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A Fuzzy Modified Gaussian Air Pollution Dispersion Model

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Abstract: Many air dispersion models have been developed to calculate concentration of pollutants in different distances from the emission source. These models have different precision subject to some errors relating to discrete stability classes which would affect the lateral and vertical dispersion coefficient calculations. In order to reduce these errors in the present investigation, a fuzzy rule-based pollution dispersion model is developed. Structure of the proposed fuzzy model is based upon established mathematical equations in the literature. The fuzzy model, however, resolves the resultant problems of the mutation between piecewise stability classes, dispersion coefficients as well as mathematical equations by considering fuzzy constraints instead of crisp ones. Efficiency of the proposed model is represented via a real numerical example and comparison of the results with other existing models.

Key words: Air pollution dispersion, fuzzy rule base, atmospheric stability classes

INTRODUCTION

Air pollution dispersion models are used to make an informed emission control policy at a wide range of scales. All models are subject to scientific uncertainty, but the way this is handled for air quality management policy is different depending on the scale of the modeling and the impact under consideration (Colvile *et al*., 2002). Uncertainty refers to the lack of knowledge or information about an unknown quantity whose true value could be established if a perfect measurement device were available. Both temporal variability and uncertainty affect Gaussian modeling results. Temporal variability in Gaussian model results present primarily through meteorology and emission rates, because weather conditions and processing rates vary over time (Sax and Isakov, 2003).

Uncertainty, on the other hand, refers to the variance or standard deviation in the input data and the modeled output results. Dispersion models provide a deterministic estimate of pollutant concentrations. Without accounting for uncertainty in a model, a deterministic estimate is obtained rather than a probabilistic one, for any location in the modeling domain (Yegnan *et al*., 2002). Uncertainty in Gaussian models can be categorized into three components: input, parameter and conceptual uncertainty. Input uncertainty arises when inputs to an air quality model, such as meteorological data or emissions, are themselves uncertain due to measurement error, estimation error, or inherent variability. Parameter uncertainty is present because a single model parameter value can never completely characterize a modeling domain. Finally, conceptual uncertainty occurs because simple mathematical and numerical parameterizations used to represent dispersion model equations in programming code cannot completely characterize complex physical processes and associated inherent naturally occurring variability (Sax and Isakov, 2003). Incorporation of uncertainty in

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dispersion modeling has been considered by Colvile *et al*. (2002), Yegnan *et al*. (2002), Dabberdt and Miller (2002), Alst *et al*. (1998) and Sax and Isakov (2003) for instance. Fuzzy sets theory serves as robust techniques to model uncertainty of the type of ambiguity and to analyze the behavior of the system without involving in the details. Methods based on this theory should be applied in the context of environmental numbers. The boundaries between an acceptable and an unacceptable concentration is not to be considered as sharp, but as fuzzy, with implications for subsequent action plans. The use of fuzzy numbers is proposed as a suitable technique for handling environmental criteria and tackling decisions made under uncertainty.

Fuzzy set theory is, therefore, suitable to make decisions in complex systems when the context of the problem in which has been applied is often unclear (Onkal *et al*., 2004; Fisher, 2003; Pokrovsky *et al*., 2002; Murtha, 1995; Shao, 1999; Baum *et al*., 1997; Liu and Chaudrasekar, 2000) as in the environmental applications. This paper presents a fuzzy model to measure pollution dispersion based on the Gaussian plume function and direct fuzzy modeling. A method to extract a FRB based on the expertise knowledge and FRB to specify the stability class and some heuristic relations to calculate the coefficients of the Gaussian plume function as well as the final value for pollutant concentration is also proposed. The proposed model is based on the Hanna's model in order to improve the results (Hanna *et al*., 2003). the evaluation of the proposed model and comparison of the results with the Hanna's model has been conducted too.

CONVENTIONAL AIR POLLUTION DISPERSION MODELS

It is assumed that the concentration resulting from continuous releases in the urban canopy layer is represented by the standard Gaussian formula. All variables and parameters represent averages over about an hour time period (Hanna *et al*., 2003). The Gaussian plume function can be used to predict the ground level pollutant concentration under different stability conditions given a pollution source. According to this function, the value of concentration is calculated as:

$$C=\frac{kQ_C}{2\pi u\sigma_y\sigma_z}(\exp(-\frac{(y-y_0)^2}{2{\sigma_y}^2}))(\exp(-\frac{(z-h_e)^2}{2{\sigma_z}^2})+\exp(-\frac{(z+h_e)^2}{2{\sigma_z}^2})) \tag{1}$$

