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Hybrid Soft Computing Analytics of Cardiorespiratory Morbidity and Mortality Risk Due to Air Pollution

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Abstract. During the last decades, climate change has been contributing significantly to the increase of Ozone and Particulate Matter in major urban centers. This might result in additional enhancement of serious seasonal respiratory and cardiovascular diseases incidents. This research effort introduces an innovative hybrid approach that fuzzifies the involved features. The final target is the development of a Mamdani fuzzy inference system with weighted fuzzy rules. The system's output comprises of the partial meteorological and air pollution risk indices per season. Fuzzy conjunction T-Norms have been employed to estimate the unified risk index. Moreover, the effect of one to seven days delay regarding high values of the above indices to the morbidity and mortality indicators in the prefecture of Thessaloniki has been studied. Hybrid Fuzzy Chi Square Test has been performed to identify the degree of dependences between the unified air pollution-meteorological risk indices and serious health even mortality cardiorespiratory problems.

Keywords: Mamdani fuzzy inference system · Fuzzy chi square test · Fuzzy risk indices · Air pollution index · Mortality · Morbidity · Thessaloniki

1 Introduction

Air pollution (AIPO) is one of the most serious problems of modern societies. It is related to the concentration of all sorts of substances, to radiation or other forms of energy in quantity or duration, which can cause an increase in hospital admissions and a reduction in life expectancy. Under certain conditions, concentrations of primary (CO, NO, NO_2, SO_2) or secondary pollutants (O_3) are likely to reach critical alarm levels that create inappropriate living conditions, increasing the incidence of myocardial infarction and stroke. The quantification of urban residents' morbidity and mortality due to meteorological conditions that intensify concentrations of air pollutants is considered a

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multifactorial and complex problem. It is usually necessary to carry out an in-depth spatio-temporal analysis of extreme meteorological conditions that maximize the problem as well as to discover the temporal delay of the atmospheric conditions' influence on the morbidity and mortality of urban population. Another key issue is the discovery of the combined effect of meteorological conditions and pollutants in urban centers.

This paper introduces an innovative air pollution analytics approach with its corresponding system. One of its basic contributions is the creation of fuzzy weighted rules applied on the parameters that determine the morbidity and mortality of the inhabitants of Thessaloniki city, on a seasonal basis. Two partial Risk indices (produced by fuzzy rules) have been developed to analyze the daily Risk due to meteorological parameters (DRMP) and due to air pollutants respectively (DRAP), on a seasonal basis. In addition, a unified Risk index (URI) has been introduced by applying fuzzy T-Norm conjunction operation on the DRMP and DRAP partial indices.

Correlation analysis has been performed between the *Linguistics/Fuzzy sets (L/FS)* corresponding to the above three developed indices and the morbidity and mortality Risk *Linguistics* in Thessaloniki using the hybrid Fuzzy Chi Square Test approach.

In general, the use of this hybrid approach determines not only the existence of dependences but also the degree of dependence among the *L/FS*. This is achieved by fuzzyfying the Chi-Square Test P-Values. This dependence is expressed by using properly designed L/FS such as *Low*, *Medium* and *High* obtained by fuzzy membership functions (FMF).

1.1 Related Literature - Motivation

Various studies [2, 19, 23] in the literature have analyzed the combined effect of meteorological parameters, atmospheric pollution and socio-economic characteristics of residents on morbidity and mortality from cardiovascular and respiratory diseases.

Sarigiannis et al. [17] proposed a survey which deals with the assessment of health impact and the respective economic cost attributed to particulate matter (PM) emitted into the atmosphere from biomass burning for space heating, focusing on the differences between the warm and cold seasons in 2011–2012 and 2012–2013 in Thessaloniki. Vlachokostas et al. [21] presented a methodological approach in order to estimate health damages from particulate and photochemical urban air pollution and assess the order of magnitude as regards the corresponding social costs in urban scale. Zoumakis et al. [24] analyzed mortality during heat waves in Northern Greece, separately for June, July and August, during the period 1970–2009, and to quantify a preliminary relationship between heat stress and excess mortality, taking into consideration the population adaptation to the local climate. Kassomenos et al. [10] studied the sources and the factors affecting the particulate pollution in Thessaloniki. Hourly PM_X concentrations from two monitoring sites were therefore correlated to gaseous pollutant concentrations and meteorological parameters during the 2-year period between June 2006 and May 2008. Papanastasiou et al. [15] used meteorological and AIPO data which observed in Athens, Thessaloniki and Volos were analyzed to assess the air quality and the thermal comfort conditions and studied their synergy, when extreme hot weather prevailed in Greece during the period 2001–2010. Kyriakidis et al. [12] employed a number of Computational Intelligence algorithms to study the forecasting of the hourly and daily Common Air Quality Index. These algorithms included artificial neural networks, decision trees and regression models combined with different datasets. Voukantsis et al. [22] formulated and employed a novel hybrid scheme in the selection process of input variables for the forecasting models, involving a combination of linear regression and artificial neural networks (multi-layer perceptron) models. The latter ones were used for the forecasting of the daily mean concentrations of PM_{10} and $PM_{2.5}$ for the next day. Prasad et al. [16] developed an ANFIS model predictor which considers the value of meteorological factors and previous day's pollutant concentration in different combinations as the inputs to predict the 1-day advance and same day air pollution concentration. The concentrations of five air pollutants and seven meteorological parameters in the Howrah city during the period 2009 to 2011 were used for development of an ANFIS model.

