta < 0.2$.

Now it becomes rather visual that when $\alpha > 0.8, \beta < 0.2$ three out of seven pillars completely correlate with each other (‘1. Institutions’, ‘11. Business sophistication’, ‘12. Innovation’), two other (‘5. Higher education and training’ and ‘9. Technological readiness’) completely correlate with the triple 1–11–12, but not among each other, while vertices ‘2. Infrastructure’ and ‘6. Good market efficiency’ are connected by only one arc to the rest of the structure.

Obviously, for each run of α and β a series of graphs will be formed, where every consequent graph will act as a supergraph for the previous one, becoming gradually more complex and interconnected. It is interesting to compare for each run of α and β whether and how these graph structures change over the different time periods before 2013–2014.

These graph structures are a matter of further economic analysis, and it is particularly interesting to study which of the pillars of competitiveness are fully connected, like 1–5–11–12 and 1–9–11–12 in Figure 1.

Also, it is noteworthy that in the WEF’s methodology for forming the countries’ competitiveness index, there are four sub-indicators take part in two pillars each, namely: ‘Intellectual property protection’ takes part of the formation of the 1st and 12th pillar, ‘Mobile telephone subscriptions’ and ‘Fixed telephone lines’ in 2nd and 9th pillar, and ‘Reliance on professional management’ in 7th and 11th pillar.

We can hence make the conclusion, that our findings generally support the proximity between the mentioned pillars, as suggested by the presence of shared sub-indicators, yet our conclusions are much stronger and sophisticated as a result of the research.

It is also very important to make the comparison

of the calculated values in Tables 1 and 2 between years 2008–2009 and 2013–2014. We can focus the reader's attention to several particularly well outlined observations. Over the period 2008–2014, the pillars '5. Higher education and training' and '7. Labour market efficiency' have become gradually more correlated to all the rest pillars, while pillar '3. Macroeconomic stability' has become gradually less correlated. However, in general, these comparisons are a matter of detailed analysis by economists.

4 CONCLUSION

The present research aimed at discovery of some hidden patterns in the data about EU Member States' competitiveness in the period from 2008 to 2014. We conduct the analysis of the World Economic Forum's Global Competitiveness Reports, using a recently developed multicriteria decision making method, based on index matrices and intuitionistic fuzzy sets.

Using index matrices with data about how the EU Member States have performed according to the outlined twelve 'pillars of competitiveness', we construct new matrices, giving us new knowledge about how these pillars correlate and interact with each other. Moreover, the application of the method has been traced over a six-year period of time and has revealed certain changes and trends in these correlations that may yield fruitful further analyses by interested economists. The results are illustrated with data tables and graphs of the strongest correlations between the criteria.

These conclusions may also be useful for the national policy and decision makers, to better identify and strengthen the transformative forces that will drive their future economic growth. The same approach can be equally applied to other selections of countries and time periods, and comparisons with the hitherto presented results will be challenging.

Besides the comparison of the twelve pillars of competitiveness, our research plans include also exploring the correlations between the most problematic factors for doing business, as outlined in the WEF's GCRs. Further investigation how the pillars of competitiveness correlate with these most problematic factors may also prove interesting and useful.

ACKNOWLEDGEMENTS

The research work reported in the paper is partly

supported by the project AComIn "Advanced Computing for Innovation", grant 316087, funded by the FP7 Capacity Programme (Research Potential of Convergence Regions).

REFERENCES

- Atanassov K. (1983) Intuitionistic fuzzy sets, VII ITKR's Session, Sofia, June 1983 (in Bulgarian).
- Atanassov K. (1986) Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*. Vol. 20 (1), pp. 87–96.
- Atanassov K. (1991) *Generalized Nets*. World Scientific, Singapore.
- Atanassov K. (1999) *Intuitionistic Fuzzy Sets: Theory and Applications*. Physica-Verlag, Heidelberg.
- Atanassov K. (2012) *On Intuitionistic Fuzzy Sets Theory*. Springer, Berlin.
- Atanassov K., D. Mavrov, V. Atanassova (2013). Inter-criteria decision making. A new approach for multi-criteria decision making, based on index matrices and intuitionistic fuzzy sets. *Proc. of 12th International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets*, 11 Oct. 2013, Warsaw, Poland (in press).
- World Economic Forum (2008, 2013). *The Global Competitiveness Reports*. <http://www.weforum.org/issues/global-competitiveness>.
- Zadeh L. A. (1965). *Fuzzy Sets*. *Information and Control* Vol. 8, pp. 333–353.