Human health risk from trihalomethanes in drinking water evaluation with fuzzy aggregation

S. Chowdhury & T. Husain
Memorial University of Newfoundland, St. John's, NL, Canada

Abstract

The human body is most likely to ingest microbes or disinfection by-products (DBPs) in drinking water. More than 80% of water treatment plants use chlorine as a disinfectant. Approximately 14–16% of the bladder cancers in Ontario, Canada, are attributable to the drinking waters containing relatively high levels of chlorinated by-products (CBPs). In recent studies, in addition to the chronic cancer risk from CBPs, several acute effects including cardiac anomalies, stillbirth, miscarriage and pre-term delivery have been reported. In DBPs, the formation of trihalomethanes (THMs) is highest (60–70%); thus the health risk of THMs is likely to be the maximum. In this study, a framework for evaluating human health risk from THMs using fuzzy aggregation is presented. The triangular fuzzy membership functions (TFNs) are used to capture the associated uncertainties. The analytic hierarchical process (AHP) has been employed for weighting schemes of different level attributes. A sensitivity analysis has been performed to verify the importance of different weighting schemes.
Keywords: disinfection by-products (DBPs), human health risk, THMs, fuzzy aggregation and analytic hierarchy process (AHP).

1 Introduction

Use of disinfectants in drinking water supply systems virtually eliminated most of the water borne diseases [15] but has led to the formation of several DBPs, which are potential human health concern. More than 80% of water treatment plants use chlorine as disinfectant [1]. The DBPs formed during chlorination has proven history of chronic cancer risk and several acute effects to human [10, 19].

The naturally occurring organic materials (NOM) in surface water reacts with disinfectants to produce DBPs. DBPs include mainly trihalomethanes (THMs), haloacetic acids (HAAs), haloacetonitriles (HANs) and haloketones (HKs). Kim *et al.* [7] reported that the formation potential (FP) of THMs is in the ranges of 55-102.6 μg/l, followed by HAAFP (9.1-23.6 μg/l) and HANFP (10.3-33.6 μg/l), where the FP of THMs was most frequent. The frequency of THMs in drinking water is the highest than any other group of DBPs [7, 8].

The increased risks of bladder, colon and rectal cancers, as well as adverse reproductive and developmental effects are also attributable to the chlorinated by-products [18, 19]. The toxicological data for the THMs on human health is shown in Table 1. The THMs has possible cancer effects and other acute and chronic effects to human health (Table 1).

Table 1: Human health toxicological data for THMs components.

Compounds	Human Health Carcinogenicity	Reference Dose (R_fD) [mg/kg/day]	Slope Factor (SF) $[mg/kg/day]^{-1}$
Chloroform	Yes (B-2)	0.01	0.0061
Bromodichloro methane	Yes (B-2)	0.02	0.13
Bromoform	Yes (B-2)	0.02	0.0079
Dibromochloro methane	Yes (C)	0.02	0.0084

The International Programme on Chemical Safety concluded that the levels of health risks from DBPs in drinking water are extremely small in comparison to the risks associated with inadequate disinfection [6]. Approximately 3.4 million people, mostly children, die each year from water-related diseases [20]. Unquestionably, disinfection is required; thus there is a need to evaluate the associated health risk to assess the performance of treatment technology. The most dominant and frequent species of DBPs, the THMs, have been considered in this study to evaluate human health risk.

2 Human health risk assessment

In human health risk assessment different types of imprecision (variability and uncertainties) are associated. The widely used approach to capture uncertainties is Monte Carlo (MC) simulation; but imprecisely informative data cannot be analyzed in MC simulation [9]. On the contrary, Fuzzy logic provides a language for imprecise and qualitative knowledge into numerical reasoning [2, 12].

The real world's problems are sometimes defined in qualitative terms like high, medium and low by the managers, stakeholders rather than the numerical quantities. A fuzzy set is an extension of the traditional set theory in which the element has certain degree of membership μ (0 to 1) in set A; thus a smooth transition between binary logic in the traditional sets (0 or 1) is established. The triangular fuzzy numbers (TFNs) and trapezoidal fuzzy numbers (ZFNs) are

mostly used to represent the linguistic terms [9,12]. The fuzzy evaluation of human health risk is discussed in the following sections.

