An Intelligent Algorithm Integrating Fuzzy Takagi-Sugeno Inference and Bowtie Method: A Risk Assessment Application

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ABSTRACT

Bowtie approaches are powerful tools in risk analysis. From the semi-quantitative perspective, logic gates might be used in system modeling to obtain the consequence frequencies and risk information. However, the model results are affected by the uncertainty that can emerge from subjective evaluation, data variation, or lack of data. Fuzzy logic helps to deal with system uncertainty and apply intuitively specialist elicitation. Few papers, most of them related to fuzzy fault trees, only use fuzzy sets and fuzzy mathematical relations to deal with uncertainty and still obtain equations that resemble those that originated from a traditional quantitative method. This work develops an application in Python language using fuzzy sets and Takagi-Sugeno inference system, aiming to deal with the uncertainty and facilitate the assimilation of the specialist knowledge about the system. The model outputs top event and outcomes frequencies. A comparison with an arithmetic fuzzy bowtie study is accomplished to validate the results.

1. INTRODUCTION

The complexity of the chemical processes nowadays means that the system is composed of a significant number of components, various procedures, and various human responsibilities. These increase the chance of the system coming to multiple failures developing in an accident. Major chemical disasters are known by their severity: Chernobyl (1986), Bophal (1984), and Seveso (1976). The risk assessment concept emerges as an important tool involving mathematical and analytical methods providing the safety of chemical industries. Khan & Abbasi (1998) said that the science behinds risk assessment, which emerged in recent years, approaches three critical aspects of accident in the chemical process: the progress of techniques and tools to forecast accidents, the improvement of techniques and tools to analyze consequences of these possible accidents and progress of management strategies to prepare for emergencies or mitigate damage. Khan, Rathnayaka, and Ahmed (2007), by categorizing risk techniques (approaching the last two of three key aspects cited) in quantitative, qualitative, semi-quantitative, and hybrid, pointed out that quantitative and hybrid techniques researches have increased in the last years in the field.

The bowtie technique is used as a combination of a fault tree and an event tree and, although very promising, has not been explored in the technical and scientific literature. The combination of logical operators allows the calculation of the frequency of consequences of an accident, while the frequency of that accident is calculated by entering the frequency of basic events. Most works do not consider an important aspect of the bowtie: method, the barriers (control measure to prevent a threat or mitigate a consequence). And this perspective of the method is largely adopted in an industry context, where the bowtie initially emerged as a qualitative tool [3]. These two appointments, about the academic and industry contexts, show that a new method providing the aggregation of quantitative and qualitative aspects, considering the bowtie structure used in the industry, is an excellent opportunity to be studied.

But the calculation carried out by the quantitative or hybrid techniques is usually affected by the imprecision and vagueness inherent from the data used as input. This information can be originated from the subjective knowledge of the specialist about the system or a database with a lack of data. To deal with this problem, fuzzy theory can overcome the imprecision and vagueness, once resembling human reasoning from a mathematical interpretation. Also, the inference methods included in the fuzzy theory can capture the operator's knowledge about the system and turn it into logical rules (IF-THEN). Two of these methods can be highlighted: Mamdani and Takagi-Sugeno. All the works related to the fuzzy bowtie approach only use fuzzy sets to define linguistic terms and arithmetic operations between them but don't use inference methods. The inference method as part of the fuzzy bowtie method can better consolidate all the subjectivity knowledge about the relation between two basic events.

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This paper provides a new fuzzy bowtie method, which Takagi-Sugeno was used as an inference method. A case study of an isobutane storage tank rupture presented in Markowski et al. (2009), applying an arithmetic fuzzy technique, served as a comparison basis to the system responses once the bowtie from this work was built based on that work. Using this method, the paper intends to show how bowtie can be helpful as a hybrid tool. Using fuzzy logic can deliver a more precise result and better aggregate the subjective knowledge about the process.

2. Fuzzy Fundamentals

The fuzzy theory is derived from the concept of multivalued logic developed by notable logicians Jan Lukasiewicz, Bertrand Russel, and Max Black, a concept from the early 1930s. When introduced at that time, the theory was not coined by the term fuzzy, and it was usually called the term ‘vagueness’. The term fuzzy came to be used when Professor Lofti Zadeh developed his theory coining the term ‘fuzzy’[5].

The theory developed by Zadeh defines the fuzzy sets, in what each element of that has set membership degree. It differs from the classical set theory, in which the components are classified into two groups: members and nonmembers. The fuzzy logic allows classifying the elements between a range of 0 to 1, called membership degree. This theory characteristic supports the mathematical interpretation of terms and expressions used by specialists or operators in process safety meetings (very high, fairly high, or high). The membership degree is defined by the membership functions (Figure 1). different types of these functions: Triangular, Trapezoidal, Gaussian, Sigmoid. They are chosen considering the characteristics of the application.

$$\mu_A(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a} & a < x \le b \\ 1 & b < x \le c \\ \dfrac{d-x}{d-c} & c < x \le d \\ 0, & x > d \end{cases}$$

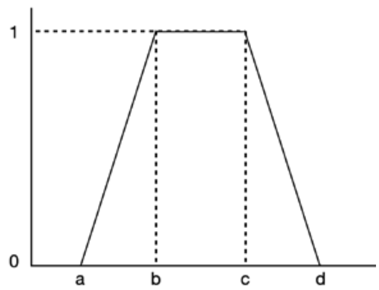


Figure 1 Trapezoidal membership function

The fuzzy theory embraces the called fuzzy rule-based system, prevalent in control process applications. It is used to make decisions and turn this into heuristic rules. As to structure a rule-based system, four steps must be accomplished.

