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THE (DOMINANCE BASED) ROUGH SET APPROACH APPLIED TO AIR POLLUTION IN A HIGH RISK RATE INDUSTRIAL AREA

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Abstract

This study presents a Rough Set Analysis (RSA) application, partially based on dominance in relation to air micro-pollution management in an industrial place with a high environmental risk rate, such as the industrial area of Siracusa, located in the South of Italy. This new data analysis instrument has been applied to different decisional problems in various fields with considerable success. Therefore, it is believed that it could also be used for the environmental issue related to multi-attribute sorting, considering both qualitative and quantitative attributes and criteria, such as sulphur oxides (SO_x), nitrogen oxides (NO_x), Methane (CH_4), non-methane hydrocarbons (NMCH) and some meteorological variables, such as air temperature and the relative humidity index. After outlining some basic concepts of the RSA theory, the most significant results obtained from the RSA specific application are presented and discussed particularly examples of decisional rules, attribute relevance and some other methodological features are offered to improve understanding and advantages of the approach.
The decisional rules obtained can also be usefully implemented in order to explain and manage the risk of air pollution.

Key words: air pollution, environmental criteria, industrial areas, rough sets

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1. Introduction

Heavy metals can pose health hazards to man and air pollution in a region depends on the emission of pollutants and local meteorological conditions. The probability of air pollution episodes occurring may be estimated based on simple atmospheric dispersion models with proper meteorological data and predefined typical air pollution sources. A lot of studies do not give enough information about the possible relation between sampling and meteorological parameters, as well as means of their optimal correspondence in order to enable modelling and determination of patterns which are characteristic of the investigated area (Chen et al., 2003; Chen et al., 2017; Vukovich, 2003, Sherwell, 2003). Developing conceptual models enables decision-makers at many levels to assess air quality as a whole rather than on a pollutant by pollutant concentration. By developing a holistic approach to air quality, it is possible, to assess he wider benefits of permitting development in existing air quality hotspots more effectively thereby avoiding the development of air quality ceilings; and to consider air quality within its wider meteorological context (Bojkov, 1986; Capsa et al., 2016; Premec, 2002). By establishing why and when air pollution accidences may occur across a region, strategies should be designed and implemented so as to deal with such episodes. The possibility of forecasting pollutant concentration near the ground with high spatial detail offers the opportunity of constantly monitoring and managing the territory.

Air quality modelling procedures can forecast the behaviour of the substances emitted from identified sources, using data from meteorological instruments. These models can supply the distribution

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of pollutant concentrations on the ground, and are used for thermoelectric power plant management and are useful in the case of exceptional events such as when a highly dangerous pollutant escape (Iordache and Dunea, 2013; Xue et al., 2000).

This study analyses the main relationships between air micro-pollution and meteorological conditions of the area surrounding Siracusa a city located in Sicily. This was done by measuring air samples from a receiving station near a small town called Melilli, a Sicilian industrial area with a high environmental risk rate (ARPA, 2002; DATE, 2006).

This station has been chosen because it allows the production of a complete picture with respect to the number of micro-pollution data and meteorological variables descriptions (Armendia, 1989). Then the most reliable parameters for the phenomena of the dispersion of micro-pollution were identified and also the various critical scenarios were checked, so that all available air pollution sources were considered (Di Lorenzo, 2001; Hsin-Chung, 2001; Mitran et al., 2012; Seinfeld, 1986). In particular, a specially designed model, with forecasting abilities of air pollution, has been developed, working independently from the knowledge of the local sources (Biamino et al., 2001). This monitoring model uses temperature and wind vertical profiles, measured by RASS (Radar Analysis Support System, a radar manufacturer-independent system for evaluating the different elements of a radar by connecting to signals) and SODAR (Sonic Detection And Ranging, a meteorological instrument used as a wind profiler to measure the scattering of sound waves by atmospheric turbulence) and concentration data from ground stations. The local values are correlated to the characteristics of the thermal profile and the direction and intensity of the wind at a selected altitude. On the basis of stored and statistically analyzed data, the model is able to forecast the pollution in the area surrounding the ground station (Tinarelli, 1994).

