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An example of intercriteria analysis application to weather parameters

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Abstract: Herewith discussed is an example of the application of the approach of InterCriteria Analysis to weather and weather related parameters (criteria).
Keywords: Intercriteria analysis, Cnsonance, Dissonance, Weather analysis.
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1 Introduction

Weather analysis and prediction has always been a field of intense work and the weather forecast – a challenge. The correlation analysis of weather parameters can provide vital information regarding agronomy, monitoring the levels of artificial water reservoirs, vermin population, hazards of forest fires, and, relation between weather and non-weather parameters.

Currently developed is a novel approach which uses the concept of intuitionistic fuzziness and index matrices, called InterCriteria Analysis (ICA). Under this approach, arrays of data obtained by the measurement of many objects against many criteria are processed until correlations are calculated for each pair of criteria in the form of intuitionistic fuzzy pairs of values in the [0;1]-interval. The InterCriteria Analysis can be successfully applied to problems, where measuring according to some of the criteria is slower or more expensive, which results in delaying or raising the cost of the overall process of decision making. When solving such problems it is necessary to adopt an approach for reasonable elimination of these criteria, in order to achieve economy and efficiency. The approach is based on two mathematical formalisms: the algebraic apparatus of index matrices for processing of data arrays of diverse dimensions [1], and the intuitionistic fuzzy sets as a mathematical tool for treating uncertainty [2]. The basics of the ICA approach were given in [3].

Here we make the first attempt of applying the ICA approach to weather datasets. Depending on the input data, the method can successfully provide information about highly correlating weather parameters and thus reduce the number of measurements, removing expensive or time consuming processes. An example is the relation between cloud thickness and height, and the amount of rain, and many more possible relations. In the long run, the main goal is to discover if correlations between weather parameters can be discovered in order to suggest reasonable reaction in case of insufficient data.

Additionally, one of the topics of the present paper is to analyze the overall influence of a single parameter over the output data, in other words, whether all data parameters have equivalent significance for the algorithm, or some of them can be removed. Another direction of investigation is the data reduction, as large data arrays can be difficult to process. An experiment that aims to reduce the amount of input data without influencing the relation functions has been carried out.

2 An example of intercriteria analysis application to weather parameters

The method, called intercriteria analysis, applies the concepts of intuitionistic fuzzy sets and index matrices over an array of data that consist of objects and criteria. It is introduced in [4]. All notations used below, are from there.

Here, the intercriteria analysis is applied over the data gathered by the meteorological station in the city of Burgas in the period of 1st of April to 30th of April. The measurements are taken during the time interval between 9:00 and 12:00 AM. The assumptions that can be made are specifically for the city of Burgas and part of Burgas area. The data processed by the algorithm can be found on the following link [5]. The monitored set of criteria amounts to 13 weather parameters, 'criteria' per established ICA terminology:

- 1 - minimal air temperature,
- 2 - minimal moisture,
- 3 - maximum air temperature,
- 4 - air temperature of dewing,
- 5 - moisture,
- 6 - wind direction in degrees,
- 7 - wind speed m/s,
- 8 - altitude in meters,
- 9 - clouds average height,
- 10 - visibility,
- 11 - amount of rain liters per km^2,
- 12 - atmospheric pressure,
- 13 - atmospheric pressure difference per 3h.

The expected relations are between criteria 1, 2, 3 and 4, between criteria 6 and 7, and criteria 5, 8 and 12.

After the data array is processed by the algorithm, the result is a square 13×13 matrix which contains intuitionistic fuzzy pairs of numbers, giving the correlation between any two criteria from the set. According to the ICA terminology, the evaluated objects are the 30 days of April. Since it is easier to visualize the matrix of IF pairs in the form of two matrices, one containing the membership, and the other containing the non-membership parts of the IF pair, the resultant data is given in Tables 1 and 2, where it is further conditionally formatted for better representation. In Table 1 the maximal membership values are depicted in green color and the minimal ones in red. In Table 2 the minimal non-membership values are depicted in green color and the maximal in red.