Where:

$$k=\begin{cases}1 & ;x<\frac{uT_d}{2}\\ \frac{0.5uT_d}{x} & ;x>\frac{uT_d}{2}\end{cases} \tag{2}$$

C	:	Concentration (g m^{-3}).
k	:	Modification coefficient.
Q_c	:	Continuous mass emission rate (g sec^{-1}).
σ_y, σ_z	:	Lateral and vertical dispersion coefficients.
u	:	Wind speed representing the speed of the plume over its trajectory (m sec^{-1}).
x, y, z	:	Lateral and vertical positions where the concentration is being calculated (m).
y_0, h_e	:	The lateral and vertical positions of the plume centerline (m).
T_d	:	Time period (sec).

Dispersion coefficients, σ_y and σ_z depend on the atmospheric stability class and increase with the downwind distance from the pollution source. They are fundamental to all Gaussian based air pollution dispersion models. They can be determined very roughly by reading off a graph, but they can more accurately be determined by CSUN (2006):

$$\sigma_y = ax^{0.893} \tag{3}$$

$$\sigma_z = bx^c - d \tag{4}$$

Where, the values of a, b, c and d are experimentally determined after specification of the stability class. Pasquill (1961) introduced a method of estimating atmospheric stability, incorporating considerations of both mechanical and buoyant turbulence. It is a simple method, as it is easy to use and tends to give satisfactory results. The Pasquill Turner Method (PTM) makes the use of observations of wind speed, cloud cover and the time of day to classify atmospheric stability with distinguishable indices. It is based upon the work of Pasquill, which has been revised by Turner (1964) by the introduction of incoming solar radiation in terms of solar elevation angle and cloud amount and height. The importance of this method lies in the relation of atmospheric dispersion coefficients and classified stability for mechanically and thermally generated boundary-layer turbulence (Mitchell, 1982; Gifford, 1976). PTM classes of stability give valid dispersion coefficients for an extended distance of up to 10 km downwind of a source or this can be increased up to 100 km after some transformations have taken place (Turner, 1997). For complex terrain, this distance is decreased and direct turbulence measurements are necessary (Zoras *et al*., 2006). However, this stability calculation uses the Pasquill (1961, 1974) method modified by Gifford (1962) and applied to computers by Turner (1961, 1964). Some of the stability classification schemes currently used in practice is summarized, with their limitations, in Table 1.

Pasquill's scheme is commonly and widely used. The Pasquill's stability values range from 1 to 7. Low values indicate that the atmosphere is unstable and that smoke will be dispersed easily, forming high plumes resembling cumulonimbus clouds. Midrange values indicate that the atmosphere is neutral, with possible weak, sporadic buoyancy providing some dispersion. High values indicate that the atmosphere is stable and buoyant forces are weak, trapping smoke close the ground (Mohan and Siddiqui, 1998).

Because of the discreteness of the stability classes and finite interval of parameter values corresponding to each category, conditions on the boarder line between two categories are not well defined and as such an inherent error to the extent of half the range of the category on either side is possible. In spite of these limitations, this scheme is extensively used mainly because of the availability of cloud cover and wind speed data on a routine basis, mostly through national weather station network (Daoo *et al*., 2004). Given the stability class, the values of coefficient a, b, c and d based on Turner's scheme are determined according to Table 2. Atmospheric stability plays the most important role in transport and dispersion of pollutants. It can be defined as the atmospheric tendency to resist or enhance vertical motion or alternatively, to suppress or augment existing turbulence. Generally, the difficulty involved in measuring atmospheric stability causes it to not to be evaluated. However, different methods are used for determination of stability with varying degrees of complexity (Zoras *et al*., 2006). Several methods might be used to determine stability classes (Irwin, 1982; Mohan and Siddiqui, 1998; EPA, 2000, 1993, 1987). Here, we use Turner's method to specify stability class because of method's simplicity and popularity which Surface Wind Speed (SWS) and Cloud Cover (CC) are used to specify Stability Class (SC). In this method, seven stability classes are considered which are indicated by letters A-F each of which is associated with a linguistic term.

Table 1: Stability classification schemes currently in use (Daoo *et al*., 2004)

Schemes	Parameters involved	User Body	Remarks
Pasquill	Cloud cover and wind speed.	Most widely used scheme.	Valid for idealized conditions; does not consider surface roughness, stratification effects; stability defined broadly and in a discrete manner; can be used as a general guideline or reference scheme.
Turner	Net radiation and wind speed.	Widely used in Japan.	Considers cloud effects but not roughness effects; based on a more directly related parameter; classes are defined in a more refined way.
Smith	Sensible heat flux and friction velocity.	Currently in use at NRPB, UK.	Considers roughness, thermal stratification, cloud effects explicitly.
Golder	Monin-Obukhov scale length.	Recommended by USNRC, USA.	Considers effects of roughness, stratification, clouds implicitly; classes defined more accurately and in a more refined way.

