InterCriteria Analysis Applied to Various EU Enterprises

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Abstract: The present research aims to detect certain correlations between four economic indicators, against which have been evaluated the economic entities of the European Union with 27 Member States, as split into four categories: micro, small, medium and large enterprises. The mathematical formalism employed for revealing these dependencies, particularly termed here 'positive' and 'negative consonances', is a novel decision support approach, called InterCriteria Analysis, which is based on the theoretical foundations of the intuitionistic fuzzy sets and the augmented matrix calculus of index matrices. The proposed approach can be useful in processes of decision making and policy making, and it can be seamlessly integrated and further extended to other related application areas and problems, where it is reasonable to seek correlations between a variety of economic and other indicators.

1 INTRODUCTION

In present work, we make the consequent step in a series of research, aimed at proposing the application of the novel approach of InterCriteria Analysis (ICA) to economic data, aimed at the discovery of correlations between important economic indicators, based on available economic data. At this new step, we take as input information about the economic enterprises in the EU27, the European Union with 27 Member States, as grouped in the four types of enterprises with respect to the scale: micro, small, medium and large enterprises, (Calogirou, et al., 2010).

The indicators against which these four types of EU27 enterprises have been evaluated are four, namely: 'Number of enterprises', 'Number of persons employed', 'Turnover' and 'Value added at factor cost'. Potential discovery of correlations (in this approach termed as *positive consonances*) between economic indicators can bring new knowledge and improve decision making and policy making processes.

The ICA approach is specifically designed for datasets comprising evaluations, or measurements of multiple objects against multiple criteria. In the initial formulation of the method, the aim was to detect correlations between the criteria, in order to eliminate future evaluations/measurements against some of the criteria, which exhibit high enough correlations with others. This might be the desire, when some of the criteria are for some reason deemed unfavourable, for instance come at a higher cost than other criteria, are harder, more expensive and/or more time consuming to measure or evaluate. Elimination or reduction of these unfavourable criteria from the future evaluations or measurements may be desirable from business point of view in order to reduce cost, time or complexity of the process.

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This paper is organized as follows. The basic mathematical concepts employed in the ICA method are presented in Section 2. In Section 3, we present the input data and the results of their processing. We report of the findings, produced by the algorithm and formulate our conclusions in the last Section 4.

2 INTERCRITERIA ANALYSIS METHOD

The building blocks of the presented InterCriteria Analysis for decision support are the two concepts of intuitionistic fuzziness and index matrices.

Intuitionistic fuzzy sets defined by Atanassov (Atanassov, 1983; Atanassov, 1986; Atanassov, 1999; Atanassov, 2012) are one of the most popular and well investigated extensions of the concept of fuzzy sets, defined by Zadeh (Zadeh, 1965). Besides the traditional function of membership $\mu_A(x)$ defined in fuzzy sets to evaluate the membership of an element x to the set A with a real number in the [0; 1]-interval, in intuitionistic fuzzy sets (IFSs) a second function has been introduced, $\nu_A(x)$ defining respectively the non-membership of the element x to the set A, which may coexist with the membership function. More formally the IFS itself is formally denoted by:

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

and the following conditions hold:

$$0 \le \mu_A(x) \le 1,\ 0 \le \nu_A(x) \le 1,$$
$$0 \le \mu_A(x) + \nu_A(x) \le 1.$$

Multiple relations, operations, modal and topological operators have been defined over IFS, showing that IFSs are a non-trivial extension of the concept of fuzzy sets.

The second concept, on which the proposed method is based, is the concept of index matrix, a matrix which features two index sets. The basics of the theory behind the index matrices is described in (Atanassov, 1991), and recently developed further on in (Atanassov, 2014).

