Fuzzy Cognitive Maps for Long-Term Prognosis of the Evolution of Atmospheric Pollution, Based on Climate Change Scenarios: The Case of Athens

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Abstract. Air pollution is related to the concentration of harmful substances in the lower layers of the atmosphere and it is one of the most serious problems threatening the modern way of life. Determination of the conditions that cause maximization of the problem and assessment of the catalytic effect of relative humidity and temperature are important research subjects in the evaluation of environmental risk. This research effort describes an innovative model towards the forecasting of both primary and secondary air pollutants in the center of Athens, by employing Soft Computing Techniques. More specifically, Fuzzy Cognitive Maps are used to analyze the conditions and to correlate the factors contributing to air pollution. According to the climate change scenarios till 2100, there is going to be a serious fluctuation of the average temperature and rainfall in a global scale. This modeling effort aims in forecasting the evolution of the air pollutants concentrations in Athens as a consequence of the upcoming climate change.

Keywords: Fuzzy Cognitive Maps · Air pollutants · Climate change models · Soft Computing Techniques

1 Introduction

Air pollution is the condition in which air is contaminated by foreign substances, radiation or other forms of energy, in quantities or duration that can have harmful or poisonous effects in the health of living organisms. Moreover, they can upset the ecological balance in large or small geographical scale. These pollutants are either emitted directly by various human activities, like energy production from solid or liquid fuels, transport, industry and heating and they are known as primary ones

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(e.g. CO, NO, NO_2, SO_2) or they are formed in the atmosphere under proper conditions and they are known as secondary ones (e.g. O_3). The assessment of air pollution consequences requires a comprehensive spatiotemporal analysis of the favoring conditions and the search for interrelations between pollutants and meteorological plus photochemical factors affecting it [2–4]. This research effort proposes an innovative analytical Soft Computing model towards long term estimation of the pollutants concentrations. More specifically it carries out a descriptive representation of complex correlations between atmospheric pollutants with the method of Fuzzy Cognitive Maps (FCM), based on historical data of the Athens center for the period 2000–2012. Additionally, it proposes a sophisticated method of predicting the values of pollutants in relation to the fluctuation of temperature and rainfall values, as reflected by the number of projections of climate model GFDL_CM2.0 for the period 2020–2099.

1.1 Related Literature - Data

Important research efforts have been carried out on the short term, towards forecasting of the air quality in medium cities or major urban centers like Athens, using statistical methods and without taking into serious consideration the effect of the fluctuation of temperature and precipitation in the 21st century due to climate change [15].

Gordaliza et al. [6] developed coherent storylines about ordinary people living under diverse scenarios of low/high CO_2. Luiz et al. [12] constructed FCM in order to understand the viability of Clean Development Mechanism (CDM) projects in South Africa and how they would influence greenhouse gas (GHG) emissions. Zhang et al. [20] explored the application of fuzzy cognitive maps on getting stakeholders' perspectives and they employed graph theory indices on quantifying them. Pathinathan and Ponnivalavan [16] analyzed the hazards of plastic pollution using Induced Fuzzy Cognitive Maps (IFCMs). IFCMs are a fuzzy-graph modeling approach based on expert's opinion. Amer et al. [1] developed three future scenarios using FCM for the national wind energy sector of a developing country. Mesa-Frias et al. [13] developed a novel method based on FCM to quantify the framing assumptions in the assessment of health impact. Fons et al. [5] proposed a model of an eco-industrial park and used FCM to analyze the impacts of this model in terms of pollution and waste disposal.

The motivation for this research was the development of a rational system, capable of analyzing effectively the actual conditions during incidents of high air pollution in urban areas and also to model the long term evolution of emissions due to climate change. FCM were developed based exclusively on measurable factors resulting from the correlation analysis of the actual data and not on the opinion of experts as usually. The above perspectives add validity and reliability in the overall inference process. Moreover, the development and use of a fuzzy system to forecast future values of air pollutants based on climate change scenarios is an interesting innovation that significantly improves the quality and value of the proposed model. The design, development and testing of this system are described herein. The topography of Athens prevents the diffusion of pollutants. The pollution data come from the "Patissia" area in the center of Athens. Relativity data analysis with FCM was performed for the air pollution measuring station of "Patissia" for the period 2000 to 2012, in order to obtain a symbolic representation of existing complex correlations between the atmospheric pollutants. The above measuring station (who is distinguished for its consistency and reliability as a few missing values were observed) is storing hourly values of CO (in mg/m^3), (NO, NO_2, O_3 and SO_2 in μg/m^3). During a day the station of Patissia is full of traffic and this is the reason of high values of air pollution concentrations. Additionally, records related to six meteorological factors namely: air temperature (Temp), relative humidity RH), air pressure(PR), solar radiation (SR), wind speed (WS) and wind direction (WD) were obtained from the station of "Thiseion" 9 km far from the sea.