The novel method of data analysis applied to the study of air micro-pollution management, the rough set approach, considers objects described by a lot of both qualitative and quantitative attributes. In this context inconsistencies need not to be removed prior to the analysis, and also allow for highlighting the attributes which contribute most to air pollution among those taken into account for the assessment. Furthermore, thanks to this approach, it was possible to identify the influence of these inconsistencies on giving also some useful information about the management of pollution.

Moreover, this method recognises redundant attributes. This concerns the elimination of superfluous data from the data table, without deteriorating the quality of the information contained in the original table, permitting enormous savings in data collection. Moreover, the rough set theory also shows *posteriori* the relative importance of the considered attributes, without requiring a priori any elicitation or assessment of technical parameters (such as importance weights, trade-off etc.), which are often very difficult to establish and never easily understandable by decision makers.

The results hereby obtained are just an example of the rough set analysis application, in order to understand how and why it is possible to apply this approach to environmental problems. This paper in divided in other 5 sections, total 6; in section 2 we explain the rough sets theory and its main methodological features; Section 3 shows air micro-pollution analyzed data; in Section 4 we present the main decision rules obtained; we discuss in Section 5 the interpretations of the results from the methodological and operational points of view; Section 6 concludes this paper.

2. Methods

The rough sets theory, introduced by Pawlak (Pawlak 1982; 1991; 1994) has proved to be an excellent tool for data analysis, even in presence of inconsistencies and ambiguities. The main idea of the rough set approach is that some information is associated with every object in the universe (data to be analyzed) is associated a certain amount of information (data, knowledge), expressed by means of some attributes used for their description (for example, if the objects are air pollution monitoring stations, attributes may be air temperature, the relative humidity index, direction and wind speed, quantities of some micro pollution, etc.).

Objects having the same description in terms of these attributes are called indiscernible; the indiscernibility relation thus generated induces a partition of the universe into blocks of indiscernible objects, called elementary sets or granules of knowledge, which therefore result in information granulation. We can summarise the main characteristics of the rough set approach as follows. With respect to input information (object description), both quantitative and qualitative data can be considered, even if they present some inconsistencies. With reference to output, information about the relevance of attributes and the quality of approximation can be acquired, and the final results (relationships between conditional and decisional attributes) are expressed in the form of "if..., then..." decisional rules, using the most relevant attributes, which are expressions that decision makers find easier to understand (Clasadonte et al., 2004; 2007; 2008).

The original rough set approach based on the indiscernibility relation is not, however, able to deal with preference ordered attribute domains (so called criteria) and preference ordered decision classes (sorting problem), very often crucial for application to real problems in the field of multi-criteria decision analysis. In the case of air pollution problems, for example, we can define some different classes of pollution according to an increasing level of some micro-pollutants (SO_x, NOx,), but not all the attributes describing objects can be modelled as criteria, because is not possible beforehand to define an increasing or decreasing preference in their domains (for example, wind direction and so on).

To be able to deal with criteria and ordered decision classes, Greco et al. (Greco et al. 2001a; 2002; 2006; 2007; 2010a; 2010b) have proposed an extension of the original rough set theory, mainly based on the substitution of the indiscernibility relation by a dominance relation in the rough approximation of decision classes and called Dominance-based rough Set Approach (DRSA).

The dominance relation is typical of preference ordered domains: we say that object (a) dominates object (b), if, and only if, (a) is at least as good as (b) with respect to all considered criteria. Since we are considering conditional attributes with not preference ordered domain and decision attributes with ordered domains in the pollution problem at hand, a particular approach should be used: we have to consider the indiscernibility relation with respect to the former, and the assignment to ordered classes with respect to the latter. This can be easily modelled by introducing some appropriate thresholds which characterize different levels of air pollution or just by the presence or the absence of pollution for the decision classes. Of course, both interesting and useful sensitivity analyses can be made by moving the level of these thresholds (Clasadonte et al., 2004; Matarazzo et al., 2000, 2008).