In the ICA approach, the raw data for processing are put within an index matrix M of m rows $\{O_1, \ldots, O_m\}$ and n columns $\{C_1, \ldots, C_n\}$, where for every p, q $(1 \le p \le m,\ 1 \le q \le n)$, O_p in an evaluated object, C_q is an evaluation criterion, and $e_{O_pC_q}$ is the evaluation of the p-th object against the q-th criterion, 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.

$$M = \begin{array}{c|ccccccc} & C_1 & \cdots & C_k & \cdots & C_l & \cdots & C_n \\ \hline O_1 & e_{O_1,C_1} & \cdots & e_{O_1,C_k} & \cdots & e_{O_1,C_l} & \cdots & e_{O_1,C_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ O_i & e_{O_i,C_1} & \cdots & e_{O_i,C_k} & \cdots & e_{O_i,C_l} & \cdots & e_{O_i,C_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ O_j & e_{O_j,C_1} & \cdots & e_{O_j,C_k} & \cdots & e_{O_j,C_l} & \cdots & e_{O_j,C_n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\ O_m & e_{O_m,C_1} & \cdots & e_{O_m,C_j} & \cdots & e_{O_m,C_l} & \cdots & e_{O_m,C_n} \end{array},$$

From the requirement for comparability above, it follows that for each i, j, k it holds the relation $R(e_{O_iC_k}, e_{O_jC_k})$. 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 $S^{\mu}_{k,l}$ be the number of cases in which the relations $R(e_{O_iC_k}, e_{O_jC_k})$ and $R(e_{O_i\,C_l}, e_{O_jC_l})$ are simultaneously satisfied. Let also $S^{\nu}_{k,l}$ be the number of cases in which the relations $R(e_{O_iC_k}, e_{O_jC_k})$ and its dual $\bar{R}(e_{O_iC_l}, e_{O_jC_l})$ are simultaneously satisfied. As the total number of pairwise comparisons between the object is $m(m-1)/2$, it is seen that there hold the inequalities:

$$0 \le S^{\mu}_{k,l} + S^{\nu}_{k,l} \le \frac{m(m-1)}{2}.$$

For every k, l, such that $1 \le k \le l \le m$, and for $m \ge 2$ two numbers are defined:

$$\mu_{C_k,C_l} = 2\frac{S^{\mu}_{k,l}}{m(m-1)},\ \nu_{C_k,C_l} = 2\frac{S^{\nu}_{k,l}}{m(m-1)}.$$

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:

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

From practical considerations, it has been more flexible to work with two index matrices M^{μ} and M^{ν}, rather than with the index matrix M^{*} of IF pairs.

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 α, $\beta \in [0; 1]$ be the threshold values, against which we compare the values of μ_{C_k,C_l} and ν_{C_k,C_l}. 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.

The approach is completely data driven, and each new application would require taking specific threshold values α, β that will yield reliable results.

3 DATA PROCESSING

Here we dispose of and analyse the following input datasets from (Calogirou, et al., 2010):

- The number of enterprises in EU27, by country, divided to the four categories: Micro, Small, Medium and Large (p. 16, Table 4)
- The number of persons employed in EU27, by country, divided to the four categories: Micro, Small, Medium and Large (p. 18, Table 6)
- The Turnover (millions of €) in the EU27, by country, divided to the four categories: Micro, Small, Medium and Large (p. 20, Table 8)
- Value added at factor cost (millions of €), by country, divided to the four categories: Micro, Small, Medium and Large (p. 22, Table 10).

These four source datasets we rearrange in a way to discover for each of the four indicators: 'Number of enterprises (NE)', 'Number of persons employed (PE)', 'Turnover (TO)' and 'Value added at factor cost (VA)' what are the correlations between them in the different scale, given by the type of enterprises: 'Micro', 'Small', 'Medium' and 'Large'.

During this processing, we remove both the rows and the columns titled 'Total' and 'Pct', and remain to work only with the data countries by indicators, that are homogeneous in nature.

In these new 4 processed datasets (Tables 1–4), for each type of enterprise, we have one index matrix with 27 rows being the countries in the EU27, and 4 columns for the four indicators.