During data pre-processing all the records with missing values for one or more parameters were removed from the dataset. Outliers are very important as they are always considered for the activation of the civil protection mechanisms. For this reason, they were not removed from the datasets in order to obtain representative training samples offering potential generalization in future forecasting models. Finally in order to tackle the problem of features with different range, in which the higher values most affect the cost function with respect to the characteristics of the smaller ones, without being more important, a normalization process was performed in the interval [−1, +1].

2 Theoretical Framework and Methodology

2.1 Correlation Analysis

In order to test the level of linear relationship between meteorological parameters and air pollutants, the typical relativity analysis was performed, using the parametric correlation coefficient of Pearson (r). The Pearson linear correlation coefficient between two parameters X and Y is defined based on a sample of n pairs of observations $(x_i, y_i)\ i = 1, 2, \ldots, n$, and it is denoted as $r(X, Y)$ or more briefly as r. The variables $\bar{x}$ and $\bar{y}$ are the averages of $(\mathrm{xi}, \mathrm{yi})$. The r is the covariance (CovX,Y) of the two variables divided by the product of their standard deviations (sx,sy). It is given by the following Eq. 1:

$$r = \frac{s_{xy}}{s_x s_y} = \frac{\sum_{i=1}^{v}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{v}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{v}(y_i - \bar{y})^2}} = \frac{\sum_{i=1}^{\mathrm{v}} x_i y_i - v\bar{x}\bar{y}}{\sqrt{\sum_{i=1}^{\mathrm{v}} x_i^2 - v\bar{x}^2}\sqrt{\sum_{i=1}^{\mathrm{v}} y_i^2 - v\bar{y}^2}} \quad (1)$$

The correlation coefficient is a pure number in the interval [−1, 1]. More specifically, when $0 < r \le 1$, then *X, Y* are linearly positively correlated and when $-1 < r < 0$, then *X, Y* are negatively correlated. When $r = 0$ or close to zero there is no correlation between them.

2.2 Fuzzy Cognitive Maps

FCM are fuzzy-graph structures. In the model of a fuzzy cognitive map, the nodes are linked together by edges and each edge connecting two nodes describes the change in the activation value. The direction of the edge implies which node affects the other.

The sign of the causality relationship is positive if there is a direct influence, negative if there is an inverse influence relation and zero if the two nodes are uncorrelated. The causal relationships are described by the use of fuzzy linguistics and they are fuzzified by using membership functions taking values in the closed interval [−1, 1] [14, 17, 18].

Unlike the majority of complex dynamic systems, characterized by nonlinearity and high uncertainty, the fuzzy cognitive maps use advanced learning techniques in order to choose appropriate weights for the causal connections between the examined variables. This is done in order to reflect the examined problem with absolute realism.

Combining the theoretical background of fuzzy logic, FCM cover the comparison and characterization purpose of the reference sets, towards modeling and solving complex problems for which there is no structured mathematical model.