This research paper has been motivated by the lack of an integrated approach that would estimate the cumulative effect of the atmospheric conditions' correlations over public health (viewing the problem in a holistic manner). This means that we consider the combinatorial effect of meteorological features and air pollutants' concentrations. Additionally, to the best of our knowledge there is no approach in the literature trying to model time-lag effects of atmospheric conditions on public health using soft computing techniques. Specifically, there is lack of a holistic model that would analyze and realize the combinatorial effect of the meteorological-pollutants features to the respiratory and cardiovascular diseases incidents. On the other hand, the employment of the fuzzy X^2 test in environmental or medical cases is quite innovative.

Therefore, the proposed research attempts to fill a significant gap in the literature using fuzzy logic methods. It employs seasonal indices related to the parameters that maximize their values due to the processes and the mechanisms of the atmosphere, negatively affecting the public health of the inhabitants of Thessaloniki.

The basic innovation of the proposed model is based on the creation of the two partial risk indices the DRMP and the DRAP that were mentioned before. This is achieved through the employment of fuzzy weighted rules on a seasonal approach. More specifically for each season the system considers the meteorological conditions that maximize the problem of AIPO. In this way, it is possible to find the conditions for creating either the smoke cloud or the photochemical.

The determination of the unified risk index per season is based on the combined effect of the overall meteorological and the overall pollution indices, through the fuzzy conjunction T-NORM operators. The aim of the research is to find the dependences between the fuzzy linguistics corresponding to the three above indices with the morbidity and mortality L/FS not only on the same day but also with a delay of up to 7 days (0–7 days).

The produced system can be used by civil protection authority for the benefit of the residents of Thessaloniki. More specifically it can be used as a forecasting system on a short-term basis aiming to inform local authorities, citizens and hospitals on its output. This can significantly help the work of civil protection authority by providing alerts for hospitals due to specific pollution – weather conditions. In this way the hospital infrastructure will be ready to accept emergency incidents. This in-depth study strengthens civil protection mechanisms by serving as a tool for informing the public or hospitals on the potential of adverse meteorological conditions and smog or photochemical cloud development.

Additionally, finding correlations due to the delay of the effects of atmospheric conditions on public health can act as an information system for managing extraordinary and increased imports into public hospitals even several days after the occurrence of adverse atmospheric conditions.

1.2 Research Data

Aiming to produce a symbolic representation of the complex correlations between atmospheric pollutants with morbidity and mortality in Thessaloniki, a statistical analysis of twelve AIPO measuring stations for the period 2000–2013 was carried out. The averages of the pollutants' values from the twelve stations were calculated as the selected stations record the atmospheric pollution from all the prefecture of Thessaloniki. In most of the data records missing values were observed for periods of hours, days even months for the whole period of 2000–2013, probably due to malfunction. The SO_2, CO and O_3 pollutants are recorded hourly whereas only average daily values are measured for the PM_{10} and $PM_{2.5}$ particles.

The average daily values of CO and O_3 have been estimated after the calculation of the maximum daily average rolling values per 8 h.

Generally, all values are measured in μg/m^3, except for CO which is measured in mg/m^3. Except from the five air pollutants three meteorological features were employed namely: Air Temperature (AirTemp), Relative Humidity (RH), and sunshine hours (SUN) gathered from Thessaloniki airport station (Micra).

The following table contains a brief presentation of the measuring stations with statistical analytics (Table 1).

Table 1. Statistics of the measuring stations

ID	Station's name	Code	Missing values	Correct Data Vectors	Station's data
1	Aristotle University	APT	33.24%	12,679	O_3, NO, NO_2, SO_2
2	Agias Sofias	AGS	35.86%	18,272	O_3, NO, NO_2, CO, SO_2, PM_{10}
3	Kalamaria	KAL	54.43%	11,982	O_3, NO, NO_2, CO, SO_2, PM_{10}
4	Kordelio	KOD	31.83%	19,418	O_3, NO, NO_2, CO, SO_2, PM_{10}
5	Neochorouda	NEO	33.9%	9,656	O_3, NO, NO_2, PM_{10}
6	Panorama	PAO	32.18%	12,880	O_3, NO, NO_2, PM_{10}
7	Sindos	SIN	29.09%	20,199	O_3, NO, NO_2, CO, SO_2, PM_{10}
8	Egnatia	EGN	8.498%	31,419	O_3, NO, NO_2, CO, SO_2, PM_{10}, $PM_{2.5}$
9	25th March	25 M	5.68%	28,941	O_3, NO, NO_2, CO, SO_2, PM_{10}
10	Lagkadas	LAG	13.32%	26,594	O_3, NO, NO_2, CO, SO_2, PM_{10}
11	Eptapyrgio	EPT	12.01%	26,997	O_3, NO, NO_2, CO, SO_2, PM_{10}, $PM_{2.5}$
12	Malakopi		38.74%	18,797	O_3, NO, NO_2, CO, SO_2, PM_{10}
13	Macedonia Airport	Mikra	0.39%	40,751	Meteorological Station
14	AVERAGE OF ALL POLLUTION STATIONS		25.32%	21,429	O_3, NO, NO_2, CO, SO_2, PM_{10}, $PM_{2.5}$

During data pre-processing up to 75% of the daily hourly values or 75% of the hourly current 8-hour average values for CO and O3 were considered as coming from reliable measurements. As far as extreme prices are concerned, they were considered important as based on them emergency patient imports are intensified, thus it was considered appropriate not to remove them from our data.

In terms of disease selection, circulatory system diseases (I00–I99) and respiratory diseases (J00–J99) were categorized based on the tenth review of the ICD-10 International Statistical Classification of Diseases and Related Health Problems [9]. The rejection of patients' cases with injuries, traffic, poisoning, in-hospital illnesses or transported from other regional hospitals was necessary for the reliability of the data.