The available information allows the detection of the described elements in the same way it creates the set of objects similar among them (indiscernible). The indiscernibility relation generates a partition of U into elementary sets (composed by indiscernible objects). From the universe U, any subset X can be expressed either precisely (as a union of elementary sets) or or approximately. In the latter case, the subset *X* may be characterized by two ordinary sets, called the *lower* and *upper approximations*. The lower approximation of X is made up of all the elements x which surely belong to the subset X, while the upper approximation of x contains all the objects X of U which could belong to the subset X. A rough set is defined by means of these two approximations, which coincide in the case of an ordinary set.

The difference between the two approximations represents the boundary region, whose elements cannot be characterized with certainty as belonging or not to *X* (by using the available information). When the objects X of the universe U are split into decision classes, the concept of approximation can be extended to the partition of the entire universe U in these classes. This allows a Decisions Table (DT) to be built, where each object of universe U is described using some independent variables, called conditional attributes, and each object is assigned to a class of this partition, as dependent variable or decisional attribute.

All of them allow an index to be identified, called the quality of classification; it expresses the ratio between the objects which have been correctly classified and the total of the elements of the table of decisions. Therefore, it can measure the goodness of the classification just mentioned. This index lies between 0 (any object is not clearly classified) and 1 (all the objects of the universe are correctly classified),

The quality of the classification is determined by considering all the conditioned attributes presented in a table of decisions. Besides, the classification quality may be unaltered if certain conditioned attributes are eliminated, because they are superfluous. The minimal sets of the attributes which maintain the same classification quality of the entire table of unchanged decisions are called reducts. The intersection among all the reducts generates the core (the set of the most important attributes which cannot be eliminated without deteriorating the quality of the classification). Therefore, the attributes belonging to the core are indispensable, while the attributes belonging to the reducts are exchangeable with one another. The others are actually superfluous. This kind of information, characteristic of rough set approach, is very useful for planning and performing any kind of data analysis in an efficient and economic.

In the end, the relations existing among conditional attributes and decisional attributes are expressed by the sentence “if… then…”, defined by the methodology as decision rules, where the antecedent expresses the values (“performances”) assumed by one or more conditional attribute and the consequent result expresses the value of the decisional attribute. The rules inferred from lower approximation are called certainty, while the rules obtained by upper approximation are called probable. These rules are expressed in a natural language, simple to understand and they are useful for the decision maker in understanding the studied phenomenon and for decision support (Slowinski, 1992). This means that the proposed approach is actually able to explain the reasons of a particular pollution situation, also showing the real examples of these (traceability of decisions), and is able to support the management in preventing pollution damages, showing them the situations where some critical events are most probable. Moreover, parameters like the support and the confidence ones help the decision maker in their choice of the most relevant rules. Support represents the number of the objects which satisfy both the conditional part of the rule and the decisional part, while confidence (expressed in percentage) expresses the ratio between support and the number of the objects which satisfy only the conditional part of the rule (in other words, the degree of probability that a decision happens (takes place) considering a particular condition). Consequently, the rough sets could be very efficiently applied on the case of uncertainty derived from the granularity of information. Actually, granules of condition attributes are used (object having the same descriptions) to approximate granules of decision (assignment to some decision classes). In the case of DRSA, moreover, the rough sets are also able to take into consideration the graduality of the monotonic property of the performances of each considered criterion, making comparisons between objects and describing their assignment to the ordered decision classes (multicriteria sorting).

This approach is therefore very different with respect to the fuzzy sets, where the linguistic imprecision due to the use of natural language is mainly considered, and the membership function aims at indicating in what degree each object belongs to a particular class. Of course, the two approaches are not mutually exclusive, but they can actually be used in a complementary way (Greco et al, 1999; 2005). Using a terminology from image representation, we could say that rough sets are related to the pixels of an image (its resolution), while the fuzzy sets represent the number of grey levels between black and white. An operational level, the implementation of rough sets based on indiscernibility relation requires the discretization of quantitative attributes by considering significant thresholds, while qualitative attributes can be used without any transformation. We observe that if we used the dominance-based rough set approach, no discretization is required.