2.1 Identification of basic attributes

The THMs, consists of chloroform, bromodichloromethane, bromoform and dibromochloromethane, in which chloroform is 70-90% of the total THMs [5]. The human health risk (a) has been divided into two generalized attributes (a_1 for cancer risk; a_2 for non-cancer risk) as shown in Figure 1. In the level 3, the attribute a_1 is broken into four basic attributes: a_{11}, a_{12}, a_{13} and a_{14} for cancer risk from chloroform, bromodichloromethane, bromoform and dibromochloromethane respectively. The attribute a_2 has been broken into four basic attributes: a_{21}, a_{22}, a_{23} and a_{24} for non-cancer risk from chloroform, bromodichloromethane, bromoform and dibromochloromethane respectively (Figure 1).

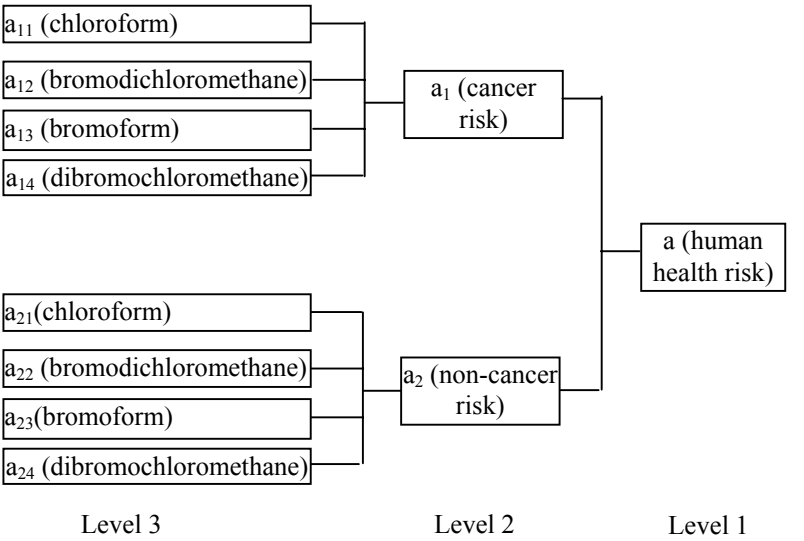

Figure 1: Framework for basic attributes and fuzzy evaluation.

2.2 Fuzzification of the basic attributes

The basic attributes are generally expressed in 5-11 granules [11, 12] to incorporate the experts' judgments. In this study, five linguistic terms (granules)-worst, bad, fair, good and best have been taken for simplicity. Too many scales (granules) may induce complex mathematical calculation. After defining the fuzzy subsets, the basic attributes are expressed with the membership grades in the predefined five granules (μ_1, μ_2, μ_3, μ_4, μ_5) for worst, bad, fair, good and best respectively. It is shown in Figure 2, where for example, an element P is defined in five granules. Let us assume that the data for P as (0.5,0.62,0.7) which indicates the TFN in the range of 0.5-0.7 with most likely value of 0.62. This is mapped in Figure 2. If the variable P intersects any granule more than once, the

maximum operator is used [21]. The membership grade for μ_1(worst) = 0, μ_2(bad) = 0.33, μ_3(fair) = max (0.97, 0.88) = 0.97, μ_4(good) = 0.36 and μ_5(best) = 0 were noted; thus the fuzzy sets for P becomes (0, 0.33, 0.97, 0.36, 0).

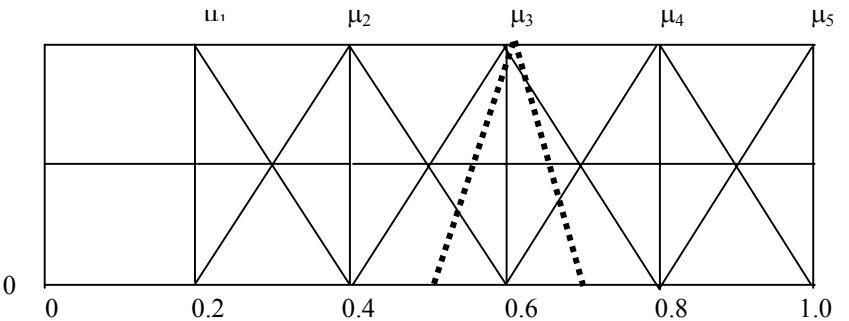

Figure 2: Defining fuzzy membership function.