The collection of morbidity data was carried out by all public hospitals in the Prefecture of Thessaloniki. At county level, the collection of morbidity data for circulatory and respiratory diseases was carried out by the Hellenic Statistical Authority (ELSTAT).

2 Theoretical Frameworks and Methodology

2.1 Mamdani Fuzzy Inference System and Fuzzy Rules

Fuzzy logic is a modeling attempt close to the human way of thinking and inference, providing approximate reasoning mechanisms and inference/decision-making since the human brain tends to make the approximate reasoning based on qualitative perception criteria despite precise reasoning based a multitude of data.

In Mamdani FIS, human knowledge is illustrated in the form of fuzzy IF/THEN rules. The FRs are a mechanism of knowledge representation which is reflected in the hypothetical proposals, peculiar to the human way of thinking. The fuzzy sets expressing Linguistics are combined together and create Mamdani FR representing the knowledge available about a system. They are expressed in the following form:

$$IF\ x\ is\ A\ (Linguistic\ antecedent)\ THEN\ y\ is\ B\ (Linguistic\ consequent) \tag{1}$$

where A and B are L/FS corresponding to parameters x and y which are defined in the universe of discourse X and Y respectively. The expression "*x is A and y is B*" are fuzzy proposals. The above rule 1, defines a fuzzy implication relation (between the parameters x and y) which correlates the truth level of the antecedent to the corresponding truth of the consequent. It is a fact that x belongs to the L/FS A with a degree of membership (DOM) and the same stands between y and B. Finally the output of the consequent is de-fuzzified by a proper function (*centroid*) and we obtain a crisp value which is a final numeric result. Its benefit is that it can be handled by a computational approach or a sensor [8].

The implementation of the Mamdani Inference System containing the corresponding FRs was done under the Matlab platform that offers an integrated fuzzy development, analysis and visualization environment [18].

2.2 T-Norm Fuzzy Conjunction

This paper attempts to calculate the URI, resulting from the cumulative effect of all the related factors, after performing integration operations on all individual fuzzy sets. This task is carried out, by using specific fuzzy conjunction "AND" operators known as T-Norms in the literature. The *Min*, the *Algebraic*, the *Drastic*, the *Einstein* and the *Hamacher Products* act as *T-Norms* [3, 5, 8, 11, 13, 14]. The *Min T-Norms* are unifiers of partial risk indices and they are quite optimistic as they are assigning the minimum risk value to the overall index [7, 8].

2.3 Chi-Square Test and Fuzzy Chi Square Test

The Chi-Squared hypothesis-testing is a non-parametric statistical test in which the sampling distribution of the test statistic is a chi-square distribution when the null hypothesis is true. The null hypothesis H_0 usually refers to a general statement or default position that there is no relationship between two measured phenomena, or no difference among groups. The H_0 is assumed to be true until evidence suggest otherwise [4, 6]. The statistical control index used for this assessment is the test statistic X^2.

$$X^2 = \sum \frac{(f_{o}-f_{e})^2}{f_e} \tag{2}$$

where f_e is the expected frequency and f_o the observed one. The degrees of freedom are estimated as in Eq. 3 (for the table of labeled categories with dimensions *rXc*) (Tables 2 and 3).

$$df = (r-1)(c-1) \tag{3}$$

For the H_0 the critical values for the test statistic are estimated by the X^2 distribution after considering the degrees of freedom. If the result of the test statistic is less than the value of the Chi-Square distribution then we accept H_0 otherwise we reject it [6].

The calculated p-value prices include the possibility of error in the range [0–1]. Each error value is multiplied by 10, raised to the negative sixth power (p-value). The p-value equal to a is considered as boundary and it cannot determine the dependence or independence between the variables. The dependence is defined with p-values < a, whereas the independence with p-values > a.

Subsequently, p-values are fuzzified by using *Fuzzy Chi-Square test*, according to the specified confidence interval and to the significance level. This process of course requires the use of proper FMF, developed to estimate the level of dependence when *p-value* < *a* (in the closed interval [0-0.049999]) and the level of independence when p-value > a (in the closed interval [0.050001-1]). This is done to produce the proper *Linguistics*.

Table 2. Indicative dependence DOM using Fuzzy Linguistics (Interval [0-0.049999])

P-Value	Linguistics	High	Medium	Low
0	High	1	0	0
0.00001	High	0.99945	0	0
0.012499	High	0.37505	0.37495	0
0.0125	High/Medium	0.375	0.375	0
0.012501	Medium	0.37495	0.37505	0
0.03	Medium	0	0.75	0
0.035	Medium	0	0.5	0.2500125
0.037499	Medium	0	0.37505	0.374968
0.0375	Low	0	0.375	0.3750187
0.049999	Low	0	0	1

Table 3. Indicative Independence DOM using Fuzzy Linguistics (Interval [0.050001-1]

P-Value	Linguistics	Low	Medium	High
0.050001	Low	1	0	0
0.05001	Low	0.99997	0	0
0.287550	Low	0.374871	0.374868	0
0.287551	Medium	0.374868	0.374871	0
0.4301	Medium	0	0.75	0
0.71505	Medium	0	0.5	0.25013157
0.762518	Medium	0	0.375051	0.375047
0.762519	High	0	0.375048	0.375050
1	High	0	0	1

The following MATLAB commands were used to enhance the above for the Linguistics *Low, Medium and High*.

