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New methodology for hazardous waste classification using fuzzy set theory
Part II. Intelligent decision support system

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Abstract

In part 1 of this paper, factors that influence hazards and eco/toxicity in composite hazardous wastes were described. In part 2, a computer-aided decision support tool based on fuzzy set theory is proposed to support the classification of composite wastes. Given the chemical properties, the nature of microorganisms that may be present, the behaviour of chemicals in humans and ecosystems, and the quantities of wastes, the computer-aided tool automatically classifies the waste as benign, partially hazardous, hazardous or highly hazardous. The functionality of the computer-aided decision tool is demonstrated through nine worked examples and the results are discussed in detail.

Keywords: Waste classification; Fuzzy logic; Fuzzy sets; Uncertainty; Aggregation; Composite hazardous wastes

1. Introduction

In part I [1], both tacit and implicit knowledge on factors that influence the extent to which a certain waste is classified as hazardous or benign were presented. Through an extensive bibliographical search, knowledge on waste classification was acquired from diverse sources, exhibiting both qualitative and quantitative features characterized by varying degrees of uncertainty. As both hazard and eco/toxicity properties of a waste depend on its constituent chemicals and/or pathogens present, it is feasible for the waste classes to be graded from having a benign status to having a highly hazardous status. This is for the obvious reason that the properties of a given waste are linked to those of its constituent components and the quantity of the waste under consideration.

The European Inventory of Existing Commercial Chemical Substances (EINECS) has listed more than 100,000 substances that were marketed in Europe between 1971 and 1981, when the inventory was compiled [2]. A considerable number of these chemicals were classified as hazardous or toxic to humans or ecosystems. In addition, more than 8.4 million substances are currently commercially available globally, of which approximately 240,000 are inventoried and/or regulated chemicals according to the Chemical Abstracts Service (CAS) web site [3]. In the USA, the EPA Toxicity Substances Control Act (TSCA) inventory consists of more than 80,000 chemicals of which only approximately 43% are polymers considered to pose low toxicity risks to humans and ecosystems [4].

In view of the above statistics and others well summarized by Muir and Howard [5], it is evident that the matrices of composite wastes formed from various combinations of these chemicals can range from a benign to a highly hazardous status. It is also clear that for such a large number of chemicals, matrices of possible composite wastes can be large. This may result in costly preliminary assessment of the composite wastes using bioassay experiments. To provide a tool for rapidly establishing the hazardous status of a composite waste, we propose a new methodology for risk assessment based on fuzzy logic theory. The strength of fuzzy logic lies on its ability to provide a language with syntax and semantics to translate imprecise, vague and qualitative knowledge into numerical reasoning. This creates a feasible solution in a domain where some individual chemical data are typically either lacking entirely or do not exist in a form that can be readily incorporated into automated

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waste ranking methods. In the next section, the fundamentals of fuzzy logic are presented, which helps in understanding the fuzzy-based methodology for waste classification proposed in this study. As a way of illustrating the functionality of the proposed methodology, nine hypothetical composite wastes worked examples are presented and discussed in detail.

2. Fuzzy set theory

Fuzzy set theory [6] generalizes ordinary or classical sets in an attempt to model and simulate human linguistic reasoning in a domain characterized by incomplete, imprecise, uncertain and vague data. Therefore, as a soft computing tool, fuzzy logic provides rational and well reasoned out solutions for complex real world problems [7], such as hazardous waste classification. Essentially, in a fuzzy system the rule-base is comprised of a collection of fuzzy *IF–THEN* rules that are used by a fuzzy inference engine to determine a mapping from fuzzy sets in the input universe of discourse $V \subset R^n$ to fuzzy sets in the output universe of discourse $V \subset R$ based on fuzzy logic principles [8].

The fundamentals of fuzzy set theory are well known and detailed treatment of the subject can be found elsewhere [8–10]. However, the fundamental concepts of fuzzy logic essential to the design and development of intelligent decision support systems for hazardous waste classification are briefly summarized here for convenience.

2.1. Fuzzy membership functions

In a fuzzy system, the variables are regarded as linguistic variables to enable ‘computation with words’. Moreover, a linguistic value refers to a variable whose value is a fuzzy number or is a variable defined in linguistic terms [11]. Each linguistic value, LV, is represented by a membership function $\mu_{\mathrm{LV}}(x)$. The membership function associates each crisp input, say X_{A}, with a number, $\mu_{\mathrm{LV}}(\mathrm{x_A})$ in the range [0.1]. This number $\mu_{\mathrm{LV}}(\mathrm{x_A})$ represents the grade of the membership of X_{A} in LV or equivalently, the truth value of proposition ‘crisp value A is LV’. The overlapping of the membership functions allows an element to belong to more than one set at the same time, and the degree of membership into each set indicates to what extent the element belongs to that particular fuzzy set (Fig. 1).

To illustrate the functionality of the membership function values for the purpose of determining the linguistic value of a given variable, an illustrative example is presented. Assume that the computed hazardous waste index for the acute toxicity variable is 0.4 in a universe of discourse of 0–1. Then, according to Fig. 1, for an input of 0.4, the membership functions $\mu_{\mathrm{AC}}(x_i)$ generated are; $\mu_2 = 0.35$ in the fuzzy set labelled *very low*, $\mu_3 = 0.50$ in the set labelled *moderate*, and in the rest of the sets $\mu_1 = \mu_4 = \mu_5 = 0$ for the sets *none*, *high* and *extremely high*, respectively. Since in this work the *max–min* fuzzy inferencing algorithm was applied, hence using the membership function values ($\mu_2 = 0.35$, $\mu_3 = 0.50$) the linguistic value was determined as *very low* (min (0.35, 0.50) = 0.35).

In this study, two forms of membership distribution functions, namely, triangular- and trapezoidal-shaped functions were used to represent the input and output variables in the knowledge rule-base. Although the non-linear Π functions (Z- or S-shaped) are perhaps the more logical parallel to the human reasoning process, linear functions (triangular and trapezoidal) are an acceptable compromise as they reduce computation time considerably. A typical example of the input linguistic variable membership functions are shown in Fig. 1 for the mammalian acute toxicity input attribute. As can be seen in Fig. 1, various segments of a membership function represent the limits of our expectation that an object belongs to the corresponding fuzzy set. For instance, the acute toxicity variable is decomposed into five linguistic labels namely; *none*, *very low*, *moderate*, *high* and *extremely high*.

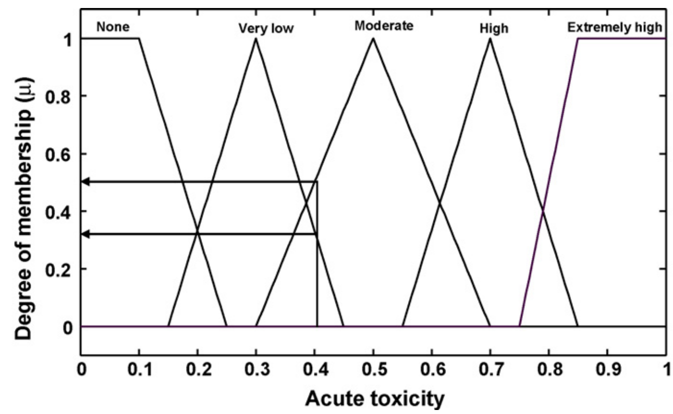

Fig. 1. Triangular and trapezoidal membership distribution functions for the mammalian a cute toxicity linguistic attribute associated with hazardous composite waste.