This study considers the basic attributes as cancer and non-cancer risks from chloroform, bromodichloromethane, bromoform and dibromochloromethane. The concentrations of the THMs components are presented in minimum, most likely and maximum format in Table 2 [8].

Table 2: THMs in tap water in Newfoundland (μg/l).

Compounds	Minimum	Most likely	Maximum
Chloroform	19.4	121.18	283.1
Bromodichloromethane	1	2	6.1
Bromoform	0.1	0.5	1.0
Dibromochloromethane	3.9	7.85	18.61

The cancer and non-cancer risk from drinking water ingestion was evaluated following USEPA [17] as

$$CDI = \frac{C_W IFD}{WT} \tag{1}$$

where, CDI = chronic daily intake (mg/kg/day); Cw = chemical concentration in drinking water (mg/l); I = drinking water ingestion rate (2 l/day for residents); F = exposure frequency (365 days/year for residents); D = exposure duration (77.1 years for Newfoundland [14]; W = Average body weight (70 kg); T = Averaging time (77.1×365 =28141 days for Newfoundland [14]

$$Cancer\ Risk = CDI \times SF \tag{2}$$

where, SF = slope factor ([mg/kg/day]$^{-1}$)

The non-carcinogenic effect defined as hazard quotient is calculated as

$$Hazard\ Quotient = \frac{CDI}{R_f D} \tag{3}$$

where, R_fD = reference dose (mg/kg/day)

The Federal Register [4] recommends the acceptable range of human health cancer risk to be 10^{-6} to 10^{-4} (logarithmic scales: -6 to -4). The membership functions for cancer risk are shown in Figure 3. The hazard quotient in the range of 0 to 1 is acceptable range for human health protection [17]. The membership functions for non-cancer risk are constructed in Figure 4. The membership functions have been constructed in logarithmic scale to capture the extremely low values of risk (Figures 3 and 4). The predicted risks are then mapped on Figure 3 (for cancer risk) and Figure 4 (for non-cancer risk) to obtain the fuzzy sets. These fuzzy sets for human health risks are shown in Table 3.

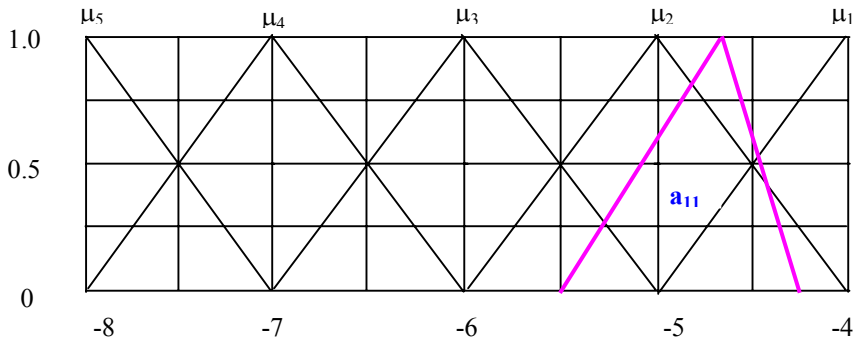

Figure 3: Membership function for cancer risk (log-scale).

Table 3: Membership functions for human health risk.

Basic attributes	Membership function
Cancer risk	**(μ_1, μ_2, μ_3, μ_4, μ_5)**
Chloroform (a_{11})	(0.52, 0.83, 0.26, 0, 0)
Bromodichloromethane (a_{12})	(0.25, 0.96, 0.29, 0, 0)
Bromoform (a_{13})	(0, 0, 0.28, 0.94, 0.33)
Dibromochloromethane (a_{14})	(0, 0.47, 0.74, 0.07, 0)
Non-cancer risk	**(μ_1, μ_2, μ_3, μ_4, μ_5)**
Chloroform (a_{21})	(0.66, 0.73, 0.18, 0, 0)
Bromodichloromethane (a_{22})	(0, 0, 0.66, 0.66, 0)
Bromoform (a_{23})	(0, 0, 0.12, 0.91, 0.49)
Dibromochloromethane (a_{24})	(0, 0.31, 0.94, 0.18, 0)

2.3 Defining relative weights

The fuzzy evaluation requires relative importance of attributes at each hierarchy level. The analytic hierarchy process (AHP) is mostly used to define relative importance of each level attributes [11]. The fundamental scales of importance to develop the priority matrix can be found in Saaty [11]. These relative weights are then normalized to unity and the priority matrix is formed in such a way that