$$HighDependence = trimf(dependence, [-0.020000\ 0.000000\ 0.020000])$$
$$MediumDependence = trimf(dependence, [0.005000\ 0.025000\ 0.045000])$$
$$LowDependence = trimf(dependence, [0.030000\ 0.049999\ 0.070000])$$

$$\mathrm{LowIndependence} = \mathrm{trimf}(\mathrm{independence}, [-0.329900\ 0.050001\ 0.430001])$$
$$\mathrm{MediumIndependence} = \mathrm{trimf}(\mathrm{independence}, [0.145100\ 0.525100\ 0.905000])$$
$$\mathrm{HighIndependence} = \mathrm{trimf}(\mathrm{independence}, [0.620000\ 1.000000\ 1.380000])$$

3 Description of the Proposed Methodology

The basic proposed modeling methodology includes the fuzzification of the crisp values of all considered parameters with triangular membership functions and their categorization by using risk Linguistics. In addition, fuzzy weighted rules were developed to produce Meteorological and Atmospheric Pollution risk indices respectively. Five T-Norms were used to perform Conjunction and create a unified index from the combination of the meteorological and the pollution indices.

A hybrid approach based mainly on the Fuzzy Chi-Square Test was applied to find the degree of dependences not only on the same day but also with a latency of up to 7 days between the Linguistics related to the three indices (*DRMP, DRAP, URI*) and the morbidity (MBI) and mortality (MTI) indices of the underlying diseases. Total research is interpreted in four distinct stages, which are analyzed below:

Step1. For each season of the year, meteorological conditions that maximize the problem of air pollution were investigated. By studying the literature related to winter [1, 20], the values of the minimum temperature, maximum humidity and sunshine were fuzzified. Based on the created fuzzy sets, the *Meteorological Smog Index (MSMI)* was defined and used. The combined effect of the lower minimum temperature values with the higher maximum humidity and the lower values of the sunshine hours corresponded to the Linguistic *High* with an assigned weight equal to 1.

Similarly, for the summer months, fuzzy weighted rules were designed by fuzzifying the values of the maximum temperature, the minimum humidity and sunshine. The result was the determination of the *Meteorological Photochemical Cloud Index* (*MPCI*). In the summer months, the combined effect of the higher maximum temperature values, of the lower minimum humidity values and the higher hours of sunshine corresponded to the Linguistic *High* with an assigned weight equal to 1.

On the other hand regarding spring and autumn we have examined the conditions created by both meteorological indices, as they are transitional seasons that sometimes contribute to the creation of the *smog cloud* and sometimes they favor the development of *photochemical cloud*. We have examined only the pollutants CO, SO_2, PM_{10}, $PM_{2.5}$ for the days that MSMI was assigned a risk Linguistic higher than the one of MPCI.

The crisp values of the features CO, SO_2, PM_{10}, $PM_{2.5}$ were fuzzified to Risk Linguistics, whereas the combination of all fuzzy sets led to the definition of the *Pollution Index due to Smog (PIDS).* For the days that had a higher MPCI we have examined the O_3 that is the result of photochemical reactions. The crisp values of O_3 were fuzzified and thus the *Pollution Index due to Photochemical Cloud (PIDP)* was obtained. Regarding the days that both meteorological risk indices were assigned the same linguistic we have selected the index with the higher fuzzy DOM (Tables 4 and 5).

Step2. For all seasons, we have examined the effect of the temporal delay of the MSMI and the MPCI indices, to the morbidity MBI and mortality MTI indices for the prefecture of Thessaloniki.

Step3. Five Conjunction T-Norms (*Min, Algebraic, Einstein, Hamacher, Lucasiewicz*) [8] were used for all seasons, to develop a unified risk index from the fuzzy conjunction between the meteorological and the pollution indices, on a daily basis (MET_POL).

Table 4. Fuzzy Sets and the corresponding Linguistics of each feature

Parameters	L/FS (Linguistics used)
Air temperature- Relative Humidity	Very Low(VL), Low(L), Medium(M), High(H),Very High(VH)
Sunshine	Low(L), Medium(M), High(H)
MSMI	Low(L), Medium(M), High(H)
MPCI	Low(L), Medium(M), High(H)
PIDS	Low(L), Medium(M), High(H)
PIDP	Low(L), Medium(M), High(H)
RECAH	Low(L), Medium(M), High(H)
DDRE	Low(L), Medium(M), High(H)

*Meteorological Smog Index (MSMI)
Meteorological Photochemical Cloud Index (MPCI)
Pollution Index due to Smog (PIDS)
Pollution Index due to Photochemical Clous (PIDP)
Respiratory Cardiological Hospitalizations (RECAH)
Deaths due to Respiratory (DDRE)