The implementation of fuzzy sets always requires the definition and specification of particular membership functions, one for each attribute, not easy to specify analytically. Therefore, both classical rough set approach and fuzzy sets are sensitive to the specification of these values and sensitivity and robustness analysis are actually useful and recommended. It is not the case of DRSA.

3. Data description

Air micro-pollution analyzed data come from an air monitoring network, working since 1975, covering an industrial area of 500 km^2, including the towns of Priolo-Melilli-Siracusa, situated in the province of Siracusa, in the region of Sicily. This industrial area was declared "a high environmental risk rate place" by the Law 349/86 and covers six surrounding towns (Augusta, Priolo, Melilli, Siracusa, Floridia, Solarino); the landscape is very varied and is formed by sandy hills, mountains and plains near the cost (Matarazzo et al., 2000; 2007).

In this territory a lot of chemical plants, energy production industries and oil refineries are found, members of a private organisation, the industrial trust for environmental safety (C.I.P.A.). In its operative centre, C.I.P.A assembles and works out different micro-pollution parameters and various meteorological variables, measured by twelve different monitoring stations. Data collection and processing is useful in statistical analysis and in upgrading air pollution management in order to avoid giving the air tested threshold qualities, previously established Matarazzo et al., 2001, 2004).

This paper only studies monitoring station in Melilli only, because in this place data concerning air micro- pollution quantity and weather conditions present at the moment of pollution sample construction are thoroughly assembled. In fact, in the Melilli monitoring station hourly quantities of some micro pollution, such as sulphur oxide, nitric oxide, non-methanic hydrocarbon, ozone, sulfonyl hydrogen, and different meteorological conditions present at the moment of their observations, such as air temperature, relative humidity index, wind direction and speed are observed and stored. Some previous studies show the evident correlation between these environmental variables and the quantity of air micro-pollution found in the samples.

Because of the complete data present in the samples studied, actions of 4 micro- pollutions (SO_x, CH_4, NMHC, NO_x) in correlation with the meteorological variables previously mentioned (Matarazzo et al., 2002; 2008) are analyzed in this paper. Data recovered from the Melilli monitoring station during two weeks, more precisely one week in January and one in August 2010 have been studied, in order to observe eventual differences of analysis results also on the basis of the different seasons of the year. Daily available recorded “objects” described both by meteorological variables (condition attributes) and by micro-pollution quantity (decision attribute) have been considered. More than 1,000 data records have been analyzed such an example of new approach could be applied. The selected condition attributes in this analysis are: the hour of observation, wind speed and wind direction, air temperature and the relative humidity index. These attributes have been chosen because in previous studies they looked like some very important factors, at a local level, influencing air micro-pollution quantity.

4. Results

In spite of the fact that data samples used are restricted to a relatively short period of time (each one only two weeks), their analysis allowed us to obtain some interesting results, which give an idea of the knowledge extraction (in terms of decision rules) from available data using the considered approach and the possibility to use this new method to improve air pollution management. As mentioned before, the final results are expressed in the form of “if..., then...” decision rules, using at any time a particular (relevant) subset of attributes (reducts), varying according to the seasons and the micro pollution considered at each time. In the following of this paper just some examples of decision rules obtained in our case study are presented, useful for understanding and describing concisely pollution actions caused by particular combinations of conditional attribute values. Such rules, as mentioned before, are very useful in explaining the main reasons of some particular pollution events, and can be also used in forecast analysis and for decision support too. The rules were chosen as the most representative among those with the highest degree of confidence, indicating the relative frequency of antecedent (if...) also matching the consequent (then...) of the considered rule.

Apart from the analysis of SO_x, CH_4 and NMHC with respect to the January observations (Tables 1 – 4), the considered rules have a confidence equal to one, that means that all the objects match both the antecedent and consequent in each rule (Matarazzo et al., 2002; 2003; 2007).

These decision rules are presented in the form of tables which are very easy to read, showing in the first column the number of the rule and in the others columns the interval values of the conditional attributes characterizing that rule. In particular, Tables 1-4 show results from Melilli Monitoring Station during January month, each table per each micro-pollutant; and Tables 5-7 show the results in Melilli Monitoring Station during August month.