2.2. Knowledge library

The intelligent decision support system described in this paper classifies hazardous waste by using knowledge encoded in the form of *IF–THEN* rules in a rule-base. Ultimately, this makes the knowledge library (base) the core of the system and, the breadth and quality of the knowledge determine the capacity of the system to render useful decision support. The antecedent and consequent parts of the fuzzy rules are of the form:

$$R^{(l)}: IF x_1 \text{ is } F_1^1 \text{ AND} \ldots x_n \text{ is } F_n^1, \quad THEN\ y \text{ is } G_1 \tag{1}$$

where F_l^i and G^{l} are fuzzy sets, $x = (x_1, \ldots, x_n)^{\mathrm{T}} \in U$ and $y \in V$ are input and output linguistic variables, respectively, with $l = 1, 2, \ldots, M$. Practice has shown that fuzzy *IF–THEN* rules provide a convenient framework to incorporate human experts’ knowledge. Each fuzzy *IF–THEN* rule (Eq. (1)) defines fuzzy set $F_1^l x \ldots x F_n^l \Rightarrow G^l$ in the product space $U \times V$.

The development of these *IF–THEN* rules defining the relationship between the linguistic variables (both inputs and outputs) and their fuzzy sets is a critical step, since they encapsulate the heuristic knowledge about the behaviour of the physical system, or hazardous waste classification in this case. More than 300 rules were derived and systematically encoded in different hierarchically interlinked knowledge rule-bases. Using these rules, computation of the overall waste class consisted of the initialization of certain primitive variables by the user, which in turn were used as inputs to compute the composite output at the next knowledge rule-base in the hierarchy. The outputs from different knowledge modules on the particular level were subsequently aggregated to yield composite values as an output to the next higher level and the process continued until the final overall waste class could be determined.

This approach is analogous to consulting several experts on a certain problem and then deriving a final conclusion based on each individual opinion. The model is flexible, robust and can allow a user to choose initial values or adjust the rules in any knowledge base on the basis of operational realities related to the wastes under scrutiny.

2.3. Fuzzy inferencing

The core of the decision-making in a fuzzy logic system is the inference system. It is instrumental in the derivation of an aggregated output from a particular knowledge base using the rules coded in the rule-bases. In practice, many fuzzy inferencing methods have been developed, with the so-called *max–min* and *max-dot* or *max-prod* [11] being the most popular. In this study, the *max–min* fuzzy inferencing algorithm proposed by Mamdani and Assilian [12] was used. In this system, the truth values of the fuzzy output variables are clipped, such that the area under the clip line determines the outcome of the rule.

Finally, a defuzzifier converts the fuzzy aggregate membership grades generated from the inference engine into a non-fuzzy output value. Again, there are various approaches to defuzzification [13,14]. The most common is Yager's centroidal method [15], which was used in this paper. Yager's method is sensitive to the contribution of each activated rule, as opposed to other methods that are biased towards rules exhibiting higher truth values or firing strengths.

3. Fuzzy assessment of waste classification

Decision-making in waste classification requires formalized steps for analysing the available data and a logical procedure for combining it. In this case, two steps were taken to make the system robust. First, the core variables to be taken into account in the classification algorithm were identified and, second, a hierarchical methodology for decomposing the problem into manageable components was used. These components were organized into various categories and sub-categories and linked in a hierarchical manner.

In practice the assessment of waste classification often entails ill-defined variables characterized by a high degree of uncertainty owing to incomplete data or inadequate knowledge of the underlying issues. With the hierarchical framework proposed here, waste classes can be determined systematically and transparently. Moreover, within this framework, both imprecise data and qualitative knowledge acquired from an extensive literature review were used to model waste classification.

3.1. Hierarchical structure

Fig. 2 depicts a hierarchically structured model for the most important factors influencing the degree of hazardousness of a given waste. In this study, the most influential factors were decomposed into five levels. This procedure led to large sets of data and knowledge which had to be accounted for in the waste classification algorithm. For any waste, the primary attributes that determine its level of hazardousness are contained in Level-I, viz. chemical properties and the presence of pathogens commonly referred to as potential effects, the exposure potency, and quantity of the waste.

Normally, during evaluation of the final aggregated class for a composite waste, the exposure potential should be multiplied by the health and ecological effects, as well as the quantity of

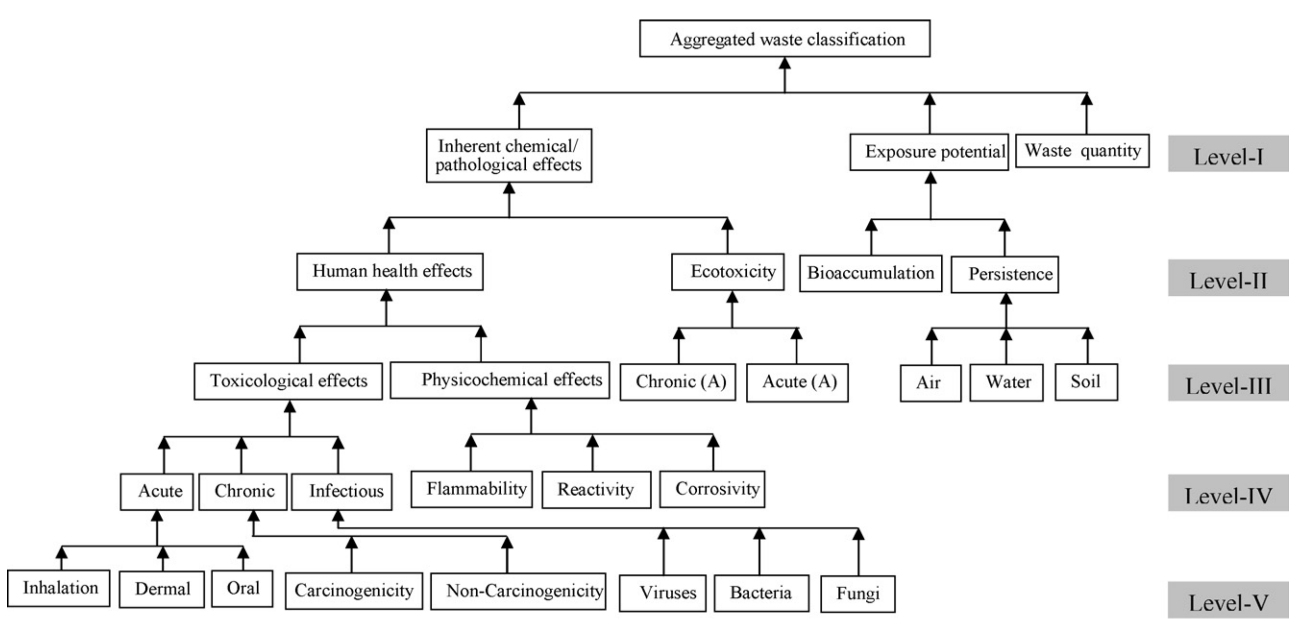

Fig. 2. Hierarchical flowchart linking the hazard and eco/toxicity properties that influence waste classification (A: Aquatic).

waste. The reason for this is that a higher level of either variable increases the importance of the other. For instance, increased human toxicity and ecotoxicity are more serious when the chemicals under scrutiny have a tendency to bioaccumulate or persist for long periods in the environment than when they are not. In fact, the extent of chemical and pathogenic effects also depends on the actual quantities entering into the environment and getting in contact with various living organisms. These synergistic effects of the attributes in Level-I were accounted for in the fuzzy *IF–THEN* rules in the first level knowledge rule-base.

The underlying attributes that determine the aggregate value of each primary attribute in Level-I are distinctive, and each has a different chain length, as can be seen from Level-II. Each primary attribute was broken down to its basic attributes where information and/or data are known (Fig. 2). The inherent chemical and pathological effects, and exposure potency Level-I attributes were further sub-divided into Level-II attributes, i.e. inherent chemicals- and pathogens-effects was divided into human health risks and ecotoxicity, and similarly the exposure potency was divided into bioaccumulation and persistence attributes. However, the waste quantity attribute could not be broken down any further and was determined directly at Level-I. The inherent waste properties owing to the nature of the chemicals and pathogens present, as well as the exposure potency were further sub-divided into Level-III through the Level-V attributes, where further sub-division became infeasible. For example, the computation of the inherent chemical properties of the waste had five levels, while the exposure potency had only three. Primarily the level at which a given leaf terminates, signifies the point where the system prompts the user for a crisp, fuzzy or a linguistically defined input to initialize the calculations for all the higher levels composite outputs in that particular leaf. The input data for the lowest level attributes were sourced from numerous bibliographical references as described in part I of this paper [1].