Table 5. Fuzzy Ruleset (Fuzzy-AND) for the determination of the Risk indices

ID	AirTemp	RH	SUN	MSMI Degree of Membership (DOM)	MPCI DOM	ID	AirTemp	RH	SUN	MSMI DOM	MPCI DOM
1	VL	VH	L	H(1)	L(0.1)	39	M	M	H	L(0.8)	M(0.2)
2	VL	VH	M	H(0.6)	L(0.2)	40	M	L	L	L(0.8)	M(0.2)
3	VL	VH	H	M(0.7)	L(0.3)	41	M	L	M	L(0.6)	M(0.5)
4	VL	H	L	H(0.8)	L(0.2)	42	M	L	H	L(0.4)	M(0.8)
5	VL	H	M	H(0.4)	L(0.3)	43	M	VL	L	L(0.7)	M(0.6)
6	VL	H	H	M(0.5)	L(0.4)	44	M	VL	M	L(0.5)	M(0.8)
7	VL	M	L	M(0.9)	L(0.4)	45	M	VL	H	L(0.3)	M(1)
8	VL	M	M	M(0.6)	L(0.5)	46	H	VH	L	M(0.3)	L(0.4)
9	VL	M	H	M(0.3)	L(0.6)	47	H	VH	M	M(0.2)	L(0.6)
10	VL	L	L	M(0.1)	L(0.6)	48	H	VH	H	M(0.1)	L(0.8)
11	VL	L	M	L(0.9)	L(0.7)	49	H	H	L	L(1)	L(0.5)
12	VL	L	H	L(0.5)	L(0.8)	50	H	H	M	L(0.9)	L(0.7)
13	VL	VL	H	L(0.4)	L(1)	51	H	H	H	L(0.8)	L(0.9)
14	VL	VL	M	L(0.7)	L(0.9)	52	H	M	L	L(0.9)	M(0.1)
15	VL	VL	L	L(1)	L(0.8)	53	H	M	M	L(0.8)	M(0.4)
16	L	VH	L	H(0.6)	L(0.5)	54	H	M	H	L(0.7)	M(0.7)
17	L	VH	M	H(0.3)	L(0.6)	55	H	L	L	L(0.8)	M(0.3)
18	L	VH	H	M(0.3)	L(0.7)	56	H	L	M	L(0.7)	H(0.3)
19	L	H	L	H(0.4)	L(0.6)	57	H	L	H	L(0.6)	H(0.4)
20	L	H	M	H(0.3)	L(0.7)	58	H	VL	L	L(0.7)	M(0.3)
21	L	H	H	M(0.3)	L(0.8)	59	H	VL	M	L(0.6)	H(0.3)
22	L	M	L	M(0.7)	L(0.7)	60	H	VL	H	L(0.5)	H(0.6)
23	L	M	M	M(0.4)	L(0.8)	61	VH	VH	L	L(1)	L(1)

(*continued*)

Table 5. (*continued*)

ID	AirTemp	RH	SUN	MSMI Degree of Membership (DOM)	MPCI DOM	ID	AirTemp	RH	SUN	MSMI DOM	MPCI DOM
24	L	M	H	M(0.1)	L(0.9)	62	VH	VH	M	L(0.9)	L(0.7)
25	L	L	L	L(0.9)	L(0.8)	63	VH	VH	H	L(0.8)	L(0.4)
26	L	L	M	L(0.7)	L(0.9)	64	VH	H	L	L(0.8)	L(0.5)
27	L	L	H	L(0.5)	L(1)	65	VH	H	M	L(0.7)	L(0.9)
28	L	VL	L	L(0.8)	M(0.1)	66	VH	H	H	L(0.6)	M(0.1)
29	L	VL	M	L(0.6)	M(0.2)	67	VH	M	L	L(0.6)	M(0.3)
30	L	VL	H	H(0.4)	M(0.3)	68	VH	M	M	L(0.5)	M(0.6)
31	M	VH	L	M(1)	L(0.3)	69	VH	M	H	L(0.4)	M(0.9)
32	M	VH	M	M(0.8)	L(0.5)	70	VH	L	L	L(0.4)	M(0.5)
33	M	VH	H	M(0.6)	L(0.7)	71	VH	L	M	L(0.3)	H(0.4)
34	M	H	L	M(0.8)	L(0.4)	72	VH	L	H	L(0.2)	H(0.8)
35	M	H	M	M(0.5)	L(0.6)	73	VH	VL	L	L(0.3)	M(0.7)
36	M	H	H	M(0.2)	L(0.8)	74	VH	VL	M	L(0.2)	H(0.6)
37	M	M	L	M(0.2)	L(0.8)	75	VH	VL	H	L(0.1)	H(1)
38	M	M	M	L(1)	L(1)						

Step4. For all seasons, we have examined the effect of the temporal delay of the Unified Risk index to the morbidity and mortality of the residents of Thessaloniki wider area (prefecture).

In stages 2 and 4 we have examined the 1–7 days temporal delay of the atmospheric conditions to the public health. In particular, the morbidity and mortality of circulatory and respiratory diseases are shifted from one day to seven days ahead (Table 6).

Table 6. Fuzzy Ruleset (Fuzzy-AND) for the determination of the Pollution Index due to Smog (PIDS)

ID	SO_2	PM_{10}	$PM_{2.5}$	CO	PIDS DOM	ID	SO_2	PM_{10}	$PM_{2.5}$	CO	PIDS DOM
1	L	L	L	L	L(1)	42	M	M	M	H	H(0.2)
2	L	L	L	M	L(0.9)	43	M	M	H	L	M(0.9)
3	L	L	L	H	L(0.6)	44	M	M	H	M	H(0.2)
4	L	L	M	L	L(0.9)	45	M	M	H	H	H(0.5)
5	L	L	M	M	M(0.2)	46	M	H	L	L	M(0.4)
6	L	L	M	H	M(0.4)	47	M	H	L	M	M(0.9)
7	L	L	H	L	L(0.6)	48	M	H	L	H	H(0.1)
8	L	L	H	M	M(0.4)	49	M	H	M	L	M(0.9)
9	L	L	H	H	M(0.7)	50	M	H	M	M	H(0.2)
10	L	M	L	L	L(0.9)	51	M	H	M	H	H(0.5)
11	L	M	L	M	M(0.2)	52	M	H	H	L	H(0.1)
12	L	M	M	M	M(0.8)	53	M	H	H	M	H(0.5)
13	L	M	M	H	M(0.9)	54	M	H	H	H	H(0.8)

(*continued*)

Table 6. (*continued*)