2.3 GFDL_CM 2.0

Flato et al. (2013) [21] finds robust relationship between the ability of the GFDL_CM2.0 model to represent interannual variability of near-surface air temperature and the amplitude of future warming. Thus, the GFDL_CM2.0 climate change model has been chosen as the most suitable for this research area. Also this model generally provides a smooth gradual temperature rise up to 2.9° C plus reduced rainfall of −245.96 mm up to 2099. The GFDL-CM2.0 is a coupled Atmospheric - Ocean general circulation model, developed at NOAA's Geophysical Fluid Dynamics Laboratory (GFDL). It is divided into four modules: the atmosphere model (AM2P13), the ocean (OM3P4), the dry (LM2) and the ice cover (SIS). The horizontal resolution of the atmospheric and land model is 2° latitude × 2.5° longitude whereas for the oceanic it is 1° × 1°. The atmospheric model has twenty-four vertical planes whereas the land model has eighteen for the heat storage and the oceanic fifty. The atmospheric model uses a B-grid dynamical core, a k-profile planetary boundary layer scheme [11] and a simple local parameterization of the vertical momentum transport by cumulus convection. The land-cover-type distribution is a combination of a potential natural vegetation of type one and a historical land use distribution dataset. GFDL-CM2.0 uses explicit fresh water fluxes to simulate the exchange of water across the air-sea interface, rather than virtual salt fluxes [7]. Subgrid-scale parameterizations of ocean model OM3.0 include K-profile parameterization (KPP) vertical mixing, neutral physics [8, 9] and a spatially dependent anisotropic viscosity [10]. Air-sea fluxes are computed on the ocean model time step, which is 1 h in OM3.0. SIS (sea ice model) is a dynamical model [19] with three-vertical layer thermodynamics (two ice, one snow), and a scheme for prognosing five different ice thickness categories and open water at each grid point. GFDL-CM2.0 model make use of the Flexible Modeling System (FMS) coupler for calculating and passing fluxes between its atmosphere, land and ocean components.

3 Description of the Proposed Model

The air pollution evolution modeling system comprises of the following four distinct algorithmic stages: Modeling, Grid, Scenarios and Forecasting. In the first stage all of the associated parameters are added and named and then they are interconnected by synapses to create the causal positive or negative correlations. The fuzzification of the correlations, i.e. the description of each interface in verbal common terms was accomplished by selecting six Linguistics namely: Three positive scales (low positive (+), middle positive (++), high positive (+++)). Three negative scales (low negative (–), middle negative (−−), high negative (−−−)) corresponding to fuzzy weights (Table 1) (Fig. 1).

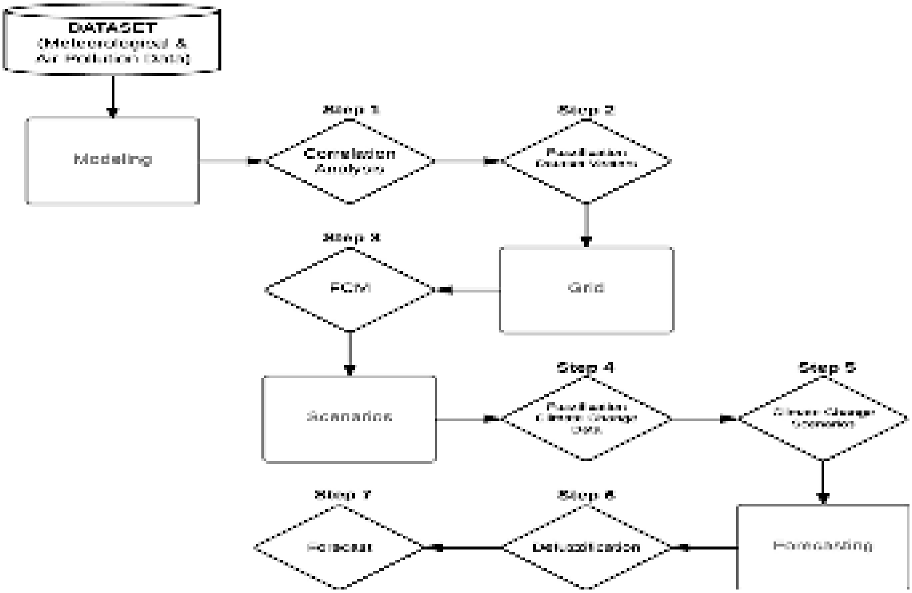

Fig. 1. Flowchart of proposed model

Table 1. Effect and value of six linguistics which corresponding to fuzzy weights

Effect	Value
high positive (+++)	1
middle positive (++)	0.5
low positive (+)	0.25
low negative (–)	−0.25
middle negative (−−)	−0.5
high negative (−−−)	−1

The description of the algorithmic steps is done in the next paragraph:

Step 1 (Modeling): Application for the calculation of the degree of correlation between the variables under consideration: Carbon monoxide (CO), nitrogen monoxide (NO), nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), temperature air (AirTemp), humidity (RH), atmospheric pressure (PR), solar radiation (SR), sunshine (SUN), wind speed (WS), wind direction (WD) and rainfall (RF).