μ	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1.000	0.957	0.770	0.708	0.374	0.413	0.275	0.194	0.157	0.258	0.019	0.561	0.338
2	0.957	1.000	0.794	0.720	0.389	0.383	0.286	0.189	0.146	0.245	0.028	0.555	0.342
3	0.770	0.794	1.000	0.794	0.518	0.428	0.340	0.333	0.161	0.198	0.082	0.473	0.391
4	0.708	0.720	0.794	1.000	0.658	0.370	0.299	0.378	0.187	0.138	0.103	0.486	0.387
5	0.374	0.389	0.518	0.658	1.000	0.361	0.406	0.596	0.305	0.131	0.237	0.434	0.531
6	0.413	0.383	0.428	0.370	0.361	1.000	0.529	0.486	0.305	0.372	0.194	0.445	0.563
7	0.275	0.286	0.340	0.299	0.406	0.529	1.000	0.505	0.288	0.338	0.232	0.331	0.542
8	0.194	0.189	0.333	0.378	0.596	0.486	0.505	1.000	0.546	0.262	0.301	0.323	0.535
9	0.157	0.146	0.161	0.187	0.305	0.305	0.288	0.546	1.000	0.355	0.413	0.206	0.305
10	0.258	0.245	0.198	0.138	0.131	0.372	0.338	0.262	0.355	1.000	0.381	0.305	0.363
11	0.019	0.028	0.082	0.103	0.237	0.194	0.232	0.301	0.413	0.381	1.000	0.103	0.168
12	0.561	0.555	0.473	0.486	0.434	0.445	0.331	0.323	0.206	0.305	0.103	1.000	0.501
13	0.338	0.342	0.391	0.387	0.531	0.563	0.542	0.535	0.305	0.363	0.168	0.501	1.000

Table 1: Values for $\mu_{C_iC_j}$ for April

ν	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.000	0.030	0.219	0.282	0.604	0.503	0.634	0.703	0.378	0.297	0.230	0.428	0.637
2	0.030	0.000	0.191	0.265	0.581	0.525	0.619	0.699	0.389	0.310	0.222	0.430	0.628
3	0.219	0.191	0.000	0.198	0.458	0.490	0.572	0.561	0.372	0.355	0.161	0.518	0.585
4	0.282	0.265	0.198	0.000	0.318	0.548	0.613	0.520	0.351	0.415	0.135	0.505	0.589
5	0.604	0.581	0.458	0.318	0.000	0.542	0.490	0.284	0.222	0.411	0.026	0.542	0.430
6	0.503	0.525	0.490	0.548	0.542	0.000	0.314	0.357	0.211	0.176	0.110	0.469	0.335
7	0.634	0.619	0.572	0.613	0.490	0.314	0.000	0.323	0.230	0.230	0.065	0.581	0.355
8	0.703	0.699	0.561	0.520	0.284	0.357	0.323	0.000	0.058	0.275	0.013	0.572	0.348
9	0.378	0.389	0.372	0.351	0.222	0.211	0.230	0.058	0.000	0.118	0.017	0.323	0.243
10	0.297	0.310	0.355	0.415	0.411	0.176	0.230	0.275	0.118	0.000	0.082	0.247	0.196
11	0.230	0.222	0.161	0.135	0.026	0.110	0.065	0.013	0.017	0.082	0.000	0.144	0.082
12	0.428	0.430	0.518	0.505	0.542	0.469	0.581	0.572	0.323	0.247	0.144	0.000	0.475
13	0.637	0.628	0.585	0.589	0.430	0.335	0.355	0.348	0.243	0.196	0.082	0.475	0.000

Table 2: Values for $\nu_{C_iC_j}$ for April

Concerning the specifics of Burgas area climate that is under investigation in the present work, the data in Tables 3 and 4 contain the expected relations between the weather parameters. There are parameters such as 4, 11 and 13 that do not change significantly, it can be interpreted as a result of the April climate conditions in Burgas. There are not weather phenomena such as intense rain, snow, temperature drops or peaks [SM].

On the other hand the data array is large enough to conduct several experiments - first to determine whether removing weather parameters with small amplitude of change or constant behavior will impact the performance of the algorithm. We analyze the input data and make the decision to remove from the input Tables weather parameters 4, 11 and 13, which exhibit constant or very slightly varying values across the investigated period. Tables 3 and 4 show the results of applying the ICA approach on all the data, with the segment with parameter (criterion) 11 (amount of rain) being removed.