The threshold values chosen for the decisional attribute are also indicated. Since the dominance approach is used for the decisional attribute, pollution is reached by definition of whether the observed values are equal or greater than the threshold value of the corresponding micro-pollution element. In each Table, the attributes are the following: Attribute 1: hour of observation; Attribute 2: air temperature (C°); Attribute 3: air relative humidity index (per cent); Attribute 4: wind speed (Mt/sec); Attribute 5: wind direction (degrees); Attribute 6: wind direction respect to wind speed (measured by SODAR). The rules in the above Tables represent only a few of many rules obtained by applying this method and presented here, as easily understandable samples of the results of this analysis. All these rules are of the type "At least", in the sense that if the antecedence is verified, the level of the corresponding micro-pollution is greater than the threshold value, and the selected rules involve at most only two attributes each time in the conditional part.

In the following lines some examples of how reading the decisional rules are presented from Tables 1 – 7. Rule 18 (Table 4): between hours 10.00 – 21.00, if the air relative humidity index lies in the interval 75.5-83, then the NOx level is at least 20 gr/Nm^3, with a confidence of 1. Rule 33 (Table 6): if the air temperature is between 25.9 – 28.7 C° and air relative humidity index lies in the interval 37.6 – 42.9, then the CH_4 level is at least 845 μgr/Nm^3 with a confidence of 1. The rules in the above tables represent only a few of many rules obtained by applying this method and presented here, as easily understandable samples of the results of this analysis. All these rules are of the type "At least", in the sense that if the antecedence is verified, the level of the corresponding micro-pollution is greater than the threshold value, and the selected rules involve at most only two attributes each time in the conditional part.

Table 1. Melilli Monitoring Station, January 2010- Sox; Threshold = 70 gr/Nm^3

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*	*Confidence*
1		11.5-12.5					0.54
2					95-124		0.54
3						81.9-137.7	0.46
4	13-16				87-143		0.58
5			52.3-83		78-16		0.58
			52.3-83			81,9-117,9	0.58
7					78-116	81.9-117.9	0.58

Table 2. Melilli Monitoring Station, January 2010 CH_4; Threshold = 950 gr/Nm3

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*	*Confidence*
8	13-17	9.5-10.6					0.21
9	14-17				139-201		0.21
10	13-17					134.2-190.2	0.21

Table 3. Melilli Monitoring Station, January 2010 NMHC, Threshold = 90 gr/Nm3

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*	*Confidence*
11		11-11.6					0.36
12					96-146		0.40
13						107.3–149.7	0.37
14					105-146	107.3-149.7	0.42

Table 4. Melilli Monitoring Station, January 2010 NOx, Threshold = 20 gr/Nm3, Confidence = 1

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*
15					51-139	
16						66.4–111.5
17	11-14	10.5-11.4				
18	10-21		75.5-83			
19		9.7-11.6				18.8-117.9
20			49.6-87		63-120	
21			53.8-87			67.3-111.5
22				1.1-3.4	67-112	

Table 5. Melilli Monitoring Station, August 2010 SOx, Threshold = 10 gr/Nm^3. Confidence = 1

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*
23			32.8–37.8			
24	10–19		38-43.1			
25		28.9–31.3	35.2-54			
26			37.2–48.6	2.7–3.3		
27			33-41.9	3–3.7		
28			37-43.1		122-146	
29			31.9-39		134-142	

Table 6. Melilli Monitoring Station, August 2010 CH4 Threshold =845 gr/Nm^3, Confidence = 1

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*
30	14–20		37.2-40.2			
31	6-14					132.5–269.1
32		26.3–30.8	37.1-39			
33		25.9–28.7	37.6–42.9			

Table 7. Melilli Monitoring Station, August 2010 NOx, Threshold = 20 gr/Nm^3, Confidence = 1

Rule	*Hour*	*Air temperature*	*Humidity*	*Wind speed*	*Wind direction*	*Wind speed and direction*
34					71-79	
35						88.9–103.8
36				3–3.7	71-108	
37					83-109	90.5–103

In the following lines some examples of how reading the decisional rules are presented from Tables 1 – 7. Rule 18 (Table 4): between hours 10.00 – 21.00, if the air relative humidity index lies in the interval 75.5-83, then the NOx level is at least 20 gr/Nm^3, with a confidence of 1. Rule 33 (Table 6): if the air temperature is between 25.9–28.7 C° and air relative humidity index lies in the interval 37.6–42.9, then the CH_4 level is at least 845 μgr/Nm^3 with a confidence of 1.