Table 2: Fitting coefficients for coefficients dispersion factors

		x(km) <1			x(km) >1		
Stability	A	b	c	d	b	c	d
A	213.0	440.80	1.941	-9.27	459.7	2.094	9.6
B	156.0	106.60	1.149	-3.30	108.2	1.098	-2.0
C	104.0	61.00	0.911	0.00	61.0	0.911	0.0
D	68.0	33.20	0.725	1.70	44.5	0.516	13.0
E	50.5	22.80	0.678	1.30	55.4	0.305	34.0
F	34.0	14.35	0.740	0.35	62.6	0.180	48.6

Table 3: Turner's method to specify stability class

Rule No.	IF surface wind speed is:	IF cloud cover is:	THEN stability class is:
1	Extremely low	ClEAR SKY	Extremely unstable
2	Very low	Midlevel	Moderately unstable
3	Low	High-level	Slightly unstable
4	Relatively low	Thick high-level	Neutral
5	Moderate	Clear sky	Moderately unstable
6	Relatively high	Midlevel	Slightly unstable
7	High	High-level	Neutral
8	Very high	Thick high-level	Neutral
9	Extremely high	Clear sky	Unstable

Moreover, nine linguistic terms for SWS and six linguistic terms (four terms for day and two terms for night) are considered to measure their values subjectively. The relation between SWS and CC as input variables with SC as output variable is set via If-Then rules. Consequently, there are $9\times6 = 54$ If Then rules. Some of the rules (only 9 rule number) are shown in Table 3. In each condition (given a certain term for SWS and a certain term for CC) only one rule is activated, so one stability class is specified.

FUZZY INFERENCE SYSTEM

Fuzzy sets theory was introduced by Zadeh (1965). It is a mathematical tool to model ambiguous concepts particularly in human decisions. In fuzzy sets theory, unlike classical sets theory, there is not a one-by-one map between a concept and a real number, but an interval of real numbers is associated with a concept, each number with a degree of membership. The radical tool in fuzzy sets theory is Membership Function (MF) which is used to state imprecise concepts such as low salary, high speed, poor quality and so on. In classical sets theory, for example, the concepts good, medium and poor as air quality may be mapped on the real numbers 3, 5 and 7, respectively, as pollution concentration. On the other hand, these concepts in fuzzy sets theory are mapped on the intervals as shown in Fig. 1.

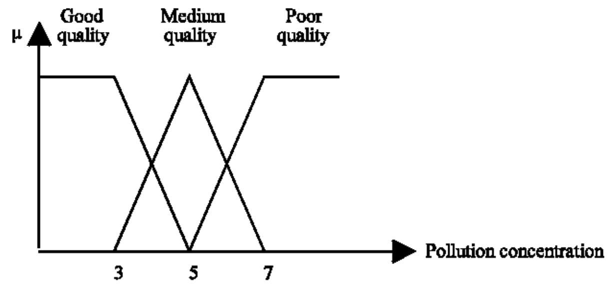

Fig. 1: The concepts good, medium and poor quality in terms of MFs

Fuzzy Rule Base

One of the most powerful techniques in the domain of fuzzy theory is Fuzzy Rule Base (FRB). A fuzzy rule base, consisting of a set of rules, is used to make input-output relation in hard or soft systems. It consists of a set of rules where each rule is an if-then preposition. The antecedent (if-part) specifies a part of input space and the consequent (then-part) indicates the output value associated with the specified input(s). Input space is partitioned by fuzzy number, but output value can be expressed by a fuzzy number or a linear function. The former case is called a Mamdani FRB and the later one is called a Takagi-Sugeno FRB.

If X_1 is low and X_2 is medium then Y is medium
If X_1 is low and X_2 is medium then $Y = 2X_1 + X_2$
Where, low and medium are linguistic terms associated with fuzzy numbers.

Since a TSFRB uses piecewise linear approximation with smooth transitions between linear functions, it is a very robust tool to model complex nonlinear functions. On the other hand, a MFRB can be used to illustrate the behavior of the system via linguistic terms associated with fuzzy numbers. As a result, TSFRBs are more precise, whereas MFRBs are more interpretable.