μ	1	2	3	4	5	6	7	8	9	10	12	13
1	1.000	0.957	0.770	0.708	0.374	0.413	0.275	0.194	0.157	0.258	0.561	0.338
2	0.957	1.000	0.794	0.720	0.389	0.383	0.286	0.189	0.146	0.245	0.555	0.342
3	0.770	0.794	1.000	0.794	0.518	0.428	0.340	0.333	0.161	0.198	0.473	0.391
4	0.708	0.720	0.794	1.000	0.658	0.370	0.299	0.378	0.187	0.138	0.486	0.387
5	0.374	0.389	0.518	0.658	1.000	0.361	0.406	0.596	0.305	0.131	0.434	0.531
6	0.413	0.383	0.428	0.370	0.361	1.000	0.529	0.486	0.305	0.372	0.445	0.563
7	0.275	0.286	0.340	0.299	0.406	0.529	1.000	0.505	0.288	0.338	0.331	0.542
8	0.194	0.189	0.333	0.378	0.596	0.486	0.505	1.000	0.546	0.262	0.323	0.535
9	0.157	0.146	0.161	0.187	0.305	0.305	0.288	0.546	1.000	0.355	0.206	0.305
10	0.258	0.245	0.198	0.138	0.131	0.372	0.338	0.262	0.355	1.000	0.305	0.363
12	0.561	0.555	0.473	0.486	0.434	0.445	0.331	0.323	0.206	0.305	1.000	0.501
13	0.338	0.342	0.391	0.387	0.531	0.563	0.542	0.535	0.305	0.363	0.501	1.000

Table 3: Correlation values for $\mu_{C_iC_j}$ without parameter 11

ν	1	2	3	4	5	6	7	8	9	10	12	13
1	0.000	0.030	0.219	0.282	0.604	0.503	0.634	0.703	0.378	0.297	0.428	0.637
2	0.030	0.000	0.191	0.265	0.581	0.525	0.619	0.699	0.389	0.310	0.430	0.628
3	0.219	0.191	0.000	0.198	0.458	0.490	0.572	0.561	0.372	0.355	0.518	0.585
4	0.282	0.265	0.198	0.000	0.318	0.548	0.613	0.520	0.351	0.415	0.505	0.589
5	0.604	0.581	0.458	0.318	0.000	0.542	0.490	0.284	0.222	0.411	0.542	0.430
6	0.503	0.525	0.490	0.548	0.542	0.000	0.314	0.357	0.211	0.176	0.469	0.335
7	0.634	0.619	0.572	0.613	0.490	0.314	0.000	0.323	0.230	0.230	0.581	0.355
8	0.703	0.699	0.561	0.520	0.284	0.357	0.323	0.000	0.058	0.275	0.572	0.348
9	0.378	0.389	0.372	0.351	0.222	0.211	0.230	0.058	0.000	0.118	0.323	0.243
10	0.297	0.310	0.355	0.415	0.411	0.176	0.230	0.275	0.118	0.000	0.247	0.196
12	0.428	0.430	0.518	0.505	0.542	0.469	0.581	0.572	0.323	0.247	0.000	0.475
13	0.637	0.628	0.585	0.589	0.430	0.335	0.355	0.348	0.243	0.196	0.475	0.000

Table 4: Correlation values for $\nu_{C_iC_j}$ without parameter 11

Our observation shows, that the removal of one of the criteria does not change the values of the IF pairs of intercriteria correlation among the rest criteria.

As can be seen from the comparison of Tables 1 and 3, and Tables 2 and 4, there is not a difference between the rest correlation coefficients. From the geometrical interpretation of the IF pairs that give the correlations between the criteria, see [4], but taking criterion 11 into account several dissonances close to the (0;0) appear in the intuitionistic triangle as can be noticed in Fig. 1. This means that by extracting criterion 11 from the input data, the amount of calculations decreases and the accuracy increases Fig. 2. The results for criteria 5 and 10 are similar to the presented results in Tables 3 and 4.