The data from Tables 1–4 concerning the micro, small, medium and large enterprises, have been analysed using a software application for InterCriteria Analysis, developed by one of the authors, Mavrov (Mavrov, 2014). The application follows the algorithm for ICA and produces from the matrix of 27 rows of countries (objects per rows) and 4 indicators (criteria per columns), two new matrices, containing respectively the membership and the non-membership parts of the IF pairs that form the IF positive, negative consonance and dissonance relations between each pair of criteria, In this case, the 4 criteria form 6 InterCriteria pairs.

Table 1: Data for the microenterprises in the EU27 countries, as evaluated against 4 criteria (in %).

EU Member	NE	PE	TA	VO
Austria	88	25	18	19
Belgium	92	30	21	19
Bulgaria	88	22	20	14
Cyprus	92	39	30	31
Czech Rep.	95	29	18	19
Denmark	87	19	23	28
Estonia	83	20	25	21
Finland	93	24	16	19
France	92	38	19	21
Germany	83	23	12	16
Greece	96	25	35	35
Hungary	94	58	21	18
Ireland	82	35	12	12
Italy	95	20	28	33
Latvia	83	47	23	19
Lithuania	88	23	13	12
Luxembourg	87	19	18	24
Malta	96	22	22	21
Netherlands	90	34	15	20
Poland	96	29	23	18
Portugal	95	39	26	24
Romania	88	42	16	14
Slovakia	76	21	13	13
Slovenia	93	25	20	20
Spain	92	28	23	27

Sweden	94	15	18	20
United Kingdom	87	22	14	18

Table 2: Data for the small enterprises in the EU27 countries, as evaluated against 4 criteria (in %).

EU Member	NE	PE	TA	VO
Austria	11	23	23	20
Belgium	7	22	20	20
Bulgaria	9	24	21	18
Cyprus	7	25	29	26
Czech Rep.	4	19	18	16
Denmark	11	22	22	21
Estonia	14	25	29	25
Finland	6	28	14	16
France	6	26	19	19
Germany	14	19	16	18
Greece	3	21	23	20
Hungary	5	17	18	16
Ireland	15	19	20	17
Italy	5	26	23	23
Latvia	14	22	28	27
Lithuania	9	25	24	23
Luxembourg	11	24	24	20
Malta	4	28	22	20
Netherlands	8	20	21	21
Poland	3	21	13	12
Portugal	5	12	23	22
Romania	9	23	21	16
Slovakia	19	20	16	15
Slovenia	6	21	19	19
Spain	7	18	24	24
Sweden	5	18	18	18
United Kingdom	10	18	16	16

Table 3: Data for the medium enterprises in the EU27 countries, as evaluated against 4 criteria (in %).

EU Member	NE	PE	TA	VO
Austria	2	19	22	21
Belgium	1	16	19	19
Bulgaria	2	24	22	21
Cyprus	1	20	24	21
Czech Rep.	1	20	24	20
Denmark	2	19	22	19
Estonia	3	21	28	30
Finland	1	26	18	18
France	1	15	17	16
Germany	2	18	20	19
Greece	0	16	19	17
Hungary	1	12	19	18
Ireland	3	16	25	23
Italy	1	23	20	16
Latvia	3	12	28	28
Lithuania	2	26	27	29
Luxembourg	2	23	17	19
Malta	1	26	26	23
Netherlands	1	20	26	21
Poland	1	17	23	22
Portugal	1	19	22	21
Romania	2	16	21	20
Slovakia	4	23	21	18
Slovenia	1	18	24	21
Spain	1	21	20	17
Sweden	1	23	19	18
United Kingdom	2	15	18	17

Table 4: Data for the large enterprises in the EU27 countries, as evaluated against 4 criteria (in %).