5. Discussions

The decision rules concerning CH_4 and NMHC of January 2010 (Tables 2, 3) have a very low confidence level; this means that the considered attributes are not sufficient to explain the phenomenon. Perhaps some attributes are missing and therefore in order to improve this result it would be useful to consider further attributes. This is another important methodological feature of the rough set approach: underlining that sometimes more information is needed to better describe some object in order to be able to arrive at well-founded conclusions, that is with a high degree of confidence. On the other hand, the same analysis regarding the observations of August give very interesting results; we can observe the particular relevance of the degree of humidity in the CH_4 level (Table 6) and the crucial role of the wind direction and speed in NMHC analysis (Table 3).

We can also observe that sometimes (rules 11, 15, 19) it is possible to explain a result using only one attribute, that is with very short and simple decision rules. It should be remembered that hat a general property of the rough set approach is on that uses all conditional attributes, instead of only attributes from a reduct, we can obtain more concise rules, that is with a greater variety a fewer number of attributes in the conditional part of the rules.

With respect to SO_x we used a greater value for the threshold in January both in order to present the relative pollution level more clearly, as well as to obtain an acceptable confidence degree for same decision rules. Both the analyses of NO_x give excellent results in terms of confidence with respect to all the decision rules obtained, where we can observe a greater relevance of the attributes hour of observation, air temperature and humidity degree in the analysis of the January data, while a crucial role in the August results is played by winds.

Actually, an initial idea about the relevance of the conditional attributes can be directly revealed by the presence frequency of each conditional attribute in the decisional rules, as shown in the Tables 1-7 (see for example how important the conditional attribute for air relative humidity is in Table 5). Some more sophisticatedly important indices can also be computed, for example according to the Shapley value in the cooperative games in the framework of game theory; the main idea is to compute the contribution to the quality of results due to adding another attribute in the conditional part of the rules. In other words, the involvement of each attribute in all coalition of attributes, measuring therefore also the interaction (synergy or redundancy) between the attributes is investigated (Greco et al, 2001a; b). It should be observed that this kind of importance is therefore an output of the analysis within the rough set approach, and not an input information, as usually happens when we use other approaches, as for example weighted sum, for the evaluation of some objects.

Moreover, the results also show interesting interpretations in terms of a particular kind of trade-off. From the analysis of the couples of decision rules (26,27) (32,33) we can easily observe some cases of trade-off between the values of the couple of attributes in the classical meaning of "compensation". From rules (32,33) there is a relationship between air temperature and degree of humidity, in the sense that the different value of air temperature can be compensated by the different degree of humidity obtaining the same results in terms of pollution. A similar relationship can be observed in the pair of decision rules (26,27) with respect to the degree of humidity and wind speed. This means a certain capacity of compensation is allowed (trade-off) between the performances of a couple of attributes: a better value on one attribute is able to compensate the worst value on the other and vice-versa.

By observing the following couples of rules (5,6) (9,10) (20,21), we can see that it is possible to obtain the same results in terms of levels of pollution considering the combination of one fixed attribute and gradually another one attribute associated with it (exchange of attributes). So, for example, from the couple of rules (5,6), it can be observed that the same result in terms of level of pollution, with the same degree of confidence, is the consequence of the degree of humidity between 52.3-83 and wind direction between 78-116 (rule 5), or the consequence of the same degree of humidity associated to the wind speed and wind direction between 81.9-117.9 (rule 6).