ID	SO_2	PM_{10}	$PM_{2.5}$	CO	PIDS DOM	ID	SO_2	PM_{10}	$PM_{2.5}$	CO	PIDS DOM
14	L	M	H	L	M(0.4)	55	H	L	L	L	L(0.6)
15	L	M	H	M	M(0.9)	56	H	L	L	M	M(0.4)
16	L	M	L	H	M(0.4)	57	H	L	L	H	M(0.7)
17	L	M	M	L	M(0.2)	58	H	L	M	L	M(0.4)
18	L	M	H	H	H(0.1)	59	H	L	M	M	M(0.9)
19	L	H	L	L	L(0.6)	60	H	L	M	H	H(0.1)
20	L	H	L	M	M(0.4)	61	H	L	H	L	M(0.7)
21	L	H	L	H	M(0.7)	62	H	L	H	M	H(0.1)
22	L	H	M	L	M(0.4)	63	H	L	H	H	H(0.4)
23	L	H	M	M	M(0.9)	64	H	M	L	L	M(0.4)
24	L	H	M	H	H(0.1)	65	H	M	L	M	M(0.9)
25	L	H	H	L	M(0.7)	66	H	M	L	H	H(0.1)
26	L	H	H	M	H(0.1)	67	H	M	M	L	M(0.9)
27	L	H	H	H	H(0.4)	68	H	M	M	M	H(0.2)
28	M	L	L	L	L(0.9)	69	H	M	M	H	H(0.5)
29	M	L	L	M	M(0.2)	70	H	M	H	L	H(0.1)
30	M	L	L	H	M(0.4)	71	H	M	H	M	H(0.5)
31	M	L	M	L	M(0.2)	72	H	M	H	H	H(0.8)
32	M	L	M	M	M(0.8)	73	H	H	L	L	M(0.7)
33	M	L	M	H	M(0.9)	74	H	H	L	M	H(0.1)
34	M	L	H	L	M(0.4)	75	H	H	L	H	H(0.4)
35	M	L	H	M	M(0.9)	76	H	H	M	L	H(0.1)
36	M	L	H	H	H(0.1)	77	H	H	M	M	H(0.5)
37	M	M	L	L	M(0.2)	78	H	H	M	H	H(0.8)
38	M	M	L	M	M(0.8)	79	H	H	H	L	H(0.4)
39	M	M	L	H	M(0.9)	80	H	H	H	M	H(0.8)
40	M	M	M	L	M(0.8)	81	H	H	H	H	H(1)
41	M	M	M	M	M(1)						

Fuzzy Chi Square Test was used for all stages per season to estimate the degree of dependency between the linguistics of the three indices and the linguistics of morbidity and mortality due to Cardiovascular and respiratory diseases, setting a confidence interval of 95%.

4 Results and Discussion

After extensive tests were conducted for all the seasons of the year, all possible cases of dependence between the L/FS of the three developed indices and the L/FS of the morbidity and mortality of cardiovascular and respiratory diseases were examined. Degrees of membership close to the value of 1, declare a higher level of correlation of the raw value to the fuzzy set (Linguistic). Many cases under consideration have attributed a high degree of membership (participation) to the fuzzy set corresponding to the Linguistic "strong dependence", stating that they represent to a satisfactory degree the reported fuzzy set.

This has been done in order to go one step further than the X square test. We not only wish to see if there is a relation (dependency or independency) but we mainly wish to see its level of strength. It is important to know if the X square test has offered a strong or a weak or a moderate dependency. This would help a lot the reasoning of the fuzzy inference system. For example, in this paper in many cases the degrees of membership to the fuzzy set "strong dependency" fall in the interval [0.7–1] which declares high dependency.

The most important dependence and strong correlation results are presented below:

Winter:

For the winter season, the Smog Pollution Index (PIDS) showed a high level of dependence (HLDEP) with a DOM equal to 0.90755 with cardiovascular deaths on the same day. It also proved to have HLDEP equal to 0.81575 with cardiovascular hospitalizations after a lag of 4 days.

Spring and autumn:

During the Spring-Autumn period the Meteorological risk index (METI) has proven to be highly related with a DOM 0.8637 with the respiratory deaths after a lag of 6 days. The pollution index (POLI) was highly related at a level equal to 0.9916 with the cardiovascular hospitalizations during the same day.

Summer:

For the summer, the MPCI (photochemical cloud meteorological index) was related to the respiratory hospitalizations with a DOM 0.69295 after a lag of 3 days (Table 7).

The PIDP (Pollution index related to photochemical cloud) was highly related to the cardiovascular deaths with a DOM equal to 0.83575 at the same day and it was also related to the respiratory hospitalizations with a DOM 0.7772 with a temporal delay of 4 days.

Winter:

During the winter the Unified risk index produced by the Min T-Norm (Min-URI) has shown an extremely HLDEP with a DOM 0.94755 with the cardiovascular deaths on the same day. Also the Min-URI appeared to have a high dependence with the cardiovascular and respiratory hospitalizations under a temporal lag of 4 to 6 days. The URI obtained by the Algebraic Product T-Norm (Alg_URI) had a high relation to the cardiovascular hospitalizations after a time lag of 4 days with a DOM equal to 0.70105.

Summer:

For the summer, the Alg_URI is highly related to the cardiovascular and respiratory morbidity and mortality not only of the same day but through a time lag of 7 days.

The URI produced by the Einstein T-Norm had a high dependence with a DOM 0.84595 with the cardiovascular hospitalizations after a time lag of 5 days.

The Hamacher URI was highly correlated to the cardiovascular and respiratory hospitalizations with a time delay of 3 days.