Although the role of a FRB is like a mathematical function, more computations are required to obtain the output. Given a TSFRB and input vector $X = (x_1, x_2, ..., x_m)$, the inference procedure is as follows (Zimmermann, 1996; Terano *et al*., 1992; Ross, 2004):

- Fuzzification: Calculate the degree of membership of the jth element of the input vector in its corresponding fuzzy number in the ith rule, i.e.,

$$\mu_{ij}(x_j);\ i = 1, 2, ..., c;\ j = 1, 2, ..., m \tag{5}$$

- Degree of matching: Calculate the degree of matching of the input vector with the ith rule as:

$$\mu_i(X) = \min\{\mu_{ij}(x_j)\ \ ; j = 1, 2, ..., m\}\ ; i = 1, 2, ..., c \tag{6}$$

- Output of each rule: Calculate the output of each rule using input vector and consequent of the rule:

$$y_i(X) = a_{i0} + \sum_{j=1}^{m} a_{ij}.x_j \tag{7}$$

- Aggregation: Calculate weighted average of the outputs in the above equation as:

$$y(X) = \frac{\sum_{i=1}^{c} \mu_i(X).y_i(X)}{\sum_{i=1}^{c} \mu_i(X)} \tag{8}$$

y(X) is the final output of the FRB. Note that y_i (X) can just consist of fixed coefficients, i.e., y_i (X) = a_{i0}. In this case, step 3 in the inference procedure is redundant.

Fuzzy Modeling

A FRB can be extracted in two ways: direct approach and indirect approach. The rules are specified from the expertise knowledge in direct approach, whereas they are extracted from input-output data of the system in indirect approach. There are many methods proposed by different authors to extract a FRB from input-output data (Takagi and Sugeno, 1985; Sugeno and Yasukawa, 1993; Chen and Linkens, 2004; Kim *et al*., 1997; Kosko, 1997). In both approaches proper partitioning of the input space is a key matter that influences the accuracy of the obtained FRB. In direct approach, we should take some steps:

- Specify the universe of discourse for each dimension of the input space as well as the output space,
- Cover the universes of discourse by fuzzy numbers, each of which associated with a linguistic term,
- Make all combinations of the linguistic terms for input variables,
- Ask the expert to assign each combination a linguistic term out of the considered ones for the output.

Consequently, partitioning of the input space is carried out based the fuzzy numbers associated with the linguistic terms and the expert specifies which amount of output should be assigned to each partition. In this study, triangular and one-side trapezoidal MFs are considered to cover the universes of discourse. Figure 2 shows triangular and one-side trapezoidal Mfs. These MFs are mathematically presented as:

$$\mu(x) = \max\{0, \min\{\frac{x-l}{m-l}, \frac{n-x}{n-m}\}\} \tag{9}$$

$$\mu(x) = \max\{0, \min\{\frac{n-x}{n-m}, 1\}\} \tag{10}$$

$$\mu(x) = \max\{0, \min\{\frac{x-l}{m-l}, 1\}\} \tag{11}$$

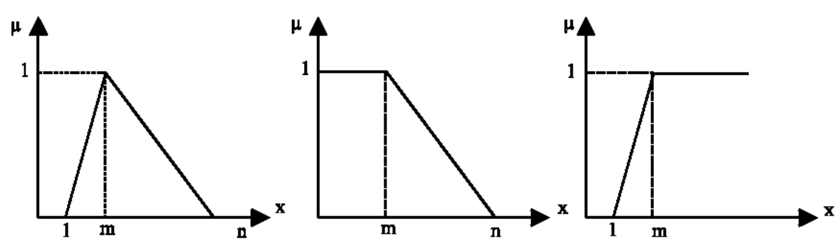

Fig. 2: MFs: Triangular, left one-side trapezoidal and right one-side trapezoidal

It should be noted that the number of linguistic terms that cover the universe of discourse of each variable depends on its sensitivity. The more sensitive variable requires more linguistic terms. Direct approach is mostly used to extract a MFRB rather than a TSFRB, for it is difficult for the experts to specify linear functions subjectively. Note that in indirect approaches, clustering algorithms are usually used in partitioning of the input space.