By using the fuzzy system, the inputs at the lowest leaf level were combined to yield the first composite output which was then passed on to the next higher level as an input. For example in Level-IV, three basic attributes, namely flammability, corrosivity and reactivity were combined in two stages to yield the physicochemical-effects in Level-III using the methodology described by Musee et al. [16]. The physicochemical effects output together with the toxicological effects output at Level-III were then used to compute the overall human health effects in Level-II, and similarly, the approach was applied systematically in the entire framework. Fig. 2 diagrammatically illustrates the complete model structure used to determine the aggregated risk assessment posed to humans and ecosystems by composite wastes.

3.2. Heuristic rules for waste classification assessment

A systematic methodology was developed to combine the effects of constituent chemicals or pathogen(s) into a final waste classification algorithm. As the information and data available in this domain are diverse, a unique protocol for data manipulation was designed at the lowest attribute level where user inputs were required. For consistency purposes, several heuristic rules were used in determining the toxicological and pathogenic effects in a composite waste, namely

- The toxicity effect of a composite waste is an additive effect of the constituent components. Therefore, the addition of individual chemical dose effects provides a good approximation for waste classification;
- The infection effects owing to the presence of pathogens (fungi, viruses, bacteria) are dependent on the quantities of the individual wastes under consideration. Consequently, if viruses were the most dominant pathogens in the waste by quantity (expressed in percentages), then the infectious effects were presumed to be predominantly attributable to viruses, though the contributions of other pathogens present were also accounted for;
- The exposure potential of a given composite waste depends on the constituent chemical(s), where the chemical with the highest persistent and bioaccumulative values in any of the three environmental media (air, water or soil) was used as the fuzzy numerical system input. For instance, in any composite waste under study, the highest of the bioaccumulation and persistence values of the constituents were determined and used as inputs for the computation of exposure potency. This rule is reasonable, since the values of the half-life and the octanol–water partition coefficients express the persistence and bioaccumulation factor (BAF), respectively, and are chemically intensive properties independent of the quantities of waste under consideration. This implies that a chemical with high values on either or both of these properties exerted the most influence on the level of exposure potency of the hazardous waste in the environment, as none of these effects in living organisms depend on the quantity of waste.

3.3. Data evaluation

Before presenting the results derived from the proposed algorithm, it is necessary to describe how the data obtained from literature were handled in order to contextualize the final results presented in this paper. To illustrate the plausibility of classifying composite wastes using the properties of the constituent chemicals (physicochemical, toxicological, ecotoxicity, and exposure potential), a data set of 35 chemicals was collected (Table 1). The data were sourced from a number of data banks, and wherever possible, each of the lowest level attributes in a given hierarchical leaf was provided with all the relevant information. Nevertheless, it was observed that large differences exist in the data available in literature, particularly in terms of values and units associated with these values. These differences in data were presumably owing to differences in measurement protocols and the biological species involved in the generation of the data by various researchers and institutions. Other reasons for these differences could probably be attributable to different conditions of measurement, or observation, or arising from discrepancies between measured and calculated values.

By way of example, the acute toxicity attribute for aquatic organisms (e.g. fish, invertebrates, and algae) was found to be expressed in different exposure times of 24, 48 or 96 h in differ-

Table 1
Toxicity, physicochemical, ecotoxicity and exposure potency data sets for 35 chemicals

	Chemical substance	CAS#	Physicochemical properties		Toxicity (humans)							Exposure potency				Ecotoxicity			
			Fl	R	Acute			Chronic				Persistence			Bio	Acute (F, D, Al.)		Chronic (F, D, Al.)	
					Inh. LC_{50} (mg/l)	O LD_{50} (mg/kg)	D1 LD_{50} (mg/kg)	Cancer		Non-cancer		Air (d)	Water (d)	Soil (d)	BCF/BAF (d)	LC_{50} (96 h)	EC_{50} (48 h)	LC_{50} (14 d)	EC_{50} (14 d)
								A	W	A	W								
1	Hexachlorobenzene	118-74-1	0	0	3.6	3,500	No data	3.2E+3	4.7E+3	6.1E+4	9E+4	1,564	2,088	2,088	12,240–21,140	3-F, 20E-3-Al	8.3E-3-D	No data	No data
2	1,2,4-Trichlorobenzene	120-82-1	0	0	300	1,100	11,400	0	0	3E+1	2.1E+2	55.2	180	180	120–1,320	2.9-F	0.4-D	2.4-F	3.4-D
3	Formic acid	64-18-6	0	2	7.4	730–1,830	No data	0	0	1.7E−1	4.7E−3	No data	No data	No data	0.22	46–100 F	60-D 100-A	No data	No data
4	Acetonitrile	75-05-8	3	0	16,000	4,000	1,250	0	0	1.6E+2	7E+1	54	56	28	0.3–0.4	1640-F	10000-D	NA	NA
5	Hexachloro-1,3-butadiene	87-68-3	1	1	102	25	NA	8.5E+1	1.1E+2	1.5E+4	8E+4	1,194	180	180	2,163	NA	NA	NA	NA
6	Cadmium*[1]	7440-43-9	1	1	8	2,330	NA	8.3E+1	3.9E−49	5E+6	3.6E+5	0	0	0	No data	Insoluble in water		Insoluble in water	
7	Hydrogen cyanide	74-90-8	4	2	0.16	4.5	6.9	0	0	2.1E+4	1.9E+4	No data	No data	No data	0.20	0.12	No data	2.2-F	No data
8	Phenol*[1]	108-95-2	2	0	0.316	530	670	0	0	5.7E−2	5.4E−3	0	5	5	2	24.9-F	42-D	0.28-F	3
9	Formaldehyde	50-00-0	4	0	0.48	500	270	3E−3	3E−4	4.8	5.2E−1	0.125	7	7	Not bioaccumu-lative	24.8-F	21-D	No	Chronic effect
10	Allyl alcohol	107-18-6	3	0	0.165	64–105	48 or 89	0	0	1.7	2.3	0.61	0	27	Not bioaccumu-lative	0.32	0.5	NA	NA
11	Carbon tetrachloride	56-23-5	0	0	8	2,350–2,920	5,070	8.2E+2	7.8E+2	1.4E+4	1.3E+4	400 years	1000 years	5 (volatile)	30	43-F	29(35)-D	None	None
12	Bis(tributylin) oxide	56-35-9	No data	No data	0.065	112 (180)	900	0	0	2.8E+3	2.5E+4	1.1–18	0	0	900–30,000	3.4-F	0.0046-D	No data	0.00018-D
13	Tetrachloroethyene	127-18-4	0	0	4	320–8,850	5,000	1.8	1.4	2.2E+2	1.5E+2	60	14	0 (volatile)	25.8–77.1	13.4–23.8-F	7.49–8.5-D	1.4–2.8-F	1.1-D
14	Benzene	71-43-2	3	0	13.05–52.2	930–7,000	8,260	1	8.5E−1	1.7E+1	1.4E+1	13.4	**	7.2–38.4	6–24	6–15-F	140–320-D	No data	1-D
15	Toluene*[1]	108-88-3	3	0	12.5–28.8	635–5,580	8,390–18,090	0	0	1.0	1.3	0.125	**	***	90	28–66-F	11.5-D	13.7	No data
16	Glyphosate	1071-83-6	0	0	1.3	>5,000	>5,000	0.01	0.073	49	350	No data	8.1	14.9	0.18	10-F	0.015-D	0	0
17	Gamma-HCH (Lindane)	58-89-9	1	0	1.56	88	1,000	36	130	3.8E+3	1.2E+4	No data	281–301	No data	1,400	0.13–48-F	0.048–1.6	0.0091–0.024-F	No data
18	Methylene chloride	75-09-2	1	0	73,000	1,600	>2,000	0.61	0.37	44	25	No data	704	No data	2–40	502-F	220-D	240-F	No data
19	*P*-phenylenediamine	106-50-3	0	1	No data	80	5,000	0	0	0.42	0.069	0.6	0.16	0	0.38	0.06-F	0.4-A	No data	0.1–0.18-D
20	Sec-butyl alcohol (butan-2-ol)	78-92-2	3	0	48.5	6,500	No data	0	0	0.6	0.27	2	5	0	1.71	3760-F; 950-A	No data	No data	No data
21	Ethylene oxide	75-21-8	4	3	1.59–4.14	72–320	Not irritant	31	15	2E+3	9.3E+3	71.6	12.2	No data	0.35	84–F	No data	No data	No data
22	Methyl chloride (chloromethane)	74–87–3	4	0	5.3	1,800	No data	35	2	5.4E+2	3E+2	>150	>10 years	No data	Not bioaccumu-lative	270-F	No data	No data	No data
23	Parathion-methyl	298-00-0	3	1	0.135	4	2,000	0	0	1.5E+3	4.8E+3	32 min	40	No data	71	No data	7.3	No data	No data
24	Nitrobenzene	98-95-3	2	0	0.75	580–640	450–760	0	0	35	270	Not	Persistent		3.1–4.8	42.60-F	35–50-D	No data	35-D
25	1,4-Dioxane	123-91-1	3	1	51.3	5,000–6,500	7,500–8,000	3.1E−2	9.6E−2	3.8E−2	1.2E−1	0.34–3.1	28–540	28–180	0.2–0.7	>8000-F	24–8400-D	No data	No data
26	Ethyl benzene	100-41-4	3	0	17.2	3,500	15,000–20,000	0	0	0.33	0.8	38 years	Not	Persistent	1–79.34	12.1-F	9.2-D	No data	No data
27	Triallate	2303-17-5	0	0	5.3	1,100	5,000	0.19	0.041	92	20	No data	61.3	18	1,280–1,520	1.3-F	91-D	No data	No data
28	Hexachlorocyclo-pentadiene	77-47-4	0	0	0.035	315–1,300	150–820	0	0	50	250	0.021–4	< 88.5	< 100	1,230	0.180-F	0.12-D, 0.08-A	0.0144-F	No data
29	Fenthion	55-38-9	0	0	0.0–1.2	200–300	1,680	0	0	7.9E+3	3.6E+4	<12 h	240	< 1	Not bioaccumu-lative	2.7E-3–0.87-F	0.006-D, 1.79-A	1-D	No data
30	Dicofol	115-32-2	1	0	5	500	2,000	76	230	5.8E+3	1.7E+4	No data	0.33	30–60	10,000–25,000	0.065–1.6-F, 0.14-D,	0.073-A	0.4-D	No data
31	Acrylaldehyde (Acrolein)	107-02-8	3	2	0.018–0.021	42	200	0	0	2.2E+3	1.1E+4	No data	21–69	No data	344	0.014-F	0.051–0.08	No data	No data
32	Chlorobenzene	108-90-7	3	0	18	1,110–2,455	>2,200	0	0	2.9	14	7.5	75	Not persistent	41–447	7.4–22.6-F	0.59–19.9-D	0.021-F	2.5-D
33	Acetone	67-64-01	3	0	76.1	1,800–9,750	20	0	0	0.36	0.23	10	Not	Persistent	0.69	6,210–8,120-F	>15,000-D	No data	4,550–4,800-D
34	1,1,1-Trichloroethane	71-55-6	1	1	18	>2,000	>15,000	0	0	200	190	>180	1 year	Not persistent	0.7–9	52.8-F	2384-D	133-F	No data
35	Acrylonitrile	107-13-1	3	2	1.3	81	148	1.8	1.7	88	65	5	0	0	48	25-F	7.6-D	0.34–3.6-F	No data