Step 2: Partitioning of the variables with negative correlation from the ones with positive correlation, with the use of the assigned Linguistics over the initial crisp values. Three successive and overlapping triangular membership functions were employed in order to classify the correlations to the corresponding fuzzy sets (Linguistics) "Low", "Medium" and "High". The following Table 2 presents clearly the fuzzification of the correlation results (assignment of the corresponding Linguistics).

Table 2. Fuzzification of the correlation analysis with proper Linguistics

	CO	NO	NO_2	O_3	SO_2	AirTemp	RH	PR	SR	SUN	WS	WD	RF
CO	1	+++	++	−−−	++	−	+	+	−	+	−−−	+	−−−
NO	+++	1	++	−−−	++	−−	++	+	−	+	−−	+	−−−
NO_2	+++	+++	1	−−−	++	+	−	−	+	+	−−	+	−−−
O_3	−−−	−−−	−−−	1	−−	++	−−−	−	+	+	+++	−	−−−
SO_2	+++	+++	++	−−−	1	−−−	+	++	−	−	−−	+	−−−
AirTemp	−	−	++	+++	−−	1	−−−	−	+++	+++	+	+	−−
RH	++	+++	−	−−−	+	−−−	1	+	−−−	−−−	−−	−	+++
PR	+	+	−	−	+++	−−−	+	1	−	−	−	−−	−−−
SR	−	−	+	+	−	++	−−−	−	1	+++	++	+	−−−
SUN	+	+	++	++	−	++	−−−	−	+++	1	++	+	−−−
WS	−−−	−−−	−−	+++	−−	+	−−	−	++	++	1	−	+
WD	++	++	+++	−−	+	+	−	−−−	++	++	−−	1	+
RF	−−−	−−−	−−−	−−−	−−−	−−	+++	−−−	−−−	−−−	+	+	1

Step 3 (Grid): It involves the design of the FCM following the input and the interconnection of all correlated variables, based on the Linguistics that emerged after the fuzzyfication of the crisp numerical values.

The algorithm simulating the interactions between two nodes of the FCM was implemented by performing a repetitive calculation of the new link value corresponding to each node. This value depends on the weight of the node from which an edge begins and also on the weight of the edge joining the two nodes. The transfer function estimates the new value of each node and the weight of each connection. The negative type of influence is depicted with an orange color and the positive with a blue color. The degree of influence depends on the thickness of each line. The higher the influence the thicker the line, as you can see in the Fig. 2 (Table 3).

Table 3. The degree of influence

	CO	NO	NO_2	O_3	SO_2	AirTemp	RF
AirTemp	−	−	++	+++	−−	1	−−
RF	−−−	−−−	−−−	−−−	−−−	−−	1

The degree of influence between some variables depicted in the Fig. 2.

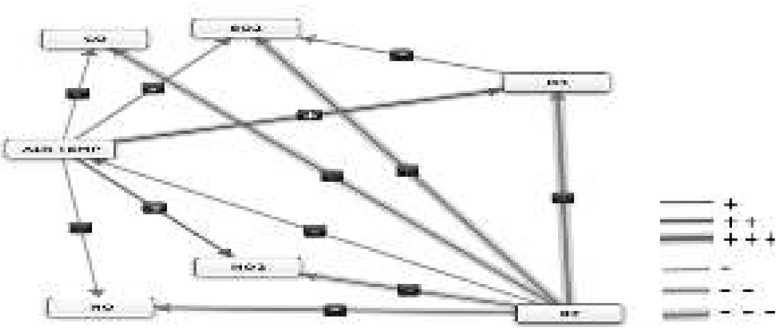

Fig. 2. A FCM between air temperature, rainfall and air pollutants. (Color figure online)

3.1 Scenarios and Forecasting

In the third stage, the changes in the values of temperature and precipitation due to climate change (CC) for the period 2020 till 2099 are fuzzified in order to obtain the corresponding linguistics. The whole process is based on the GFDL_CM2.0 CC model. This phase also includes extended testing of various scenarios.

Step 4 (Scenarios): Partitioning of the scenarios variables, based on the changes in temperature and precipitation, according to the global climate model GFDL_CM2.0.