THE PROPOSED FRB FOR DETERMINATION OF THE STABILITY AND COEFFICIENTS

When historical input-output data of a system is exist, some techniques such as regression, neural networks and indirect fuzzy modeling can be used to model the behavior of the system. On the other hand, in the case that no input-output data exist, direct fuzzy modeling based on the expertise knowledge is one of the best techniques to attempt prognosis into the behavior of the system and to model it. The FRB obtained based on direct fuzzy modeling, though appears as sounds to be a rough model and is a robust model that can be modified via input-output data in future. Based on the method described in previous section, we construct our FRBs. In the first FRB, the objective is to construct an FRB to specify stability class. Therefore, SWS and CC are considered as input variables and SC is considered as output variable. In order to comply Turner's method to construct the FRB, two distinctive FRBs are constructed: an FRB to specify the S.C. in day and an FRB to specify the SC at night. To this end, the universe of discourse of CC is twice partitioned by fuzzy numbers according to Fig. 3-4. Likewise, the universe of discourse of SWS is partitioned according to Fig. 5. We also consider seven singletons as the possible stability classes each of them associated with a number according to Fig. 6. (In which A: extremely unstable, B: moderately unstable, C: slightly unstable, D: neutral, E: slightly stable, F: moderately stable, G: extremely stable).

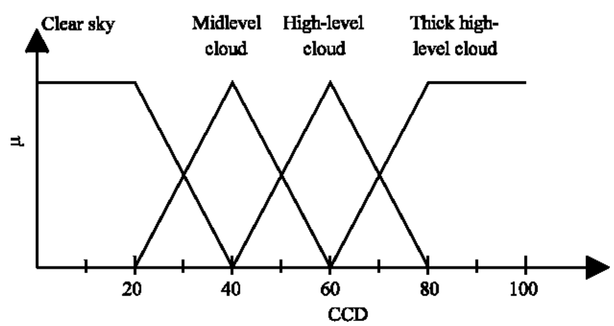

Fig. 3: Covering the universe of discourse of Cloud Cover in Day (CCD) by fuzzy numbers

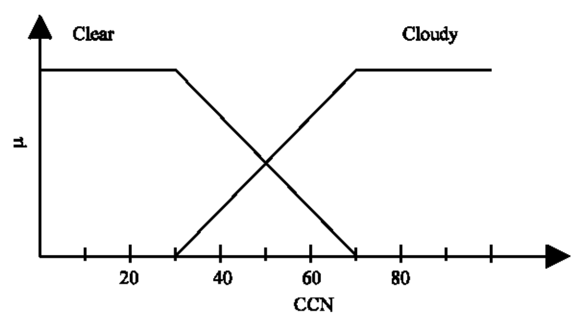

Fig. 4: Covering the universe of discourse of Cloud Cover at night (CCN) by fuzzy numbers

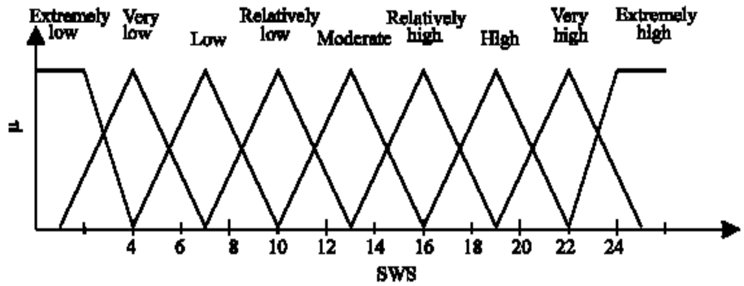

Fig. 5: Covering the universe of discourse of Surface Wind Speed (SWS) by fuzzy numbers

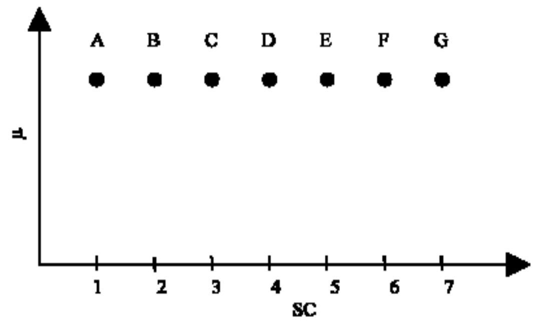

Fig. 6: Covering the universe of discourse of Stability Class (SC) by fuzzy numbers