Fl: flammability; R: reactivity; Inh.: inhalation; O: oral; D1: dermal, C: cancer; O: oral; Bio: bioaccumulation; F: fish; D: daphnia; Al.: algae; NA: not available; *[1] implies that data for 48 h or 14 days was extrapolated using the available data published in literature; 0 implies that the chemical do not produce the effect under investigation. ** Do not hydrolyze in water; *** vaporizes immediately from the soil. *Pimephales promelas* or *Ictalurus punctatus* (fish, fresh water) flow through for 96 h (this is the type of fish used in the calculations reported in this article), and for the invertebrates, the daphnia magna (crustacean) data for 14 days was used.

ent units, viz. lethal concentration (LC) or effect concentration (EC) of 0, 50, 90 or even 100. In this paper, LC_{50} for 96 h and EC_{50} for 48 h were used because of their ready availability in literature pertaining to freshwater fishes (*Pimephales promelas* and *Ictalurus punctatus*) and crustaceans (daphnids), respectively. In addition, limited chronic aquatic toxicity data for most of the 35 chemicals used in our study, led to acute aquatic toxicity data being solely used for modeling ecotoxicity. On the other hand, some of the data for particular attributes were expressed in ranges for several chemicals. In accordance to the general practice of experts, in our algorithm, we used mostly the data corresponding to the worst case scenario to optimise safety arising in planning possible mitigating alternatives for managing the waste under question.

Two of the 35 chemicals (hydrogen cyanide and formic acid) had no data for the persistence attribute. In our case, we assumed that these chemicals were not persistent in any of the three environmental media. However, as data become available, the 0 values can be substituted. In such an eventuality, it would be prudent to check if any significant changes might occur to the final waste classification ranking, where one or both of these chemicals are constituent components. Where persistence data for only one environmental medium for a certain chemical was available, it was automatically used as the system input.

To demonstrate the feasibility of the proposed algorithm for waste classification, nine hypothetical composite wastes, each containing five chemicals with known human toxicity, physicochemistry, ecotoxicity and exposure potential, as reported in Table 1, were generated. To analyse the waste and rank its level of hazardousness, the system required a total of 71 inputs (qualitative or quantitative) to initialize the classification process. The system results generated are presented and discussed in detail in Section 4.

Fuzzy algorithm works with numerical data and so the qualitative classification of the effects related to infection from pathogens had to be transformed from symbolic into numerical values. For each category of pathogens, the linguistic values were transformed into numerical scores in the range from 0 to 1. Importantly, these scores were defined as fuzzy numbers to incorporate vagueness and fuzziness in human judgment in classifying infectious effects owing to pathogens. The numerical scores for the fuzzy system were determined using simple linear algebraic equations and the overall level of effects depicted the predominant category of pathogens present in the waste, expressed as a percentage.

For example, according to the UN classification of infectious substances, viruses are grouped into four categories (Group-I, Group-II, Group-III and Group-IV). In our algorithm, these categories were represented by using both fuzzy triangular and trapezoidal distribution functions, as shown in Fig. 3 (detailed description of these classes was presented in part I of this work [1]). To obtain numerical scores, four linear algebraic equations were developed to compute the crisp input values in accordance to the dominant virus group, as a function of the constituent percentage of the viruses to the entire population of pathogens. For instance, if the predominant viruses are Group-III viruses, then the fuzzy input number was computed using the linear equation:

$$V_{\mathrm{III}} = 0.35 + 0.3P \quad (2)$$

where P ($0 \le P \le 1$) is the overall percentage of viruses in the waste.

Similar equations were developed for other virus groups as well as the fungal and bacterial pathogens. These equations are empirical and therefore subject to change depending on the needs the user of the decision support tool described in this paper. The full equations used for the classification of the infectious pathogens in the hazardous waste are provided in Appendix A.

4. Illustrative case studies

In these illustrative examples, the composite wastes studied can be generically described as a simple mixture of chemicals. According to Feron et al. [17], a simple mixture of chemicals, regarded in this study as a composite waste, is defined as a mixture comprising a relatively small number of chemicals (mostly less than 10) whose composition is qualitatively and quantitatively known [18]. For illustrative purposes, each composite waste in our study were limited to five chemicals, for each of which 13 data inputs were required to initialize hazard identification and assessment of the waste. In total, the system required 71 user inputs to initialize the computing algorithm in order to classify a given composite waste.