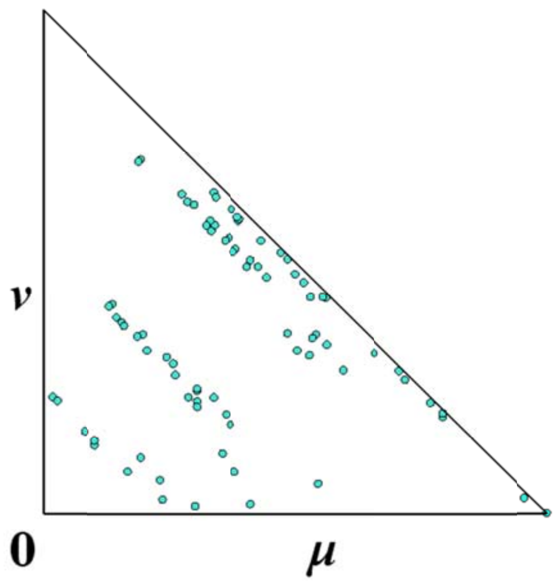

Figure 1. ICA results with criterion 11

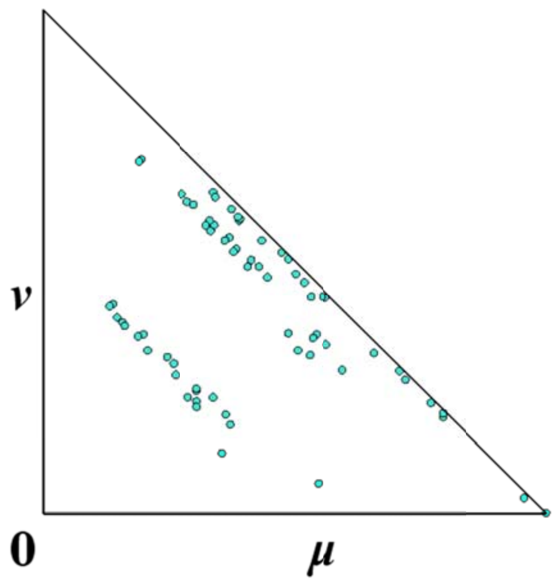

Figure 2. ICA results without criterion 11

From the point of view of developing the ICA methodology, it is noteworthy also that apart of removal of some of the evaluating criteria, in certain situations it might be necessary to remove some of the evaluated objects. Decision which objects to remove and which – to leave – is completely dependent on the problem area. We reason that in our case of meteorological data skipping, for instance, the first or the last half of the month may lead to non-comparable results, especially in transitional months and seasons. For this reason, we made the decision to apply ICA over a set of 'objects', representing the set of even days of April. Again we produced the results for the complete set of thirteen criteria, Figure 3, and for the set of twelve criteria, with criterion 11 being removed, Figure 4.

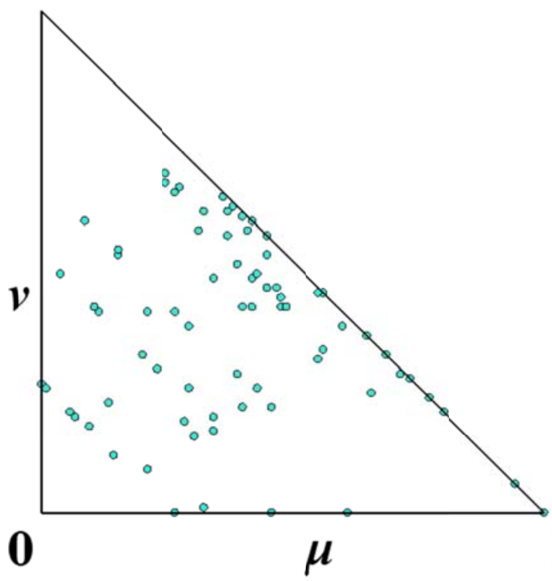

Figure 3. ICA results with criterion 11 for even days

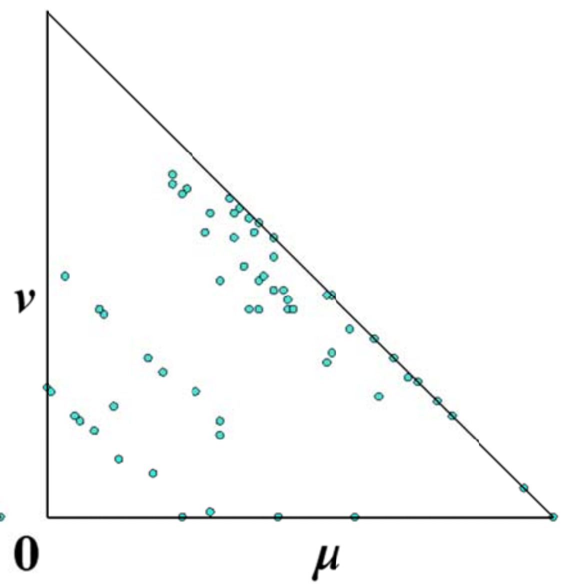

Figure 4. ICA results without criterion 11 for even days

The results of ICA over the input data, containing only the even days of April are illustrated in Tables 5 – 8. The formatting of Tables is the same as Tables 1 – 4. A slight drop from in the maximal membership and the minimal non membership can also be observed in contrast of the results obtained for all days of April – Tables 1, 2.