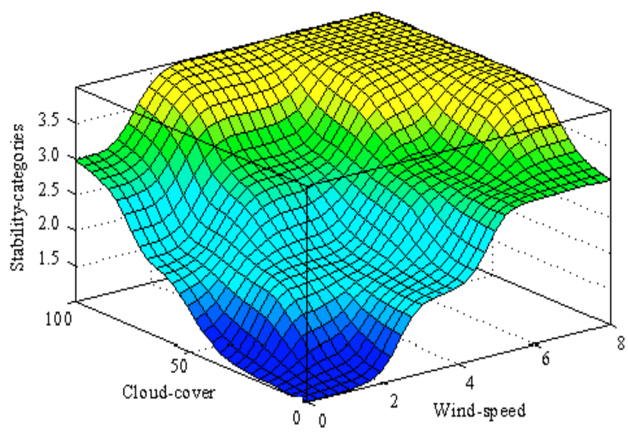

Fig. 7: The FRB representing SWS and CCD vs. SC

As a result, the combination of linguistic terms of SWS and the linguistic terms of CCD leads to a FRB with $9\times4 = 36$ rules that can be used to specify SC in day. Similarly, the combination of linguistic terms of SWS and the linguistic terms of CCN leads to a FRB with $9\times2 = 18$ rules that can be used to specify SC at night. Unlike the conventional method that specifies just one letter (out of A-G) as the SC, the proposed FRBs can specify more than a letter each of them with a degree of membership, i.e., μ_{SC} (A) - μ_{SC} (G). By considering the FRB related to specification of SC in day, a 3-dimensional function is constructed which maps SWS and CCD to SC as represented in Fig. 7.

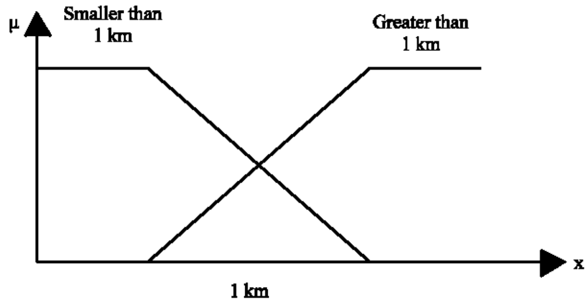

Fig. 8: Covering the universe of discourse of distance by fuzzy numbers

After specification of the stability classes, each of them with a degree of membership, a unique value for each coefficient a, b, c and d should be determined via Table 2. Let us indicate the corresponding value of coefficient a in Table 2 by a(A) -a(F), i.e., we have: a(A) = 213, a(B) = 156, a(C) = 104, a(D) = 68, a(E) = 50.5, a(F) = 34. Therefore, the final value of coefficient a is calculated as:

$$a = \frac{\sum_{k=A}^{F} \mu_{SC}(k).a(k)}{\sum_{k=A}^{F} \mu_{SC}(k)} \tag{12}$$

In order to determine the value of coefficients b, c and d, we partition the universe of discourse of x as shown in Fig. 8.

Let us indicate the corresponding value of coefficients b, c and d in Table 2 by $b_{<1}$, (A)-$b_{<1}$(F), $c_{<1}$ (A)-$c_{<1}$ (F) and $d_{<1}$ (A)-$d_{<1}$(F) in the case that x is smaller than 1. Likewise, the corresponding value of coefficients b, c and d in Table 2 is indicated by $b_{>1}$, (A)-$b_{>1}$(F), $c_{>1}$ (F) and $d_{>1}$ (A)-$d_{>1}$(F) in the case that x is greater than 1. Also, suppose $\mu_{<1}(x)$ and $\mu_{>1}(x)$ are the degree of membership of x in the fuzzy numbers smaller than 1 and greater than 1, respectively. The final value of coefficients b, c and d are calculated as:

$$b = \frac{\sum_{k=A}^{F} (\mu_{<1}(k).b_{<1}(k) + \mu_{>1}(k).b_{>1}(k))}{\sum_{k=A}^{F} (\mu_{<1}(k) + \mu_{>1}(k))} \tag{13}$$

$$c = \frac{\sum_{k=A}^{F} (\mu_{<1}(k).c_{<1}(k) + \mu_{>1}(k).c_{>1}(k))}{\sum_{k=A}^{F} (\mu_{<1}(k) + \mu_{>1}(k))} \tag{14}$$

$$d = \frac{\sum_{k=A}^{F} (\mu_{<1}(k).d_{<1}(k) + \mu_{>1}(k).d_{>1}(k))}{\sum_{k=A}^{F} (\mu_{<1}(k) + \mu_{>1}(k))} \tag{15}$$