4.1. System functionality

Fig. 4 illustrates the functional steps of the algorithm proposed in this paper. Owing to the complex relationships arising from the contributions of each chemical, in this algorithm, waste classification was approached as an unstructured decision problem, where both quantitative and qualitative data were taken into account. First, the constituent components of the waste were identified. In this case, the composite wastes were deemed to consist of chemicals and various categories of pathogens. The next step entailed analysis of the quantities of each constituent component present in the composite waste. The quantity of each chemical was expressed as a percentage in the range of 0–1.

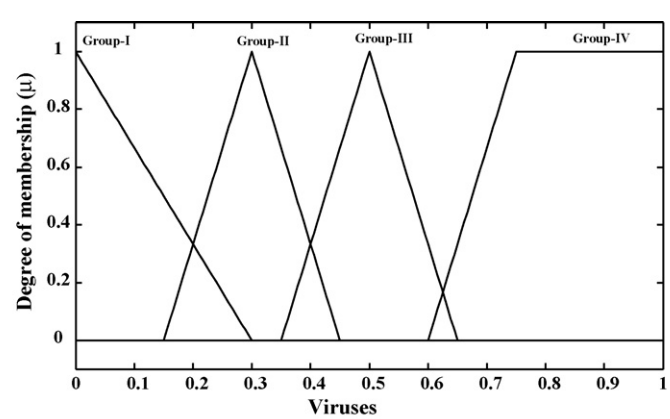

Fig. 3. The transformation of the qualitative virus classes into numerical scores in the universe of discourse of 0–1.

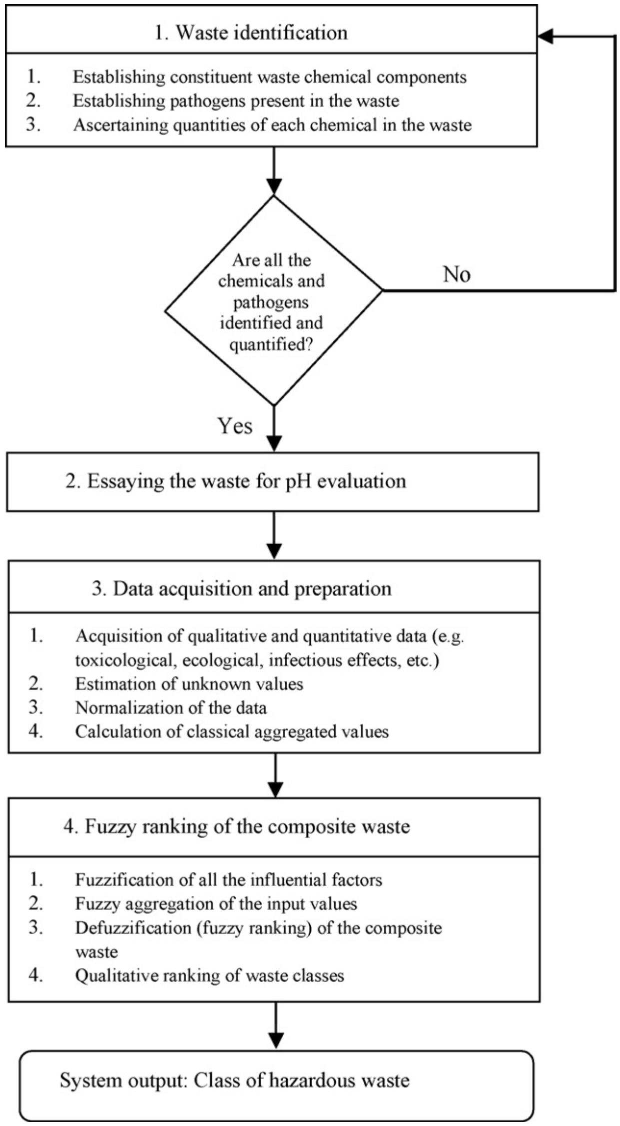

Fig. 4. System functionality for fuzzy waste classification.

Obviously the constituent chemical with the highest percentage exerted most influence on the final waste ranking.

In step two, the composite waste was assayed to determine its pH. The pH data were crucial in evaluating the corrosivity of the composite waste. Wastes with extreme pH values tended to be corrosive. In the third step, all the relevant information for each chemical was sourced from literature and normalized in formats suitable for application in the algorithm. In this case, the data acquired were either numerical, qualitative and or a percentage. Due to the diversity of the data for each chemical and the quest to increase the proposed algorithm evaluation accuracy, several normalization procedures such as calculating mean values, approximating data points using known experimental values of certain species, as well as taking logarithmic transformations to normalize distribution scales, among other, were adopted. Once normalization was complete, the aggregated values for a particular data set (e.g. flammability, reactivity, acute toxicity, etc.) in each composite waste were computed. These aggregated values were then used as fuzzy input numbers into the fuzzy systems at the lowest level of a given leave to initialize the waste classification process.

In the fourth step, the fuzzy rankings from all the knowledge rule-bases in Level-V to Level-I were aggregated and the computed lower level defuzzified output values were used as inputs to the next level to determine their respective composite fuzzy outputs. For illustrative purposes, the defuzzified Level-IV output values for acute, chronic and infectious attributes were used as inputs to compute the composite defuzzified output value for the toxicological effects attribute in Level-III. The defuzzified crisp outputs obtained at Level-I, together with the effective quantity of waste were subsequently used to calculate the final aggregated ranking of the composite waste.

4.2. Case study results and discussion

In this section, we present nine illustrative case studies representing different hypothetical composite wastes. The fuzzy inputs of the hypothetical composite wastes are summarized in Table 2.

Simulation of the input data pinpoints how different variables affect the status of a given composite waste as a function of the constituent chemicals and pathogens. The aggregated values of the variables on different levels of the hierarchical decision structure are shown in Table 3. As the solution to the waste classification problem was hierarchically structured, it is possible to examine specific attribute scores in a particular composite waste and to assess their impact on the final waste ranking. By using this information, decision-makers can formulate proper corrective or preventive measures with a view to reduce the effects of such wastes in the environment. Moreover, the designers can also use such knowledge to recommend benign chemical substitutions for some of the constituent chemicals at the design stage to mitigate the adverse effects in the event of the associated wastes entering the environment.

To demonstrate how the algorithm was applied in classifying a given waste, consider the results of the first hypothetical composite waste (W1) presented in Table 3. Different aggregated fuzzy values at different levels of the hierarchical decision tree (Fig. 2) were computed by using the constituent chemicals and pathogens, as the fuzzy inputs for various attributes defined in Row 1 of Table 2. Columns 2–12 of Table 3 show aggregated values ranging from the flammability attribute (Column 2) to the aquatic acute toxicity (Column 12). Column 13 presents the results for the highest constituent chemical value for the bioaccumulation attribute that has been logarithmically transformed on a scale of 0–5. After considering the bioaccumulation values for the constituent chemicals in W1, the highest logarithmic value of the bioaccumulation was found to be 4.48. This indicates that W1 has a very high potential to accumulate in biological systems.