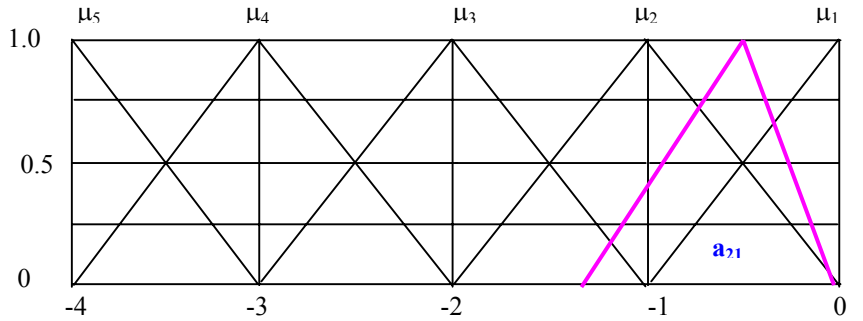

Figure 4: Membership function for non-cancer risk (log-scale).

$$W = (w_1, w_2, ...w_n) \text{ where } \sum_{k=1}^{n} w_k = 1 \tag{4}$$

A simple example to establish the priority matrix is illustrated as follows: Consider three attributes as x_{11}, x_{12} and x_{13}. It is assumed that attribute x_{11} is 2 times important than x_{12} and 3 times than x_{13}. Each element of the lower triangle in the matrix is reciprocal to the upper triangle ($I_{jk} = 1/I_{jk}$). The matrix is as

$$I = \begin{array}{c} \\ x_{11} \\ x_{12} \\ x_{13} \end{array} \begin{array}{ccc} x_{11} & x_{12} & x_{13} \\ 1 & 2 & 3 \\ 0.5 & 1 & 1.5 \\ 0.333 & 0.67 & 1 \end{array} \tag{5}$$

The matrix I can be formed by taking row wise geometric mean [11] of elements and normalization to unity as

$$I = \begin{bmatrix} 1.817 \\ 0.909 \\ 0.607 \end{bmatrix} \Rightarrow W = \begin{bmatrix} 0.545 \\ 0.273 \\ 0.182 \end{bmatrix} \tag{6}$$

Chloroform, bromodichloromethane and bromoform have been classified as 'probable human carcinogen (B–2)' and dibromochloromethane as 'possible human carcinogen (C) by the regulatory agency [16]; thus dibromochloromethane was given less priority in the weighting scheme (Table 4). To make the calculation simple, equal importance is given to each of the basic attributes for non-carcinogenic risk prediction (Table 4).

2.4 Obtain more generalized level attributes by aggregation

Once the weights and fuzzy sets for the basic attributes are determined, these are then grouped according to the hierarchy framework (Figure 1). For example, assume that at level 2, we have three basic attributes for X_1 as x_{11}, x_{12} and x_{13}. The fuzzy sub sets for the three basic attributes are

$$X_1 = \begin{bmatrix} x_{11} \\ x_{12} \\ x_{13} \end{bmatrix} = \begin{bmatrix} \mu_1^{11}, \mu_2^{11}, \mu_3^{11}, \mu_4^{11}, \mu_5^{11} \\ \mu_1^{12}, \mu_2^{12}, \mu_3^{12}, \mu_4^{12}, \mu_5^{12} \\ \mu_1^{13}, \mu_2^{13}, \mu_3^{13}, \mu_4^{13}, \mu_5^{13} \end{bmatrix} \quad (7)$$

The weight vectors for the three attributes are

$$]W_1 = [W_{11} \quad W_{12} \quad W_{13}] \quad (8)$$

The evaluation matrix A_1 for attribute X_1 is obtained as

$$A_1 = W_1 \times X_1 \quad (9)$$

These evaluation matrices are then carried over for more generalized level attributes. The procedure is followed until the final fuzzy set is obtained.

Table 4: Weighting schemes of the attributes.