EU Member	NE	PE	TA	VO
Austria	0.3	33	37	40
Belgium	0.2	33	39	42
Bulgaria	0.3	30	37	46
Cyprus	0.2	17	17	21
Czech Rep.	0.2	32	41	45
Denmark	0.3	40	33	32

Estonia	0.4	34	18	24
Finland	0.3	22	52	46
France	0.2	22	44	45
Germany	0.5	41	52	47
Greece	0.1	38	23	28
Hungary	0.2	13	41	48
Ireland	0.5	29	43	48
Italy	0.1	32	29	28
Latvia	0.3	19	20	26
Lithuania	0.3	25	35	36
Luxembourg	0.4	33	42	37
Malta	0.1	24	30	36
Netherlands	0.3	26	38	38
Poland	0.2	33	41	48
Portugal	0.1	31	30	32
Romania	0.4	18	41	50
Slovakia	1.0	36	50	54
Slovenia	0.3	36	37	40
Spain	0.1	33	33	32
Sweden	0.2	44	44	44
United Kingdom	0.4	45	51	49

Because of the diverse nature of the types of enterprises (micro, small, medium or large enterprises), it is expected that these six InterCriteria pairs will be different depending on which kind of enterprises are taken into consideration.

Thus, for the micro enterprises, for which are the data in Table 1, the two index matrices with InterCriteria pairs are respectively given in Table 5, for the small enterprises the two index matrices are given in Table 2 – in Table 6, for the medium enterprises, for which are the data in Table 3, the two index matrices are given in Table 7, and for the large enterprises for which are the data are in Table 4, the two index matrices are given in Table 8.

Respectively, the InterCriteria correlation pairs for small, medium and large enterprises are given in Tables 5–8. We can immediately note the similar patterns in the conditional formatting of the eight tables in Tables 5–8, which are highlighted in a way to outline the highest possible positive consonances.

Table 5: InterCriteria pairs in micro enterprises.

μ	NE	PE	TO	VA
NE	1.000	0.504	0.621	0.584
PE	0.504	1.000	0.496	0.413
TO	0.621	0.496	1.000	0.735
VA	0.584	0.413	0.735	1.000

ν	NE	PE	TO	VA
NE	0.000	0.396	0.256	0.285
PE	0.396	0.000	0.425	0.493
TO	0.256	0.425	0.000	0.160
VA	0.285	0.493	0.160	0.000

Table 6: InterCriteria pairs in small enterprises.

μ	NE	PE	TO	VA
NE	1.000	0.436	0.533	0.484
PE	0.436	1.000	0.567	0.527
TO	0.533	0.567	1.000	0.803
VA	0.484	0.527	0.803	1.000

ν	NE	PE	TO	VA
NE	0.000	0.447	0.362	0.387
PE	0.447	0.000	0.319	0.342
TO	0.362	0.319	0.000	0.077
VA	0.387	0.342	0.077	0.000

Table 7: InterCriteria pairs in medium enterprises.

μ	NE	PE	TO	VA
NE	1.000	0.316	0.433	0.456
PE	0.316	1.000	0.516	0.467
TO	0.433	0.516	1.000	0.781
VA	0.456	0.467	0.781	1.000

ν	NE	PE	TO	VA
NE	0.000	0.299	0.222	0.182
PE	0.299	0.000	0.376	0.385
TO	0.222	0.376	0.000	0.088
VA	0.182	0.385	0.088	0.000

Table 8: InterCriteria pairs in large enterprises.

μ	NE	PE	TO	VA
NE	1.000	0.453	0.578	0.567
PE	0.453	1.000	0.527	0.481
TO	0.578	0.527	1.000	0.829
VA	0.567	0.481	0.829	1.000

ν	NE	PE	TO	VA
NE	0.000	0.328	0.242	0.248
PE	0.328	0.000	0.399	0.450
TO	0.242	0.399	0.000	0.120
VA	0.248	0.450	0.120	0.000

4 RESULTS AND DISCUSSION

Following a recent idea about analysis of the results of application of the ICA approach, described in (Atanassova, 2015), we can interpret the IF pairs, representing the membership and the non-membership parts of the InterCriteria correlation, as coordinates of points in the IF interpretation triangle, (Atanassov, 1989).