The aggregated solutions for the chemical(s) with the highest persistence value(s) in air, water and soil media are shown in Columns 14–16, respectively. The persistence half-life values in all three the environmental media were scaled to values ranging from 0 to 1 for uniformity, as well as to aid transparent comparison in order to determine the medium in which the waste

Table 2
A complete data set for the hazard and toxicity rankings of the individual constituent chemicals in a composite waste

Waste	C1 (2)	C2 (3)	C3 (4)	C4 (5)	C5 (6)	pH (7)	NF1 (8)	NF2 (9)	NF3 (10)	NF4 (11)	NF5 (12)	NR1 (13)	NR2 (14)	NR3 (15)	NR4 (16)	NR5 (17)	IH1 (18)	IH2 (19)	IH3 (20)	IH4 (21)	IH5 (22)	OR1 (23)	OR2 (24)	OR3 (25)	OR4 (26)	0R5 (27)
W1	0.15	0.30	0.10	0.25	0.20	2.5	0	0	0	3	3	0	0	0	0	0	3.6	300	0.065	16,000	13.05	3,500	1,100	112	4,000	7,000
W2	0.23	0.18	0.30	0.16	0.13	11.8	0	1	4	0	3	2	1	2	0	0	7.4	102	0.16	4	12.5	730	25	4.5	5,000	5,000
W3	0.20	0.20	0.23	0.18	0.29	5.8	0	0	0	3	1	0	0	0	2	1	5.3	0.035	0.012	0.018	18	1,100	315	200	42	2,000
W4	0.40	0.10	0.10	0.17	0.23	5.9	4	1	2	4	3	3	1	0	0	0	1.59	8	0.316	0.48	0.165	72	2,330	530	500	70
W5	0.10	0.10	0.60	0.13	0.07	8.1	4	0	1	4	3	0	0	0	0	1	51.3	1.3	73,000	5.3	0.48	5,000	5,000	1,600	1,800	500
W6	0.25	0.30	0.15	0.15	0.15	7.6	0	3	0	1	3	0	0	0	0	0	300	16,000	8	73,000	76.1	1,100	4,000	2,920	1,600	8,000
W7	0.18	0.15	0.22	0.25	0.20	4.2	2	4	3	3	2	0	0	0	0	0	0.316	0.48	0.165	48.5	0.75	530	500	105	6,500	600
W8	0.14	0.33	0.17	0.27	0.09	3.7	3	3	2	4	3	0	1	0	3	0	48.5	0.135		1.8	17.2	6,500	4	580	100	3,500
W9	0.30	0.25	0.20	0.15	0.10	13.5	3	4	0	0	1	2	3	0	0	0	1.3	1.8	3.6	0.065	5	81	80	3,500	180	500

DE1 (28)	DE2 (29)	DE3 (30)	DE4 (31)	DE5 (32)	CAR1 (33)	CAR2 (34)	CAR3 (35)	CAR4 (36)	CAR5 (37)	NCA1 (38)	NCA2 (39)	NCA3 (40)	NCA4 (41)	NCA5 (42)	P1 (43)	P2 (44)	P3 (45)	AT1 (46)	AT2 (47)	AT3 (48)	AT4 (49)	AT5 (50)	B1 (51)	B2 (52)	B3 (53)
1E+5	11,400	900	1,250	8,260	4.7E+3	0	0	0	1	9E+3	30	2.5E+4	160	17	0.4	0.3	0.3	0.0083	2.9	0.0046	1,640	6	21,140	1,320	3E+4
1E+5	10E+5	6.9	5,000	8,390	0	110	0	1.8	0	0.17	8E+4	2.1E+4	220	13	0.6	0.3	0.1	46	100	0.12	1.1	28	0.22	2,163	0.20
5,000	150	1,680	200	15,000	0.19	0	0	0	0	92	250	3.6E+4	1.1E+4	200	0	0	0	1.3	0.08	0.0027	0.014	52.8	1,520	1,230	0
1E+5	10E+5	670	270	89	31	83	0	0.003	0	9.3E+3	5E+6	0.057	4.8	2.3	0.2	0.2	0.6	84	10E+4	0.28	21	0.32	0.35	0	2
7,500	5,000	2,000	1E+5	270	0.096	0.01	0.61	35	0.003	0.12	350	44	540	4.8	0.3	0.4	0.3	24	0.015	220	270	21	0.7	0.18	40
11,400	1,250	5,070	2,000	20	0	0	820	0.61	0	210	70	1.4E+4	44	0.36	0	0.3	0.7	2.9	1,640	43	220	6,210	200	0.4	30
670	270	89	1E+5	760	0	0.003	0	0	0	0.057	4.8	23	0.6	35	0	0.3	0.7	42	24.8	0.5	3,760	8,400	2	0	0
1E+5	2,000	450	1E+5	15,000	0	0	0	31	0	0.6	4,800	270	9,300	0.8	0.45	0.4	0.05	950	7.3	35	84	9.2	1.71	71	4.8
148	1E+5	1E+5	900	2,000	1.8	31	4.7E+3	0	230	88	930	9E+4	2.5E+4	1.4E+4	0.7	0	0.3	0.34	84	0.001	0.0046	0.065	48	0.35	2E+4

B4 (54)	B5 (55)	A1 (56)	A2 (57)	A3 (58)	A4 (59)	A5 (60)	W1 (61)	W2 (62)	W3 (63)	W4 (64)	W5 (65)	S1 (66)	S2 (67)	S3 (68)	S4 (69)	S5 (70)	WQ (tonnes) (71)	Waste management Level (72)
0.4	24	1,564	55.2	18	54	13.4	2,088	180	0	56	0	2,088	180	0	28	38.4	1,000	Partial
77.1	90	0	1,193	0	60	0.125	0	180	0	14	0	0	180	0	0	0	25	Effective
344	9	0	0	0.5	0	0	61.3	50	40	59	20	18	100	1	0	0	10	Moderate
0	0	0	0	0	0.125	0.61	12.2	0	5	7	0	0	0	5	7	27	90,000	Partial
0	0	0.125	0	0	150	3.1	7	8.1	704	3,650	540	7	14.9	0	0	180	600	Poor
2	0.69	55.2	54	1.46E+4	0	10	180	56	3.65E+5	704	0	180	28	5	0	0	3,000	Effective
1.71	0.2	0	0.125	0.61	2	0	5	7	0	5	0	5	7	27	0	0	1,000	Moderate
0	80	2	0.02	0	71.6	1.4E+4	5	40	0	12.2	0	0	0	0	0	0	30,000	Effective
2.5E+4	2.5E+4	5	71.6	1,564	10	0	0	12.2	2,088	0	0.33	0	0	2,088	0	60	6	Poor

C's, NF's, NR's, IH's, OR's, DE's, CAR's, NCA's, P's, AT's, B's, A's, W's, S's, WQ, $WQ_{eff,}$ represent constituent components, NFPA rankings for flammability, NFPA rankings for reactivity; inhalation, oral, dermal, carcinogenicity, non-carcinogenicity, pathogen percentages, aquatic chronic toxicity, bioaccumulation, persistence (A: air, W: water, S: soil), waste quantity and effective waste quantity, respectively. The numbers in the parentheses indicates the table column number. Numbers 1–5 in the first row refers to the specific constituent chemical data in a given hypothetical composite waste. For instance, all symbols with 1 imply different chemical properties of constituent chemical one in any of the nine hypothetical composite wastes.

Table 3
Complete set of system results based on inputs in Table 2

Waste (1)	NF (2)	NR (3)	IN (4)	OR (5)	DE (6)	C-CAR (7)	C-NCA (8)	GV (9)	GB (10)	GF (11)	AT (12)	B (13)	A_{in} (14)	W_{in} (15)	Si_n (16)	P_{eff} (17)	WQ_{nor} (18)
W1	1.350	0.000	1.597	0.13	0.036	0.150	0.102	0.470	0.645	0.315	0.8700	4.477	1.000	1.000	1.000	1.000	2.704
W2	1.770	1.240	1.958	7.424	4.353	0.180	0.205	0.860	0.315	0.515	0.0330	3.335	1.000	1.000	1.000	1.000	0.086
W3	0.830	0.650	34.93	0.640	0.243	0.200	0.219	0.000	0.000	0.000	1.4820	1.771	0.250	0.341	0.556	0.556	0.161
W4	3.270	1.300	2.329	0.941	0.337	0.182	0.147	0.410	0.260	0.160	0.0140	0.301	0.305	0.069	0.150	0.305	4.954
W5	1.730	0.070	0.249	0.063	0.059	0.138	0.141	0.240	0.370	0.645	0.2670	1.602	1.000	1.000	1.000	1.000	4.897
W6	1.500	0.000	0.022	0.047	0.787	0.150	0.152	0.000	0.315	0.280	0.0010	2.300	1.000	1.000	1.000	1.000	0.325
W7	2.700	0.000	2.487	0.311	0.356	0.150	0.196	0.000	0.315	0.280	0.0080	0.301	0.305	0.039	0.150	0.305	1.082
W8	3.100	1.140	2.829	8.554	0.055	0.270	0.288	0.808	0.370	0.233	0.0005	1.903	1.000	0.222	0.000	1.000	0.440
W9	2.000	1.350	2.753	0.792	0.229	0.196	0.180	0.210	0.000	0.645	4.0000	4.398	1.000	1.000	1.000	1.000	0.292