μ	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1.000	0.943	0.733	0.648	0.362	0.476	0.248	0.248	0.114	0.295	0.000	0.562	0.410
2	0.943	1.000	0.771	0.686	0.400	0.419	0.276	0.267	0.105	0.267	0.010	0.562	0.410
3	0.733	0.771	1.000	0.800	0.552	0.419	0.324	0.429	0.200	0.152	0.067	0.448	0.410
4	0.648	0.686	0.800	1.000	0.714	0.390	0.371	0.476	0.229	0.086	0.143	0.419	0.371
5	0.362	0.400	0.552	0.714	1.000	0.314	0.467	0.657	0.343	0.152	0.267	0.381	0.448
6	0.476	0.419	0.419	0.390	0.314	1.000	0.400	0.343	0.229	0.400	0.133	0.562	0.552
7	0.248	0.276	0.324	0.371	0.467	0.400	1.000	0.419	0.343	0.390	0.210	0.371	0.486
8	0.248	0.267	0.429	0.476	0.657	0.343	0.419	1.000	0.610	0.210	0.324	0.248	0.448
9	0.114	0.105	0.200	0.229	0.343	0.229	0.343	0.610	1.000	0.286	0.457	0.038	0.295
10	0.295	0.267	0.152	0.086	0.152	0.400	0.390	0.210	0.286	1.000	0.305	0.457	0.429
11	0.000	0.010	0.067	0.143	0.267	0.133	0.210	0.324	0.457	0.305	1.000	0.057	0.095
12	0.562	0.562	0.448	0.419	0.381	0.562	0.371	0.248	0.038	0.457	0.057	1.000	0.600
13	0.410	0.410	0.410	0.371	0.448	0.552	0.486	0.448	0.295	0.429	0.095	0.600	1.000

Table 5: Correlation values for $\mu_{C_i C_j}$for all even days of April

ν	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.000	0.057	0.267	0.352	0.629	0.410	0.676	0.657	0.400	0.371	0.257	0.438	0.562
2	0.057	0.000	0.229	0.314	0.590	0.467	0.648	0.638	0.410	0.400	0.248	0.438	0.562
3	0.267	0.229	0.000	0.200	0.438	0.467	0.600	0.476	0.314	0.514	0.190	0.552	0.562
4	0.352	0.314	0.200	0.000	0.276	0.495	0.552	0.429	0.286	0.581	0.114	0.581	0.600
5	0.629	0.590	0.438	0.276	0.000	0.562	0.448	0.238	0.162	0.524	0.000	0.610	0.514
6	0.410	0.467	0.467	0.495	0.562	0.000	0.410	0.467	0.286	0.210	0.219	0.324	0.305
7	0.676	0.648	0.600	0.552	0.448	0.410	0.000	0.410	0.190	0.276	0.086	0.552	0.410
8	0.657	0.638	0.476	0.429	0.238	0.467	0.410	0.000	0.000	0.400	0.010	0.657	0.448
9	0.400	0.410	0.314	0.286	0.162	0.286	0.190	0.000	0.000	0.181	0.000	0.476	0.248
10	0.371	0.400	0.514	0.581	0.524	0.210	0.276	0.400	0.181	0.000	0.152	0.210	0.248
11	0.257	0.248	0.190	0.114	0.000	0.219	0.086	0.010	0.000	0.152	0.000	0.200	0.171
12	0.438	0.438	0.552	0.581	0.610	0.324	0.552	0.657	0.476	0.210	0.200	0.000	0.371
13	0.562	0.562	0.562	0.600	0.514	0.305	0.410	0.448	0.248	0.248	0.171	0.371	0.000

Table 6: Correlation values for $\nu_{C_i C_j}$for all even days of April

As can be noticed in Tables 7 and 8, the absence of criterion 11 does not change the correlation significantly, similar to the results obtained in Tables 1 – 4. It is obvious, that by removing the odd days of April the results are not changed drastically, but the level of uncertainty has increased as illustrated in Figures 3 and 4.