We will note for the interested reader, that the intuitionistic fuzzy interpretation triangle, see Figure 1, is the IFS-specific graphical interpretation of IFSs, which is not available for graphical interpretation of the ordinary fuzzy sets, defined by Zadeh. The triangle is part of the Euclidean plane, with vertices the points (0, 0), (1, 0) and (0, 1), staying respectively for the complete uncertainty, complete truth and complete falsity as the boundary values with which elements of an IFS can be evaluated. The hypotenuse corresponds to the graphical interpretation of the [0, 1]-interval, and points belonging to it are elements of a classical fuzzy set.

In this interpretation, we can plot the 24 resultant points onto a single IF triangle: 6 InterCriteria correlation points for the 4 types of enterprises. Since we are interested in the highest InterCriteria correlations, in these terms, it means finding the points, which are closest to the complete truth in point (1, 0), which is equivalent to having their membership parts greater than a given threshold value α, and, simultaneously, their non-membership parts less than a second threshold value β. For each of the points, i.e. for each of the correlations between two different criteria C_i and C_j, $i \neq j$, we can calculate its distance from the (1, 0) point, according to the simple formula:

$$d_{C_i,C_j} = \sqrt{(1-\mu_{C_iC_j})^2 + \nu_{C_iC_j}{}^2}$$

The results are given in Table 9, and presented sorted in ascending order according to the distance.

Table 9: Ranking the InterCriteria pairs by distance to Truth (1, 0).

Enterprise type	C_i	C_j	μ_{CiCj}	ν_{CiCj}	d_{CiCj}
Large	TO	VA	0.829	0.120	0.209
Small	TO	VA	0.803	0.077	0.212
Medium	TO	VA	0.781	0.088	0.236
Micro	TO	VA	0.735	0.160	0.310
Micro	NE	TO	0.621	0.256	0.457
Large	NE	TO	0.578	0.242	0.486
Large	NE	VA	0.567	0.248	0.499
Micro	NE	VA	0.584	0.285	0.504
Small	PE	TO	0.567	0.319	0.538
Medium	NE	VA	0.456	0.182	0.574
Small	PE	VA	0.527	0.342	0.584
Small	NE	TO	0.533	0.362	0.591
Medium	NE	TO	0.433	0.222	0.609
Medium	PE	TO	0.516	0.376	0.613
Large	PE	TO	0.527	0.399	0.619
Micro	NE	PE	0.504	0.396	0.635
Large	NE	PE	0.453	0.328	0.638
Small	NE	VA	0.484	0.387	0.645
Medium	PE	VA	0.467	0.385	0.658
Micro	PE	TO	0.496	0.425	0.659
Large	PE	VA	0.481	0.450	0.687
Small	NE	PE	0.436	0.447	0.720
Medium	NE	PE	0.316	0.299	0.746
Micro	PE	VA	0.413	0.493	0.767

We can, then, make two rounds of discussions. On one hand, see Figure 1, we can seek and formulate some assumptions about the InterCriteria correlations with respect to the type of enterprise.

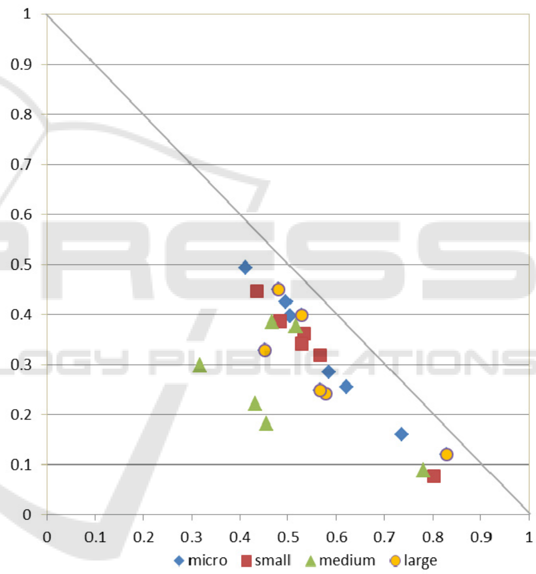

Figure 1: ICA results with respect to the type of enterprise.