HC_F (19)	HF_F (20)	HR_F (21)	HFR_F (22)	AC_F (23)	CH_F (24)	IF_F (25)	PCE_F (26)	TE_F (27)	EC_F (28)	HHE_F (29)	CP_F (30)	E_F (31)	WC_F (32)	Qualitative Waste Class (33)
0.634	0.424	0.092	0.323	0.500	0.500	0.807	0.628	0.824	0.767	0.835	0.817	0.862	0.893	Extremely high (1)
0.674	0.500	0.366	0.350	0.700	0.700	0.891	0.667	0.901	0.099	0.897	0.879	0.854	0.901	Extremely high (1)
0.163	0.327	0.280	0.241	0.500	0.700	0.090	0.367	0.700	0.500	0.700	0.700	0.550	0.700	High (1), moderate (0.25)
0.130	0.715	0.369	0.550	0.700	0.605	0.599	0.700	0.700	0.094	0.700	0.700	0.300	0.550	Moderate (1)
0.130	0.500	0.092	0.350	0.100	0.500	0.459	0.500	0.500	0.572	0.500	0.530	0.844	0.700	High (1), moderate (1)
0.090	0.466	0.092	0.350	0.300	0.507	0.227	0.500	0.500	0.091	0.500	0.500	0.856	0.550	Moderate (1)
0.427	0.649	0.092	0.489	0.504	0.675	0.227	0.699	0.645	0.092	0.657	0.631	0.300	0.448	Moderate (0.49), low (0.26)
0.508	0.690	0.366	0.532	0.810	0.833	0.887	0.700	0.892	0.090	0.901	0.901	0.842	0.901	Extremely high (1)
0.832	0.500	0.384	0.350	0.777	0.654	0.383	0.819	0.789	0.500	0.789	0.780	0.862	0.772	High (0.52), extremely high (0.22)

Cols. Column number, C-CAR, aggregated carcinogenicity; C-NCAR, aggregated non-carcinogenicity; GV, virus group, GB, bacteria group; GF, fungi group; AT, aggregated aquatic toxicity; A_{in}, maximum normalized persistence in air; W_{in}, maximum normalized persistence in water; S_{in}, maximum normalized persistence in soil, P_{eff}, effective persistence system input; HC_F, fuzzy corrosivity hazard output; HF_F, fuzzy flammability hazard output, HR_F, fuzzy reactivity hazard output; HFR_F, fuzzy flammability-reactivity hazard output; AC_F, fuzzy acute hazard output, CH_F, fuzzy chronic hazard output; IF_F, fuzzy infectious hazard output; PCE_F, fuzzy physicochemical hazard index; TE_F, fuzzy toxicological hazard index; EC_F, fuzzy ecotoxicity hazard index; HHE_F, fuzzy human health effects hazard index; CP_F, fuzzy inherent chemical and pathogens hazard index; E_F, fuzzy exposure potency index, WQ_{nor}, normalized waste quantity, and WC_F, fuzzy overall waste classification.

had the highest potential to pose a threat to both humans and the ecosystems. In the algorithm, a chemical with the highest persistence value was presumed to determine the composite's waste potential residence in the environment.

Column 17 depicts the fuzzy value of the maximum persistence (algorithm input) used as an input for evaluating the exposure potency of the entire composite waste. For the case of hypothetical composite W1 (Row 1), the results show that the waste is highly persistent in all three environmental media. That is, one or more of the chemicals had half-lives greater than 2 days for air and greater than 180 days for water and soil. In this case, the fuzzy input value of 1 was used in the waste classification algorithm. However, for composite W4 (Row 4), the algorithm input was 0.305 (Column 17), as the waste had a higher persistence in air than in water and soil based on the normalised values in Columns 14–16 (0.305, 0.069 and 0.150 for air, water and soil, respectively).

To model the exposure potency using the bioaccumulation and persistence attributes, a knowledge rule-base of 12 *IF–THEN* rules was constructed. For waste No. 1, the classically normalized input values of persistence (1) and bioaccumulation (4.477) yielded an exposure potency fuzzy index value of 0.862 ranked qualitatively as *high*. Invariably, if W1 enters into the environmental media, it has high potential of causing adverse effects due to its high exposure potency.

Column 18 of Table 3 shows the weighted hazard value related to the quantity of waste anticipated to impact on the ecosystem. For composite W1, the waste quantity is 1000 tonnes per year (Table 2, Row 1, Column 71). This is not high in terms of annual production, but nonetheless, owing to its management being rated qualitatively as 'partial' in Column 72 (Row 1, Table 2), the weighted hazard ranking was computed to be 2.704. Notably, the weighted hazard value for 1000 tonnes is given more weight in terms of its potential impact on the ecosystem in comparison to W8 (Table 2, Row 8, Column 71), despite the latter being 30 times higher in annual tonnage, but managed effectively. As a result, the weighted hazard ranking for the latter waste is evaluated to be low with a fuzzy value of 0.440.

Columns 19–21 of Table 3 present fuzzy aggregated values for the Level-IV attributes of corrosivity, flammability and reactivity, respectively. The following facts should be borne in mind. First, while all the reactivity input values for the constituent chemicals in W1 are 0, the reactivity fuzzy module output shown in Column 21 was evaluated as 0.092 on a scale of 0–1. This implies that even when all the constituent chemicals are benign in terms of reactivity or any other attribute, a fuzzy system will not compute a defuzzified output value of 0. In fact, this is a conservative value and indicates that heuristics do not accord a certainty of 0%.

Second, the flammability and reactivity fuzzy values of 0.424 and 0.092, respectively, yielded a fuzzy flammability reactivity hazard index value of 0.323 (Row 1, Column 22 of Table 3). The flammability reactivity hazard index was ranked linguistically as *moderate*. Aggregating the corrosivity fuzzy output

(0.624) and the flammability reactivity hazard index (0.323), using a knowledge rule-base of 25 rules, yielded a fuzzy physicochemical hazard index of 0.628 (Table 3, Row 1, Column 26) in Level-III. Similarly, the defuzzified modular numerical output value of 0.628 was linguistically ranked as *high*. It is clear that for W1, the final aggregated physicochemical hazard was mainly influenced by the corrosivity, owing to the highly acidic nature of the waste, as evidenced by the low pH of 2.5.

On the hierarchical leaf for computing the toxicological effects in Level-III (Fig. 2), the lowest level input values (Level-V attributes) for each of the Level-IV attributes were coded into the algorithm, i.e. acute toxicity, chronic toxicity and infectious effects (Level-IV in Fig. 2.). For W1, the input values are presented in Table 2 in Row 1, Columns 18–45 for the five constituent chemicals and three pathogens. The pathogens present in this composite waste stream in terms of population percentages were 40%, 30%, and 30% for viruses, bacteria and fungi, respectively.

By way of simulating the user system inputs, the fuzzy acute hazard index, fuzzy chronic hazard index and infectious hazard index were computed to be 0.500, 0.500, and 0.807, respectively. Owing to the dominance of Group-III type viruses and Group-III type bacteria, which exhibit high infectious effects according to the UN classification system, the overall infectious effects were ranked linguistically as *very high* to reflect the type of consortium of pathogens present in the waste. Using the fuzzy aggregated values of acute toxicity (0.500), chronic toxicity (0.500) and infectious effect (0.807), yielded a fuzzy toxicological hazard index of 0.824 (Table 3, Row 1, Column27), qualitatively ranked as *very high*. The infectious attribute in Level-IV had the highest fuzzy output value, and it exerted the highest influence on the toxicological effects of W1. The reason for this is that the input variables in the toxicological effects rule-base were accorded the same weights in the design of the *IF–THEN* rules.