μ	1	2	3	4	5	6	7	8	9	10	12	13
1	1.000	0.943	0.733	0.648	0.362	0.476	0.248	0.248	0.114	0.000	0.562	0.410
2	0.943	1.000	0.771	0.686	0.400	0.419	0.276	0.267	0.105	0.010	0.562	0.410
3	0.733	0.771	1.000	0.800	0.552	0.419	0.324	0.429	0.200	0.067	0.448	0.410
4	0.648	0.686	0.800	1.000	0.714	0.390	0.371	0.476	0.229	0.143	0.419	0.371
5	0.362	0.400	0.552	0.714	1.000	0.314	0.467	0.657	0.343	0.267	0.381	0.448
6	0.476	0.419	0.419	0.390	0.314	1.000	0.400	0.343	0.229	0.133	0.562	0.552
7	0.248	0.276	0.324	0.371	0.467	0.400	1.000	0.419	0.343	0.210	0.371	0.486
8	0.248	0.267	0.429	0.476	0.657	0.343	0.419	1.000	0.610	0.324	0.248	0.448
9	0.114	0.105	0.200	0.229	0.343	0.229	0.343	0.610	1.000	0.457	0.038	0.295
10	0.000	0.010	0.067	0.143	0.267	0.133	0.210	0.324	0.457	1.000	0.057	0.095
12	0.562	0.562	0.448	0.419	0.381	0.562	0.371	0.248	0.038	0.057	1.000	0.600
13	0.410	0.410	0.410	0.371	0.448	0.552	0.486	0.448	0.295	0.095	0.600	1.000

Table 5: Correlation values for $\mu_{C_i C_j}$ for all even days of April without criterion 11

ν	1	2	3	4	5	6	7	8	9	10	12	13
1	0.000	0.057	0.267	0.352	0.629	0.410	0.676	0.657	0.400	0.257	0.438	0.562
2	0.057	0.000	0.229	0.314	0.590	0.467	0.648	0.638	0.410	0.248	0.438	0.562
3	0.267	0.229	0.000	0.200	0.438	0.467	0.600	0.476	0.314	0.190	0.552	0.562
4	0.352	0.314	0.200	0.000	0.276	0.495	0.552	0.429	0.286	0.114	0.581	0.600
5	0.629	0.590	0.438	0.276	0.000	0.562	0.448	0.238	0.162	0.000	0.610	0.514
6	0.410	0.467	0.467	0.495	0.562	0.000	0.410	0.467	0.286	0.219	0.324	0.305
7	0.676	0.648	0.600	0.552	0.448	0.410	0.000	0.410	0.190	0.086	0.552	0.410
8	0.657	0.638	0.476	0.429	0.238	0.467	0.410	0.000	0.000	0.010	0.657	0.448
9	0.400	0.410	0.314	0.286	0.162	0.286	0.190	0.000	0.000	0.000	0.476	0.248
10	0.257	0.248	0.190	0.114	0.000	0.219	0.086	0.010	0.000	0.000	0.200	0.171
12	0.438	0.438	0.552	0.581	0.610	0.324	0.552	0.657	0.476	0.200	0.000	0.371
13	0.562	0.562	0.562	0.600	0.514	0.305	0.410	0.448	0.248	0.171	0.371	0.000

Table 8: Correlation values for $\nu_{C_i C_j}$ for all even days of April without criterion 11

3 Conclusion

In this paper we proposed an example of application of the InterCriteria Analysis approach over meteorological data for the climate of Burgas in April 2015. Comparing the results achieved by performing the ICA analysis over data for all monitored weather parameters, ‘criteria’ per ICA terminology, and over part of them, with one of the weather parameter being removed, we show that the reduction of an evaluation criterion does not affect the rest intercriteria correlation coefficients exhibited among the rest criteria.

In a second experiment, the aim was to remove a part of the evaluated objects and run the InterCriteria analytical software over the so reduced dataset, thus comparing the intercriteria correlation values with when all the objects were present. For this sake, careful consideration was made about the approach to picking the objects. The results showed the data-driven nature of the approach.

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