Finally, the obtained crisp numerical values are fuzzified, with the use of four triangular fuzzy membership functions (FMF) and eight semi-triangular fuzzy membership functions (S-FMF). Two of FMF and four of S-FMF are related to temperature changes in the closed interval [0, + 2.86] °C, which is the highest temperature increase for the area under study in the specified time interval. The first S-FMF, the FMF and the next S-FMF refer to the interval [0, 1.43 (median)] °C. These FMF correspond to the fuzzy sets: low negative (–), middle negative (−−), high negative (−−−), whereas the linguistic high negative (−−−) contains values close to the smallest estimated change. The next S-FMF, the FMF and the last S-FMF refer to the interval [1.43 (median), 2.86 (the highest fluctuation based on the model)] °C. These FMF correspond to the low positive (+), middle positive (++), high positive (+++), with the high positive (+++) being close to the maximum temperature change. In the same way, two FMF and four S-FMF were developed for the precipitation with crisp values in the interval [−108.48, −219.98] mm. Due to the fact that precipitation appears reduced in the future values, the first S-FMF, the FMF and the last S-FMF cover the precipitation reduction in the interval [−164.23, −219.98] mm which corresponds to high precipitation reduction. The next S-FMF, the FMF and the last S-FMF were used for the smaller changes [−108.48, −164.23 (median)] mm which correspond to the fuzzy sets low positive (+), middle positive (++), high positive (+++), with high positive (+++) declaring the lowest rainfall reduction (−108,48 mm) (Table 4).

Table 4. FMF and S-FMF boundaries (Temperature, rainfall)

Fuzzy sets corresponding to temperature and precipitation changes	FMF and S-FMF boundaries in the closed interval [0, + 2.86] °C	FMF and S-FMF boundaries in the closed interval [−108.48, −219.98] mm
−−− (S-FMF)	0 0.572	−220 −197.7
−− (FMF)	0.143 0.715 1.287	−214.4 −192.1 −169.8
− (S-FMF)	0.858 1.43	−186.5 −164.2
+ (S-FMF)	1.43 2.002	−164.2 −141.9
++ (FMF)	1.573 2.145 2.717	−158.6 −136.3 −114
+++ (S-FMF)	2.288 2.86	−130.7 −108.5

Step 5 (Scenarios): It includes extended testing of various scenarios based on the potential changes in the temperature and precipitation and moreover its influence in the air quality of Athens. The fuzzy Linguistics produced by the use of climate change scenarios are defuzzified in order to obtain the forecast of the potential future crisp values of the air pollutants. In this way we perform a projection in the distant future for the problem of environmental degradation due to air pollution.

Step 6 (Forecasting): For the defuzzification the centroid function was used which estimates the center of gravity of the fuzzy set distribution.

$$x = \frac{\int x \cdot \mu(x)dx}{\int \mu(x)dx} \tag{6}$$

Step 7: The index of the magnitude of change in the pollutants concentration, is calculated based on the amount of relative change of each parameters value.

$$RelativeChange = \frac{FutureValue - InitialValue}{InitialValue} \tag{7}$$

4 Results and Discussion

After applying various CC scenarios (including various potential changes in temperature and precipitation) under the GFDL_CM2.0 model for the center of Athens, the forecasted Relative Changes (RC) in the concentration of pollutants were obtained. Finally, 36 scenarios were developed by the combination of temperature and the rainfall. Table 5 presents the most important of the forecasted values.

Table 5. Relative changes of air pollutants based of the climate change scenarios

ID	AirTemp (AT)	RF	O_3	SO_2	CO	NO	NO_2
1	high negative (+0 °C)	high negative (−219.98 mm)	0	0.2	0.06	0.05	0.09
2	high negative (+0 °C)	high positive (−108.48 mm)	−0.02	0.03	−0.02	−0.01	−0.33
3	low negative (+1.43 °C)	high negative (−219.98 mm)	0.03	0.18	0.06	0.05	0.12
4	low negative (+1.43 °C)	high positive (−108.48 mm)	−0.01	−0.06	−0.05	−0.02	−0.21
5	high positive (+2.86 °C)	high negative (−219.98 mm)	0.19	0.14	0.05	0.03	0.14
6	high positive (+2.86 °C)	high positive (−108.48 mm)	0.11	−0.38	−0.29	−0.28	−0.11