We can notice from here that micro and small enterprises exhibit very similar patterns of InterCriteria consonance, with all the InterCriteria pairs exhibiting relatively low levels of uncertainty, and only the pair TO/VA exhibiting relatively high positive consonances. The same pair ranges highest among the InterCriteria correlations with the other two types of enterprises, medium and large. The large type of enterprises also exhibits relatively low uncertainty in the InterCriteria correlations, being lowest with TO/VA, PE/TO and PE/VA, and highest uncertainty featured in the rest three of the pairs. Expectedly, the most scattered is the pattern with the medium type of enterprises, where also the largest uncertainty is observed, all in the pairs containing the number of enterprises: NE/PE, NE/TO and NE/VA.

On the other hand, it is considered appropriate to analyse these 24 points as 6 groups of 4 points, grouped according to the criteria in the pair (Figure 2). We can then make some assumptions about the nature of these correlations, judging from how concentrated or how scattered the four points in each group are: the more concentrated the points for a given InterCriteria pair, the more consistent behaviour of this pair across the different scales of economic entities.

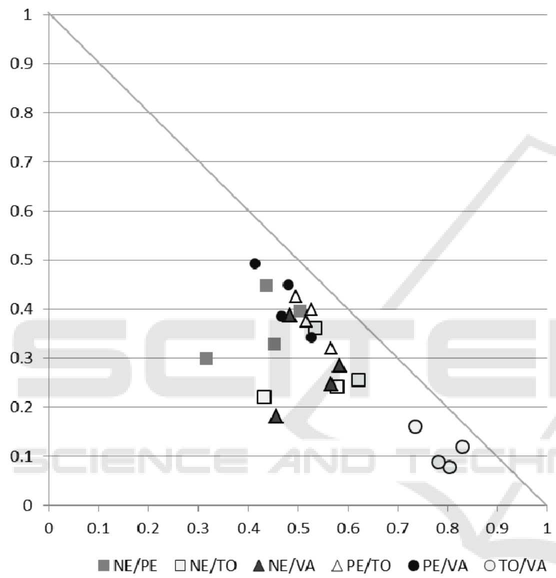

Figure 2: ICA results with respect to correlations between economic indicators.

We will immediately note what was visible from the Table 9, that that the pair of criteria TO/VA are distinctly best correlating across the different scales of economic entities, concentrated in the closest proximity to the absolute truth represented by the (1, 0) point. It is interesting however to note other, less clearly seen relations. For instance, we can note that quite similar patterns are formed for the two four-point sets corresponding to the pairs of criteria PE/VA and PE/TO: relatively parallel and closely located to the hypothenuse. In both these pairs, the distances from the (1, 0) point, according to the type of enterprise, follow in decreasing order the sequence: ‘small’ – ‘medium’ – ‘large’ – ‘micro’, with medium and large enterprises exhibiting very close results. Quite similar and closely located to each other are also the patterns for the pairs of criteria NE/TO and NE/VA.

These three observations over these particular economic data lead us to the speculation that from theoretical point of view it would be interesting to pay attention to situations when we have two criteria C_i, C_j that exhibit high positive consonance with each other, and each of them exhibit similar or identical consonance patterns in the pairs C_i–C_k and C_j–C_k, or vice versa, if C_i–C_k and C_j–C_k are two pairs of criteria with high positive consonances, would there be high positive consonance in the pair C_i–C_j. This question would be worth exploring in the light of the possibility to detect, using ICA not just pairs of correlating criteria, but also triplets, etc.

5 CONCLUSION

The present research analysed data about the micro, small, medium and large economic entities in the EU27, as evaluated against four economic indicators (criteria). The utilised method for analysis of the datasets was the novel decision support approach, called InterCriteria Analysis. The results are twofold: they outline correlations between economic indicators on these four levels of economic enterprise, new thus potentially brining new knowledge and understanding, and also contribute to elaboration of certain aspects of the methodology of ICA.

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