The computed aggregated fuzzy index values for the toxicological effects (0.824) and physicochemical effects (0.628) were then used as inputs for evaluating the overall potential human health effects of W1. The resultant fuzzy hazard index related to human health was found to be 0.835, mostly owing to the constituent chemicals and pathogens, linguistically labelled as *high* to *very high.* In this case the toxicological effects dominated as far as the potential adverse effects of W1 on human health was concerned.

In modeling the aquatic ecotoxicity in Level-II (Fig. 2), only the acute aquatic toxicity data were used, because it was mostly accessible. As the organisms (e.g. algae, fish or daphnia) used in generating the ecotoxicity data for each chemical were different, the data sourced from literature was a function of different experimental protocols and population samples. For the purpose of ensuring the consistency of results to be derived from the proposed algorithm, the ecotoxicity data were subjected to two screening tiers before it was incorporated into the fuzzy model.

If a chemical had ecotoxicity data available from more than one organism, the highest acute value was chosen (a chemical with a value less than 1 was deemed more toxic than a chemical with a value greater than 1) in accordance to experts' approach

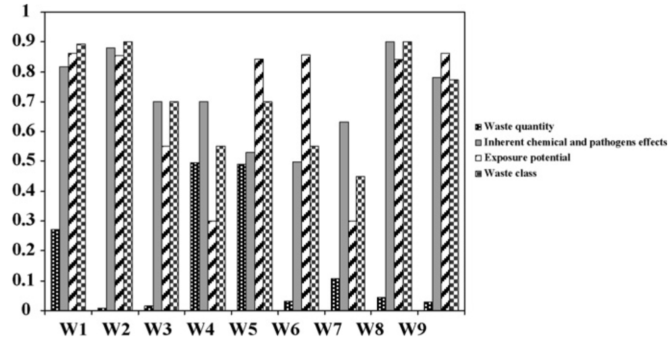

Fig. 5. Bar graphs illustrating the influence of Level-I hazard indices and the normalized waste quantity to the final waste class for nine hypothetical composite wastes.

of considering the worst case scenario (precautionary principle). That is, data value(s) for an organism indicating the potential to experience the highest aquatic acute toxic effect if the chemical was released into the environment alone was chosen as the system input. After identifying the highest value for each constituent chemical in the waste, the highest aquatic toxicity value for the composite waste was subsequently selected, using the minimum function. In the second tier, the selected value in the preceding step was normalized to a range of 0–1.

For W1, the aquatic acute toxicity data for the constituent chemicals are presented in Table 2 (Row 1, Columns 46–50) and the normalized value for the highest input data among the five chemicals is 0.870 (Table 3, Row 1, Column 12). This normalized value was linguistically ranked as *extremely* acute and the potential ecotoxicity of the waste evaluated using the fuzzy rule model was found to be 0.767 (Table 3, Row 1, Column 28). These results suggest that the fuzzy model provided fair estimates, as from casual examination of the aquatic toxicity values of the constituent chemicals one would expect W1 to be highly toxic to the ecosystem. On the other hand, this value can be improved and more representative, if the aquatic chronic toxicity data for all the constituent chemicals become available.

Fig. 5 presents bar graphs illustrating the relationship of the defuzzified fuzzy hazard indices in Level-I (chemical and pathogen effects, and exposure potency) and the normalized waste quantity (ranging from 0 to 1) to the final waste class ranking for nine composite wastes.

As mentioned previously, the rank of a waste class is influenced by input attributes in Level-I, in addition to the weights assigned to each of them during the design process of the *IF–THEN* rules. In this algorithm, the attributes related to intrinsic chemical properties and the nature of the pathogens were assigned the highest weights, followed by the exposure potency, and the contribution owing to the waste quantity that was accorded the least weight.

Waste No.s' 1 and 2 shows that the actual weight exerts negligible influence on the final waste classification. In both cases, the defuzzified input values of the other two attributes (Level-I, Fig. 2) were so high that they invoked strong synergistic effects on each other, which led to both waste hazards being linguistically classified as *extremely high*. A similar phenomenon can be deduced for hypothetical wastes No.s' 8 and 9. In the case of

W2, the ranking of the waste hazard as *extremely high* concurs with the general understanding that any waste containing high percentages of hydrogen cyanide is more likely to exhibit high toxicity properties.

As shown in Fig. 5, waste No.s' 3 and 5 have the same final waste ranking, although their inputs are markedly different. In particular, the synergistic effects of all the Level-I attributes are clearly demonstrated in these waste streams. Reducing the input value of each of the Level-I attributes led to a drastic reduction in the final waste ranking and the converse was also observed for W6, irrespective of the exposure potential being rated as *very high*. However, the moderate chemical and pathogenic toxicity and low weighted hazard associated with the quantity of the waste, contributed to the overall ranking of the waste hazard as *moderate*. Similarly, for W7, the constituent components had both *low* to *very low* linguistic rankings for the exposure potential and the waste quantity, respectively. On the other hand, the inherent properties of the constituent components had *moderate* to *high* ratings. However, the contribution of each attribute in Level-I led to the waste being rated as *low* to *moderately* hazardous. In view of the foregoing discussions, it is clear that integrating various factors that influence the waste ranking by use of fuzzy sets, even if measured in different metrics, provides a more balanced approach to preliminary classification of composite wastes.

5. Conclusions

A comprehensive classification protocol for composite wastes is lacking as those presently reported in literature have only incorporated a limited number of chemical properties or are based on pre-defined lists. Moreover, the data and information currently accessible contain varying degrees of uncertainty, e.g. expressed symbolically, or measured using different protocols and metrics. Consequently, the comparability and integration of different data sets required to build a robust hazardous waste classification model is still a major limitation, particularly where traditional classical approaches are adopted. In this two-part paper, a new classification methodology was introduced for ranking the hazards of simple composite wastes on the basis of their constituent components. Nine hypothetical examples of composite wastes were presented and discussed to illustrate the applicability of the proposed waste classification model.

The proposed methodology deals with data uncertainty, as well as difficulties in integrating different data sets without compromising the robustness of solutions. With the proposed methodology, the contributions of different chemical properties and types of the pathogens are integrated by hierarchically decomposing the problem and then applying fuzzy logic inferencing at each level. This has made it possible to develop hazard indices at various levels of the hierarchical structure and to integrate them into the next higher level, until the class of the waste is determined.

The algorithmic model for composite waste classification can be used in different ways as a decision support tool for real world waste management problems. This could include rapid assessment of waste hazardousness based on the intrinsic chemical properties and presence of pathogens, selection of less hazardous chemical substitutes in a particular application, and quantification of the extent of the hazard posed by a composite waste to both humans and ecosystems in order to develop alternatives for handling it adequately and cost effectively.

Nevertheless, application of the decision tool also has certain limits at present. The first is related to gaps in the data on the intrinsic properties of chemicals. This can be improved as more data and information on numerous chemicals becomes available in literature. Second, the system does not take into account the possibility of the formation of new compounds, owing to reaction of the constituent elements. This may result in the overall waste class being over- or under-estimated, depending on whether the reaction products are benign or more hazardous than the original reactants.

Appendix A

Set of empirical equations used for evaluating the effect of pathogens

Categories	Virus	Bacteria	Fungal
I	$V_I = P1 \times 0.3$	$B_I = P2 \times 0.4$	$F_I = P3 \times 0.4$
II	$V_{II} = 0.15 + P1 \times 0.3$	$B_{II} = 0.15 + P2 \times 0.55$	$F_{II} = 0.15 + P3 \times 0.55$
III	$V_{III} = 0.35 + P1 \times 0.3$	$B_{III} = 0.45 + P2 \times 0.55$	$F_{III} = 0.45 + P3 \times 0.55$
IV	$V_{IV} = 0.65 + P1 \times 0.35$		

These above equations are empirical and are flexible enough to allow variations based on the data set of the user so as to meet the needs of policy makers depending on hazardous waste management priorities.

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