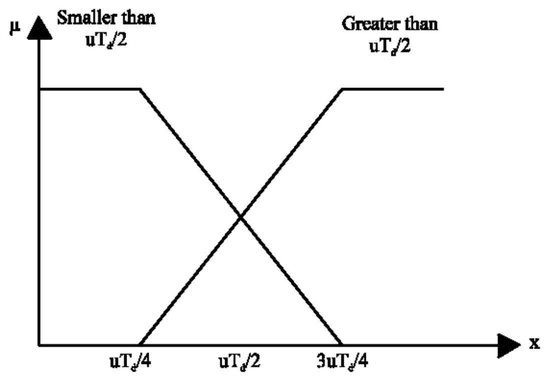

Fig. 9: Covering the universe of discourse of distance by fuzzy numbers

Where:

$$\mu_{<1}(k) = \min\{\mu_{SC}(k), \mu_{<1}(x)\} \quad ;k = A,...,F \tag{16}$$

$$\mu_{>1}(k) = \min\{\mu_{SC}(k), \mu_{>1}(x)\} \quad ;k = A,...,F \tag{17}$$

Based on the value of coefficients a, b, c and d, the lateral and vertical dispersion coefficients are calculated according to Eq. 3-4. Finally, the value of pollution concentration, C, can be calculated by Eq. 1. However, we calculate two values for C and then aggregate them. By using Eq. 2 to determine the value of k for Eq. 1, the overall function of C will have a break point for the values of x around $uT_d/2$. Hence, estimations of the function C for the points which are far from uTd/2 will be relatively precise, whereas the estimations of C for the points around uTd/2 will be imprecise. Fuzzifying the condition presented in Eq. 2 can resolve this problem. Such a fuzzification implies that both the values 1 and $uT_d/2$ are used for the points around uTd/2 each of them with the degree of membership. By using Eq. 2, the universe of discourse of x is partitioned according to Fig. 9.

The degree of membership of x in the sets smaller than $uT_d/2$ and greater than $uT_d/2$ are respectively presented by $\mu_{x<\frac{uT_d}{2}}(x)$ and $\mu_{x>\frac{uT_d}{2}}(x)$. Furthermore, two values for C are calculated in these two cases as:

$$C_{x<\frac{uT_d}{2}} = \frac{Q_C}{2\pi\sigma_y\sigma_z}(\exp(-\frac{(y-y_0)^2}{2\sigma_y^{\,2}}))(\exp(-\frac{(z-h_e)^2}{2\sigma_z^{\,2}}) + \exp(-\frac{(z+h_e)^2}{2\sigma_z^{\,2}}) \tag{18}$$

$$C_{x>\frac{uT_d}{2}} = \frac{uT_dQ_C}{4\pi\sigma_y\sigma_z}(\exp(-\frac{(y-y_0)^2}{2\sigma_y^{\,2}}))(\exp(-\frac{(z-h_e)^2}{2\sigma_z^{\,2}}) + \exp(-\frac{(z+h_e)^2}{2\sigma_z^{\,2}}) \tag{19}$$

Consequently, the final value of C is determined as:

$$C = \mu_{x<\frac{uT_d}{2}}(x).C_{x<\frac{uT_d}{2}} + \mu_{x>\frac{uT_d}{2}}(x).C_{x>\frac{uT_d}{2}} \tag{20}$$

EVALUATION OF THE PROPOSED FUZZY MODEL

The Department of Energy and collaborating organizations carried out the Urban 2000 flow and dispersion experiment in the Salt Lake City area in September and October, 2000. All SF6 releases of

Table 4: Observed hourly averaged Cmax/Q (* 10^{-6} s m^{-3}) for the six monitoring arcs and the 14 trials at Salt Lake City Urban 2000

		Arc, R (m)					
Trials	u (m sec^{-1})	156	394	675	928	1974	3907
1	0.81	317.7	79.6	14.20	3.58	3.91	1.97
2	1.13	606.3	120.1	35.40	16.20	5.67	2.81
3	0.94	836.1	154.7	29.50	12.70	4.39	0.94
4	0.76	573.1	186.7	60.60	21.10	11.30	2.53
5	0.64	149.6	77.3	22.20	13.80	3.87	1.19
6	0.91	249.4	80.5	19.30	13.60	4.09	1.35
7	1.06	402.2	118.3	20.10	12.80	8.09	1.50
8	1.01	520.0	187.7	32.40	17.90	6.08	1.98
9	1.04	200.6	25.8	28.90	9.16	10.30	2.47
10	1.21	207.6	75.8	41.80	36.40	10.50	3.13
11	3.23	115.3	37.3	11.00	7.56	2.63	1.50
12	1.51	158.0	33.0	10.60	4.05	2.03	1.19
13	2.16	153.4	31.9	9.84	8.10	3.45	1.87
14	2.31	72.9	22.7	4.22	1.78	1.48	0.58

duration 1 h from a point source, which covers a 14 km^2 area and shows the release point marked by a star near the middle of the domain and the SF6 monitors as black dots. Three sampling arcs are visible at distances of about 2, 4 and 6 km to the northwest of the release point. In addition, in the 1.3 km^2 area known as the Downtown Domain, there were grids of monitors located on block intersections and midway along the blocks. These monitors were used to define four additional arcs at distances from about 0.15 to 1 km (Allwine *et al*., 2002).