Table 7. Fuzzy Chi-Square Test between all Risk indices Linguistics and Linguistics of mortality and morbidity

Indices- Disease -Season	Statistic Test	P-Value	Linguistics of P-Value	Degree of Membership
MSMI - circulatory deaths (1 day lag) winter	8.0799	0.017599	MEDIUM	0.62995
MSMI - respiratory deaths (6 days lag) winter	4.8486	0.027668	MEDIUM	0.8666
PIDS - circulatory deaths winter	17.0991	0.001849	HIGH	0.90755
PIDS - circulatory deaths (4 days lag) winter	15.5508	0.003685	HIGH	0.81575
PIDS - respiratory hospitalization (4 days lag) winter	14.2136	0.006644	HIGH	0.6678
PIDS - respiratory deaths (7 days lag) winter	10.0136	0.006692	HIGH	0.6654
METI - circulatory deaths (3 days lag) spring& autumn	10.054	0.039594	LOW	0.4797
METI - respiratory deaths (6 days lag) spring& autumn	11.81	0.002726	HIGH	0.8637
POLI - circulatory hospitalization spring & autumn	22.3822	0.000168	HIGH	0.9916
POLI - circulatory hospitalization (1 day lag) spring & autumn	14.3268	0.006322	HIGH	0.6839
MPCI - respiratory hospitalization (3 days lag) summer	10.1855	0.006141	HIGH	0.69295
MPCI - respiratory hospitalization (6 days lag) summer	10.0138	0.006692	HIGH	0.6654
PIDP - circulatory deaths summer	8.6418	0.003285	HIGH	0.83575
PIDP - respiratory hospitalizations (3 days lag) summer	6.4048	0.011381	HIGH	0.43095
PIDP - respiratory hospitalizations (4 days lag) summer	8.0879	0.004456	HIGH	0.7772
PIDP - respiratory hospitalizations (5 days lag) summer	6.4691	0.010977	HIGH	0.45115
PIDP - circulatory deaths (5 days lag) summer	5.604	0.017919	MEDIUM	0.64595
PIDP - respiratory deaths (7 days lag) summer	6.0024	0.014287	MEDIUM	0.46435

*Meteorological Index METI
Pollution Index POLI

The Lukasiewicz URI had HLDEP with a DOM equal to 0.7799 with the cardiovascular hospitalizations with a temporal lag of 4 days and it was depended to the respiratory hospitalizations with a DOM 0.9085 at a time lag of 3 days (Table 8).

Table 8. Fuzzy Chi-Square Test of URI Linguistics and morbidity plus mortality for all seasons

Indices-Diseases-Season Winter	Statistic Test	P-Value	Linguistics of P-Value	Degree of membership
MIN - Deaths circulatory	18.3607	0.001049	HIGH	0.94755
MIN - Hospitalization circulatory (4 days lag)	15.8303	0.003255	HIGH	0.83725
MIN - Hospitalization respiratory (4 days lag)	14.2136	0.006644	HIGH	0.6678
MIN - Hospitalization circulatory (6 days lag)	13.6614	0.008458	HIGH	0.5771
MIN - Hospitalization respiratory (6 days lag)	13.0433	0.011066	HIGH	0.4467
MIN - Deaths respiratory (7 days lag)	9.7489	0.007639	HIGH	0.61805
Algebraic - Hospitalization circulatory (4 days lag)	10.2392	0.005979	HIGH	0.70105
Hamacher - Deaths respiratory (4 days lag)	5.7587	0.016407	MEDIUM	0.57035
Summer				
Min - Hospitalization respiratory (2 days lag)	7.1071	0.028622	MEDIUM	0.8189
Min - Deaths circulatory (6 days lag)	6.5369	0.038065	LOW	0.40327
Min - Hospitalization circulatory (6 days lag)	6.982	0.03047	MEDIUM	0.7265
Min - Hospitalization respiratory (6 days lag)	7.8491	0.019751	MEDIUM	0.73755
Min - Deaths respiratory (7 days lag)	7.8065	0.020176	MEDIUM	0.7588
Algebraic - Hospitalization circulatory	32.7397	<0.00001	HIGH	1
Algebraic - Hospitalization circulatory (1 day lag)	20.6015	<0.00001	HIGH	1
Algebraic - Hospitalization circulatory (4 days lag)	22.9634	<0.00001	HIGH	1
Algebraic - Hospitalization circulatory (5 days lag)	20.2869	<0.00001	HIGH	1
Algebraic - Hospitalization circulatory (6 days lag)	21.0242	<0.00001	HIGH	1

(*continued*)

Table 8. (*continued*)

Indices-Diseases-Season Winter	Statistic Test	P-Value	Linguistics of P-Value	Degree of membership
Algebraic - Hospitalization circulatory (7 days lag)	19.5166	<0.00001	HIGH	1
Algebraic - Hospitalization respiratory	25.7959	<0.00001	HIGH	1
Algebraic - Hospitalization respiratory (1 day lag)	22.7579	<0.00001	HIGH	1
Algebraic - Hospitalization respiratory (5 days lag)	20.2312	<0.00001	HIGH	1
Algebraic - Deaths circulatory	31.0503	<0.00001	HIGH	1
Algebraic - Deaths circulatory (1 day lag)	24.0131	<0.00001	HIGH	1
Algebraic - Deaths circulatory (2 days lag)	21.6494	<0.00001	HIGH	1
Algebraic - Deaths circulatory (4 days lag)	20.2473	<0.00001	HIGH	1
Algebraic - Deaths circulatory (5 days lag)	28.4996	<0.00001	HIGH	1
Algebraic - Deaths circulatory (7 days lag)	37.9859	<0.00001	HIGH	1
Algebraic - Deaths respiratory	18.944	0.000013	HIGH	0.99935
Algebraic - Deaths respiratory (1 day lag)	13.5957	0.000227	HIGH	0.98865
Algebraic - Deaths respiratory (2 days lag)	11.8405	0.000580	HIGH	0.971
Algebraic - Deaths respiratory (3 days lag)	14.3905	0.000149	HIGH	0.99255
Algebraic - Deaths respiratory (4 days lag)	12.9718	0.000316	HIGH	0.9842
Algebraic - Deaths respiratory (5 days lag)	16.4705	0.000049	HIGH	0.99755
Einstein - Deaths circulatory	4.3372	0.037288	LOW	0.3856
Einstein - Hospitalization circulatory (5 days lag)	8.7586	0.003081	HIGH	0.84595
Hamacher - Hospitalization circulatory (3 days lag)	7.1775	0.007382	HIGH	0.6309
Hamacher - Hospitalization circulatory (4 days lag)	5.4406	0.019674	MEDIUM	0.7337
Hamacher - Hospitalization respiratory (3 days lag)	23.2524	<0.00001	HIGH	1
Hamacher - Hospitalization respiratory (4 days lag)	10.0854	0.001495	HIGH	0.92525