Basic Attributes	W_2		W_1 (T_1)	W_1 (T_2)	W_1 (T_3)	W_1 (T_4)
a_{11}	0.273	a_1	0.67	0.6	0.5	0.4
a_{12}	0.273					
a_{13}	0.273					
a_{14}	0.182					
a_{21}	0.25	a_2	0.33	0.4	0.5	0.6
a_{22}	0.25					
a_{23}	0.25					
a_{24}	0.25					

2.5 Defuzzifying the final sets

The final risk is generally expressed by the crisp values, which can be obtained through defuzzification. The expression of risks in the linguistic terms like worst, bad, fair, good and best can be performed through determination of Euclidean distance of a given fuzzy sets to each of the fuzzy sets representing the linguistic expressions [14]. Many other methods [2] are available for defuzzification. In this study, the Euclidean distance method [14] is followed for simplicity in calculation. For example, if a expresses the resultant fuzzy set and w expresses the linguistic condition of worst, then the distance between a and w can be determined from

$$a = \{a(k) \mid k\}$$
$$w = \{w(k) \mid k\}$$

$$\text{Distance, } d_{aw} = \left[\sum_{k=1}^{n} \{a(k) - w(k)\}^2 \right]^{\frac{1}{2}} \quad (10)$$

The fuzzy sets with shortest distance represents the maximum possibility [14].

3 Calculation

3.1 Second stage calculation

The fuzzy subsets for cancer risk (a_1) and non-cancer risk (a_2) are integrated to determine the evaluation matrix for next hierarchy level. The evaluation matrix for a was determined using the weighting schemes and fuzzified basic attributes as

$$a_1 = [0.21 \quad 0.57 \quad 0.36 \quad 0.27 \quad 0.09] \text{ and}$$
$$a_2 = [0.17 \quad 0.26 \quad 0.48 \quad 0.44 \quad 0.12]$$

3.2 First stage calculation

The final fuzzy set for human health risk can be evaluated as
$a = [0.2, 0.47, 0.40, 0.33, 0.1]$
The final fuzzy set for human health risk can be expressed as

$$a = \frac{0.20}{\text{Worst}}, \frac{0.47}{\text{Bad}}, \frac{0.40}{\text{Fair}}, \frac{0.33}{\text{Good}}, \frac{0.1}{\text{Best}}$$

The Euclidean distances between fuzzy set 'a' and the linguistic conditions worst, bad, fair, good and best have been determined using Equation (10) as 1.06, 0.77, 0.86, 0.94 and 1.16 respectively.

4 Sensitivity analysis

The weighting schemes and classification of linguistic terms involve human judgments; thus a possibility of variation by using different weighting schemes is expected. So, it is required to perform sensitivity analysis with various weighting schemes. The weighting schemes for the basic attributes were kept unchanged for simplicity of calculation. The different weighting schemes employed in sensitivity analysis are shown in Table 4. The results for different weighting schemes are shown in Table 5. The first and second positions were occupied by the 'bad' and 'fair' in each trial (Table 5). The weighting scheme was found to have low sensitivity on changing human health risk status.

Table 5: Results of sensitivity analysis.

Linguistic grade	Euclidean distance			
	Trial 1 (T_1)	Trial 2 (T_2)	Trial 3 (T_3)	Trial 4 (T_4)
Worst (μ_1)	1.06	1.1	1.07	1.08
Bad (μ_2)	0.77	0.8	0.83	0.86
Fair (μ_3)	0.86	0.84	0.83	0.81
Good (μ_4)	0.94	0.92	0.91	0.88
Best (μ_5)	1.16	1.15	1.14	1.14

5 Summary and conclusions

The management of drinking water treatment technologies is subjective to human health risk and associated cost. For drinking water treatment system, it is required to indicate whether a treatment facility should be upgraded or replaced. In such a case, the system must be able to predict the final condition on human health risk from DBPs. The proposed methodology may a tool for such purposes.

The fuzzy aggregation has been applied to evaluate human health risk from THMs in drinking water. The values of different basic attributes showing human health risk were evaluated using equations (1-3). These were then mapped in Figures 3 (for cancer risk) and 4 (for non-cancer risk) to construct fuzzy sets. By assigning different weighting schemes (Table 4), several trials were performed to verify the effects of different weighting schemes. The human health risk condition switched between 'bad' and 'fair' in all the trials (Table 5). The weighting schemes were found to be less sensitive to change the risk status.

This study provides a framework for a human health risk assessment from THMs in drinking water supply system. This technique involves identification and fuzzification of basic attributes, assigning weights, aggregation and defuzzification. The basic attributes were fuzzified using five linguistic fuzzy subsets-worst, bad, fair, good and best. The evaluation matrix of each level was used for next higher-level assessment. The final fuzzy sets were defuzzified using Euclidean distance approach. The weighting schemes were developed using AHP.