Table 4 contains the observed hourly averaged C_{max}/Q values, in units of 10^{-6} s/m^3, for each arc in each trial (a total of 14 trials and six arcs). The Second column of the table lists the average wind speed for Trial (Hanna *et al*., 2003).The outputs of the proposed fuzzy model are presented in Table 5. For statistical comparison of predicted and observed, two criteria Bias (B) and Scatter Index (SI) are used as follows:

$$SI = \frac{\sqrt{\frac{1}{n}\sum_{k=1}^{n}(\hat{C}_k - C_k)^2}}{\frac{1}{n}\sum_{k=1}^{n}C_k} \times 100 \tag{21}$$

$$B = \frac{1}{n}\sum_{k=1}^{n}(\hat{C}_k - C_k) \tag{22}$$

Where:

C_k : Filed data
$\hat{C}_k$: Output of the fuzzy model
n : Sample size

The values B = -5.2 and SI = 15.1 are obtained for the sample data in the proposed fuzzy model which are very acceptable values, as in the Hanna's model these values are B = -20.86 and SI = 52.03. Therefore, the proposed fuzzy modified model based on the Hanna's baseline urban dispersion model evaluated with Salt Lake City and Los Angeles tracer data would result in more accurate predictions. It is clear that the present model has been developed and compared with the data were used by Hanna *et al.* (2003) and may be evaluated by other range of conditions and data.

Modification of the fuzzy model, obtained based on direct fuzzy modeling, via input-output data can be investigated. Considering other issues such as the plume structure, extension of the pollutant

Table 5: Outputs of the proposed fuzzy model, C_{max}/Q (* 10^{-6} s m^{-3})

		Arc, R (m)					
Trials	u (m sec^{-1})	156	394	675	928	1974	3907
1	0.81	387.81	66.86	21.19	10.32	1.21	0.12
2	1.13	284.95	49.02	15.37	7.67	1.26	0.14
3	0.94	337.51	57.91	18.31	9.05	1.26	0.13
4	0.76	411.76	71.25	22.57	10.90	1.18	0.12
5	0.64	530.94	96.10	31.80	15.39	1.51	0.17
6	0.91	382.27	67.92	22.67	11.59	1.71	0.19
7	1.06	332.64	59.21	19.65	10.14	1.73	0.20
8	1.01	347.52	61.77	20.55	10.58	1.73	0.20
9	1.04	338.42	60.20	20.00	10.32	1.73	0.20
10	1.21	295.46	52.93	17.46	9.05	1.70	0.21
11	3.23	227.99	53.16	21.39	12.32	3.40	1.13
12	1.51	264.03	49.62	16.95	9.02	1.98	0.33
13	2.16	200.24	39.07	13.72	7.30	1.72	0.42
14	2.31	191.18	37.65	13.33	7.10	1.69	0.43

cloud and chemical-photochemical reactions may improve the results of the proposed model in the future investigations. Moreover, principles of fuzzy modeling may be applied to determination of building downwash effects in different existing models. For instant, Fuzzy technique may be used to merge wake boundary for short and tall buildings in Hosker's model (Hosker, 1979), near and far wake concentrations in PRIME model (Schulman *et al*., 2000) and even better determination of parameter A in AERMOD model (Cimorelli, 1998). Fuzzy technique may even be used for integration of atmospheric wet and dry deposition modeling into the dispersion equations through merging some equations like equations introduced by Spotisse (2007), Baklanov and Sorensen (2001) and Sorensen *et al*. (2007), as well as to merging the factors of the introduced by Klaic (1996). It seems that applying the technique in different fields of the air pollution modeling and transport may be of future researches.

CONCLUSION

A fuzzy model to improve Hanna's baseline urban dispersion model has been proposed in this paper and used to model concentration of pollutants in a certain point. Direct fuzzy modeling has been used to construct the fuzzy rule base considering the Gaussian plume function. However, the relations of the dispersion coefficients and Gaussian plume function have been modified in the fuzzy model. Comparison of the results of the proposed model with the Hanna's model in the range of Hanna's model operational conditions showed the accuracy of the proposed model. The obtained Bias and Scatter Index for the proposed model were -5.2 and 15.1, respectively and they were -20.8 and 52.03 for Hanna's baseline urban dispersion model which show effectiveness of the fuzzy modifications of the Hanna's model.

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