(*continued*)

Table 8. (*continued*)

Indices-Diseases-Season Winter	Statistic Test	P-Value	Linguistics of P-Value	Degree of membership
Lukasiewicz - Hospitalization circulatory (5 days lag)	8.11	0.004402	HIGH	0.7799
Lukasiewicz - Hospitalization circulatory (6 days lag)	7.2356	0.007147	HIGH	0.64265
Lukasiewicz - Hospitalization respiratory (1 day lag)	5.8083	0.01595	MEDIUM	0.5475
Lukasiewicz - Hospitalization respiratory (3 days lag)	9.7127	0.00183	HIGH	0.9085
Spring & Autumn MIN - Hospitalization circulatory	32.1649	<0.00001	HIGH	1
MIN - Hospitalization circulatory (1 day lag)	18.0139	0.001226	HIGH	0.9387
MIN - Hospitalization circulatory (2 days lag)	14.4578	0.005969	HIGH	0.70155
Algebraic - Hospitalization circulatory	32.6394	<0.00001	HIGH	1
Algebraic - Hospitalization respiratory (5 days lag)	7.2267	0.026961	MEDIUM	0.90195
Algebraic - Deaths circulatory (5 days lag)	8.7982	0.003015	HIGH	0.84925
Einstein - Hospitalization circulatory	6.7215	0.034709	MEDIUM	0.51455
Einstein - Hospitalization respiratory (5 days lag)	6.6959	0.035156	MEDIUM	0.4922
Einstein - Deaths circulatory (5 days lag)	7.9346	0.00485	HIGH	0.7575
Hamacher - Deaths circulatory (2 days lag)	6.9904	0.008195	HIGH	0.59025
Hamacher - Deaths circulatory (3 days lag)	8.8459	0.002937	HIGH	0.85315
Hamacher - Deaths circulatory (4 days lag)	6.7173	0.009548	HIGH	0.5226
Lukasiewicz - Deaths circulatory (2 days lag)	6.8058	0.009086	HIGH	0.5457
Lukasiewicz - Deaths circulatory (3 days lag)	9.2065	0.002412	HIGH	0.8794
Lukasiewicz - Deaths circulatory (4 days lag)	7.3579	0.006677	HIGH	0.66615

Spring and autumn:

During the spring-autumn season the URI (of the Min and the Algebraic Product T-Norms) was extremely highly correlated with a DOM of 1 to the cardiovascular hospitalizations of the same day.

The Einstein URI was depended highly with a DOM 0.7575 with the cardiovascular deaths within a time lag of 5 days. Finally the Hamacher and Lukasiewicz URI had a very high correlation to the cardiovascular deaths at a time lag of 3 days.

Table 9 proves that for the summer all 5 URI obtained by 5 T-Norms are related to the cardiovascular hospitalizations at a level of 100%. In the spring-autumn season and also in the summer, 4 out of the 5 URI are highly related to both cardiovascular morbidity and mortality at a level of 80%. Also during the summer 4 out of the 5 URI are related to the respiratory morbidity whereas 2 out of the 5 URI are highly correlated to the respiratory mortality.

Table 9. Seasonal percentages of 5 T-Norms per season related to the morbidity and mortality due to circulatory and respiratory diseases

Season	Hospitalization circulatory	Hospitalization respiratory	Deaths circulatory	Deaths respiratory
Winter	40%	20%	20%	40%
Summer	100%	80%	80%	40%
Spring & Autumn	80%	40%	80%	0%

5 Conclusion

This paper proposes the use of an innovative holistic method of investigating meteorological parameters by season that maximize atmospheric pollution. The intelligent system developed was based on the combination of fuzzy methods with the hybrid non-parametric Fuzzy Chi-Square Test. The seasonal indices created were consolidated using five fuzzy conjunction T-norms in a combined Unifier risk index containing the hazard of all elements of the atmosphere.

The operation of this model calculated the degree of dependence between the produced fuzzy risk indices and the morbidity and mortality on the inhabitants of the prefecture of Thessaloniki. Thus, it indicated the correlation of the effects of the climatic conditions of the atmosphere on public health based on short time lags.

This modeling research effort has yielded high rates of correlations between the obtained indices and the cardiovascular-respiratory morbidity and mortality.

As future directions that could improve the proposed model, we suggest the potential use of more parameters directly related to morbidity and mortality of an urban center in order to create more combinations of fuzzy rules and sub-indicators. In this way it will be possible to derive an even stronger final adaptive unified index.

Finally, we suggest the future use of other machine learning methods (e.g. unsupervised or competitive learning) hybrid soft computing approaches (fuzzy-neural networks) and optimization algorithms.

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