Acknowledgement

The first author acknowledges the funding from NSERC through Memorial University of Newfoundland in a form of scholarship.

References

[1] American Water Works Association (AWWA). Disinfection Systems Survey Committee Report, Water Quality Division. J AWWA 9, pp. 24–43, 2000.

[2] Chen S. J. and Hwang C. L., Fuzzy Multiple Attribute Decision Making-Methods and Applications, Springer-Verlag; Berlin, Germany, ISBN: 3-540-54998-6, 1992.

[3] Clark R. M., Adams J. Q., Sethi V. and Sivaganesan M., Control of microbial contaminants and disinfection by-products for drinking water in the US: cost and performance. J Water SRT-Aqua 47(6), pp. 255–265, 1998.

[4] Federal Register, National Primary Drinking Water Regulations, USEPA. Radionuclides, 40 CFR Parts 141,142,56: 138:33050, 1991.

[5] Garcia-Villanova R. J., Garcia C., Gomez J. A., Garcia M. P. and Ardanuy R., Formation, Evaluation and Modelling of Trihalomethanes in the

drinking water of a town: I. at the municipal treatment utilities. Water Research 31(6), pp. 1299–1308, 1997.
[6] International Programme on Chemical Safety (IPCS). Disinfectants and disinfectant by-products, Environmental Health Criteria, 216, 2000.
[7] Kim J., Chung Y., Shin D., Kim M., Lee Y., Lim Y. and Lee D., Chlorination by-products in surface water treatment process. Desalination 151, pp. 1–9, 2002.
[8] Kolla R. B., Formation and Modelling of disinfect ion by-products in Newfoundland Communities. Masters Thesis; Memorial University of Newfoundland, St. John's, NL, Canada, 2004.
[9] Lee H. M., Applying fuzzy set theory to evaluate the rate of aggregative risk in software development. Fuzzy Sets and Systems 79, pp. 323–336, 1996.
[10] Mills C. J., Bull R. J., Cantor K. P., Reif J., Hrudey S. E. and Huston P., Health Risks of Drinking Water Chlorination By-products: Report of an Expert Working Group. Chronic Diseases in Canada 19(3), 2000. (Website http://www.phac-aspc.gc.ca/publicat/cdic-mcc/index.html).
[11] Saaty T. L., Multi-criteria decision-making: The Analytic Hierarchy Process. University of Pittsburgh, Pittsburgh, PA, 1988.
[12] Sadiq R., Husain T. Veitch B. and Bose N., Risk –based decision making for drilling waste discharges using a fuzzy synthetic evaluation technique. Ocean Engineering 31, pp. 1929–1953, 2004.
[13] Statistics Canada, 2005. http://www.statcan.ca/english/Pgdb/health26.htm
[14] Tee A. B., Bowman M. D. and Sinha K. C., A fuzzy mathematical approach for bridge condition evaluation. Civ. Engng Syst. 5, pp. 17–24, 1988.
[15] U.S. Centers for Disease Control and Prevention (USCDC). Summary of notifiable diseases, Morbidity and Mortality Weekly Report, CDC Surveillance summaries: Surveillance for waterborne disease outbreaks-United States, 1993–1994, 1997.
[16] United States Environmental Protection Agency (USEPA), Guidance for carcinogen risk assessment; USEPA Federal Register 51: 33992, 1986.
[17] United States Environmental Protection Agency (USEPA), Human Health Risk Assessment Protocol. EPA-530-D-98-001A; USEPA Office of Solid Waste, USA, 1988.
[18] Waller, K., Swan, S. H., DeLorenze, G., and Hopkins, B., Trihalomethanes in drinking water and spontaneous abortion. Epidemiology 9, pp. 134–140, 1998.
[19] Wigle D. T., Safe Drinking Water: A Public Health Challenge; Chronic Diseases in Canada 19(3), 2000. (Website http://www.phac-aspc.gc.ca/publicat/cdic-mcc/index.html).
[20] World Health Organization (WHO), Water and Sanitation: 2002. Available: http://www.who.int/water_sanitation_health/General/factsandfigures.htm
[21] Yager R. R. and Filev D. P., Essentials of Fuzzy Modeling and Control. John Wiley & Sons Inc, New York, 1994.