Another similar observation can be made comparing rules 6 and 7, where again the phenomenon of exchangeable attributes can be observed that in this case are the air humidity (attribute 3) and the wind direction (attribute 5). This means that the same effect in the class assignment can be obtained as result of a combination of an attribute value each time with other different attributes, as a particular very interesting "qualitative substitution effect". The exchangeable role played by some attributes in combination with a given level of another conditional attribute (in the previous example, the degree of humidity or the wind direction and speed), result in the assignment of an object to the same decision class of pollution.

Of course, in the same way interesting remarks can be made about the interactions among conditional attributes by the analysis of decision rules. So, for example, comparing rules 2 and 4 we can observe that more precise information about the wind direction (95-124, from rule 2) can be replaced by less precise information (87-143, from rule 4), but interacting with the performance of another attribute, (hour of observation, attribute 1).

With respect to the operational aspect of this approach, it is important to emphasize how obtained results can be used to capably support decision maker to manage the pollution risk. Actually, the information given by decision rules can help understand the main reasons of a pollution event, giving us the explanation of this, but also to preventing or forecasting dangerous situations, very probable when meteorological conditions similar to those described by the obtained decision rules are approaching (air temperature, humidity degree, wind direction).

Another very interesting result using this approach concerns the information we can receive by so called "non activated" rules in improving or in deteriorating the results of a decision. See, for example, rules from Table 5 and at levels of air relative humidity index. It can be observed that if this value is smaller than 31.9 or larger than 48.6, the SOx, will never be at a level higher than the threshold of $10/gr/Nm^3$ (Table 5). These rules, therefore, are able to give us useful information about "critical values" of the conditional attribute air relative humidity.

More generally, we can say that using this approach we are able to detect some threshold values of one or more condition attributes that can be considered as values to be reached or to be avoided. Of course, the meteorological variables cannot be changed by decision makers. But the rules inferred using the rough set approach can be actually used as guidelines for forecasting in some areas particular cases of pollution events, consequently giving people useful information and suggestions concerning the probable danger of air pollution.

6. Conclusions

The aim of this paper is simply to give a first idea of the possibilities offered by rough sets data analysis in the field of air pollution management.

The results obtained, apart from the above-mentioned interesting methodological aspects and information, point out other relevant profiles of the phenomenon considered. They have clearly shown, for example, the more or less important role played by each meteorological variable in the assignation of the actions to various pollution classes, the fundamental roles of the relationships between the antecedent (attributes and conditional criteria) and the consequent (decision class). They provide interesting information about the semantic importance of quantitative and qualitative trade-offs, which show also the interaction among more meteorological factors.

The main features of the study include the possibility to underline the relevance of each subset of attributes, without introducing a priori arbitrary weights; the presentation of the results in the form of a logical statement "if... then...", expressed in simple language and very easy for the decision makers to understand. It should be remembered that in this approach it isn't necessary to remove a priori some inconsistency in the data to be analyzed, but – on the contrary –this also is an important piece of information about the degree of certainty of the decision rules inferred.

Finally, with respect to managerial aims, the decision rules obtained can be used immediately as guidelines for preventing air pollution when the weather conditions match or are similar to those shown on the tables and to other rules not included in this paper.

These rules, in fact, could be the basis for the development of air quality management strategies under the impacts of climate change, that is fundamentally a risk assessment and risk management process involving priority assessment of the impacts of climate change and associated uncertainties. Risk management for air quality under the impacts of climate change includes determination of air quality targets, the selection of potential management options, and identification of effective air quality management strategies through decision-making models.

The method presented in this paper can help decision makers make appropriate responses to climate change, since it provides an integrated approach for climate risk assessment and management when developing air quality management strategies. The risk-based decision-making framework can also be applied to develop climate-responsive management strategies for the other environmental dimensions and assess costs and benefits of future environmental management policies

Like any study, this could be improved and a more in-depth study be carried out. For example, the original database could be extended, both in time limits and with reference to the variables considered. If we take into consideration data concerning different years and analyze them by using the same methodology, we can, for instance, eliminate the peculiar effects related occasionally to a-typical weather conditions. Moreover, if we extend the analysis to other meteorological variables we could obtain decisional rules which are sometimes easier and more intuitive than those obtained by using a smaller number of descriptors.

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