Attempting a thorough presentation of the most important RC observed, it is obvious that a zero increase in temperature (0 °C), combined with a large reduction of rainfall (−219.98 mm) contributes significantly to the growth of all primary pollutants while it does not affect the secondary pollutants such as O_3 (ID1). On the other hand, a very slight decrease in rainfall (−108.48 mm) helps to increase the SO_2, while helping to reduce NO_2, NO, O_3 and CO (ID2). Increasing the temperature to the value of the median (+1.43 °C) in combination with a minimum reduction of precipitation (−108.48 mm) allows the reduction of both primary and secondary pollutants (ID4), whereas absolutely the opposite (ID3) is observed when the rainfall is reduced significantly (−219.98 mm). A large increase in the temperature higher than the median (1.43 °C) and as high as the upper limit of the CC model (2.86 °C) combined with a high decrease in the millimeters of rainfall (−219.98 mm) contributes to the increase of all pollutants, especially to the increase of O_3 (ID5). Finally, a very small reduction in the millimeters of rainfall (−108.48 mm) leads to a significant reduction of all pollutants concentration except for the values of O_3 which rises significantly (ID6). An AT increase from 0 °C to 2.86 regardless the rainfall reduction results to an increase of O_3 and reduces the values of SO_2 and NO, CO. The highest values for O_3 and NO_2 appear in the extreme AT scenario (ID5) whereas the lowest air pollutants values appear in the ID2 (zero AT increase) and the highest values for SO_2, CO, NO are observed in ID1 and ID3 (stable or low increase of AT). It is important to mention that we observe the highest values for all pollutants with the highest decrease of rainfall (−219,98 mm) in ID1 and ID5 and their lowest in ID2 and ID6 scenario with the least rainfall reduction (−108, 48 mm). At Table 6 the average values of historical period of 2000–2012 used as initial values for the estimation of forecasted values. The forecasted Relative Changes (RC) determine the values of each pollutant. The last two decades of the 21st century (2080–2099) are very interesting, due to the extreme scenarios observed (ID5). According to this case the temperature will increase by 15 % (2.86 °C) which represents the Linguistic High Positive change (+++) and the precipitation will be reduced by 49 % (−219.98 mm) corresponding to the Linguistic High Negative (−−−) change. This combination will cause significant increase of all primary and secondary pollutants (presented in the following Table 6).

Table 6. Air pollutants forecasted values based on the extreme scenario

Period	O_3	SO_2	CO	NO	NO_2
2000–2012	21.64	20.53	2.47	115.79	87.11
2080–2099	25.75	23.40	2.59	119.26	99.30
Absolute increase value	**+4.11**	**+2.87**	**+0.12**	**+3.47**	**+12.19**

A potential verification of the extreme scenario will cause a significant increase in the concentrations of O_3 and NOx which will imply the increase of the cardiovascular and respiratory diseases and will be accompanied by frequent presence of thick summer photochemical smog. Also the high values of SO_2 and CO, will increase the frequency of smog during the winter months, while serious problems may occur on the surfaces of monuments and historic buildings from acid rain. Since there are no actual similar future projections and forecasting efforts for Athens we cannot check the accuracy of the obtained results. However, both the methodology employed and the produced scenarios with the forecasted evolution of air pollution till 2099 are very useful as they will motivate researchers towards more flexible modeling attempts beyond the typical statistical ones.

5 Conclusions

In this paper we have proposed the use of an innovative method for analysis and modeling of air quality. We have also developed and applied an air pollution and forecasting system which is based on CC models and uses Soft Computing techniques. More specifically, Linguistic representation of the correlations between atmospheric pollutants is performed by employing Fuzzy Cognitive Maps. Based on the above approach we have obtained relative changes of air pollutants values for the center of Athens for the period 2000–2012. Additionally, a projection in the future is performed regarding the evolution of the pollutants concentrations, based on the fluctuation of temperature and precipitation till 2100, as reflected by the projections of climate model GFDL_CM2.0. The workings of the model were tested in various scenarios and presented important information about the hazards of air quality and the effects of air pollution. From this point of view, though the forecasted results cannot be checked for accuracy, the fact that this paper introduces a flexible Soft Computing approach to produce long term projection of air quality based on scenarios of CC opens innovative horizons to researchers introducing an alternative algorithm. In the future we will try to improve the model by employing optimization methods (e.g. genetic algorithms, swarm intelligence) or hybrid approaches.

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