The first one is fuzzification, which is the conversion of a crisp value into a fuzzy value. This step is the only way to make the system entries compatible with linguistic terms represented by fuzzy sets in the rule base.

Following the fuzzification comes the knowledge base, which consists in what is known about the process. The operators' knowledge about relations between inputs and consequences will provide a practical base to define membership functions.

Once the fuzzy sets are settled, the rule base can be defined. The knowledge-basis is expressed as a set of IF-THEM rules where the knowledge of operators and specialists can be put together, as the example:

$$Frequency\ is < Very\ Low > \boldsymbol{AND}\ Frequency\ is < Low > \boldsymbol{THEN}\ Frequency\ is < Very\ Low >$$

These rules can be interpreted using various inference methods. The most recognizable are the Mamdani method (1) and the Takagi-Sugeno method (2). The first one uses linguistic variables as antecedent and consequent, and the second uses linguistic variables as antecedent and mathematical functions as consequent. Each rule will obtain a result depending on the degree of membership related to their antecedents, and the aggregation of these rules will deliver the final result.

$$\boldsymbol{IF}\ x_i \text{ is } A\ \boldsymbol{AND}\ y_i \text{ is } B\ \boldsymbol{THEN}\ z_i \text{ é } C \quad (1)$$

$$\boldsymbol{IF}\ x_i \text{ is } A\ \boldsymbol{AND}\ y_i \text{ is } B\ \boldsymbol{THEN}\ z_i = a_1 x_i + b_1 y_i \quad (2)$$

At last, the defuzzification process turns the fuzzy value into a crisp value. There are various defuzzification methods: centroid, bisector, mean of maximum, min of maximum, and max of maximum. Also, the choice of one of them depends on the application characteristics. In the case of the Takagi-Sugeno method, there is no need for defuzzification once the consequent of the rules is already a crisp value. There are different orders of Takagi-Sugeno. For instance, the rule shows an example of first-order. Also, Takagi-Sugeno zero-order can be viewed as a particular case of the Mamdani inference method, where the consequent is seen as a fuzzy singleton (Figure 2).

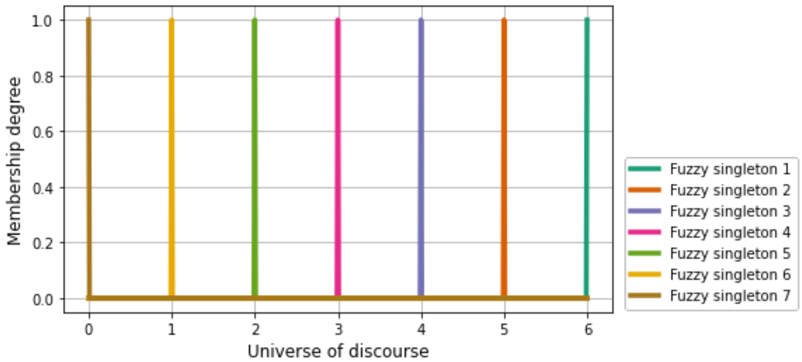


Figure 2 Example of a fuzzy singleton function

3. DESCRIPTION

3.1 Bowtie case study

The case chosen to apply the fuzzy bowtie method was the system proposed by Markowski et al. (2009). A bowtie of isobutane storage tank rupture in Figure 3 shows the combination of a fault tree and an event tree without the barriers. The main focus of this study is the inference method application.

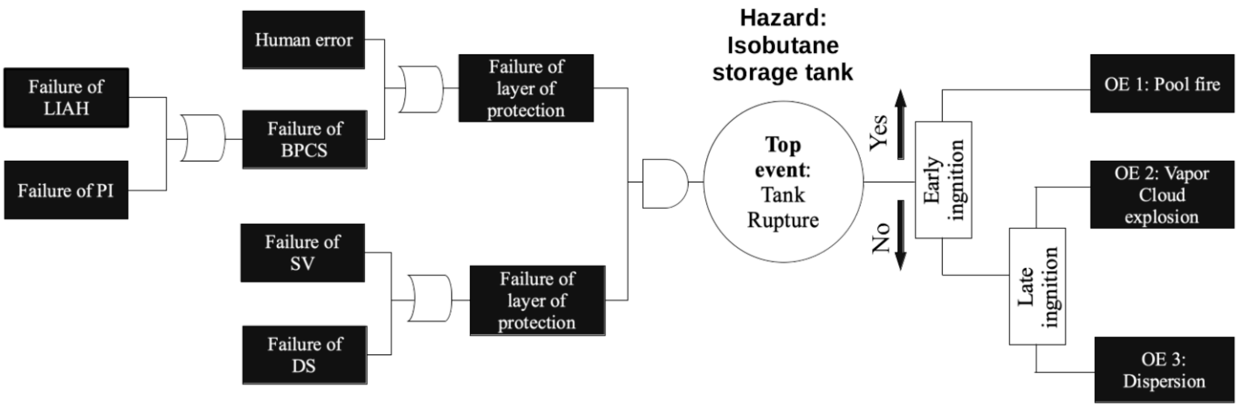


Figure 3 Bowtie designed structure (Markowski et al., 2009)

3.2 Fuzzy bowtie structure

The traditional logic operators in the previous structure, on the left side, were changed by fuzzy Takagi-Sugeno inference nodes (T-S nodes), see Figure 4. Unlike what Markowski et al. (2009) carried out on the right side, it was defined fuzzy probability numbers to YES/NO alternatives, the new structure kept the crisp values in this study.

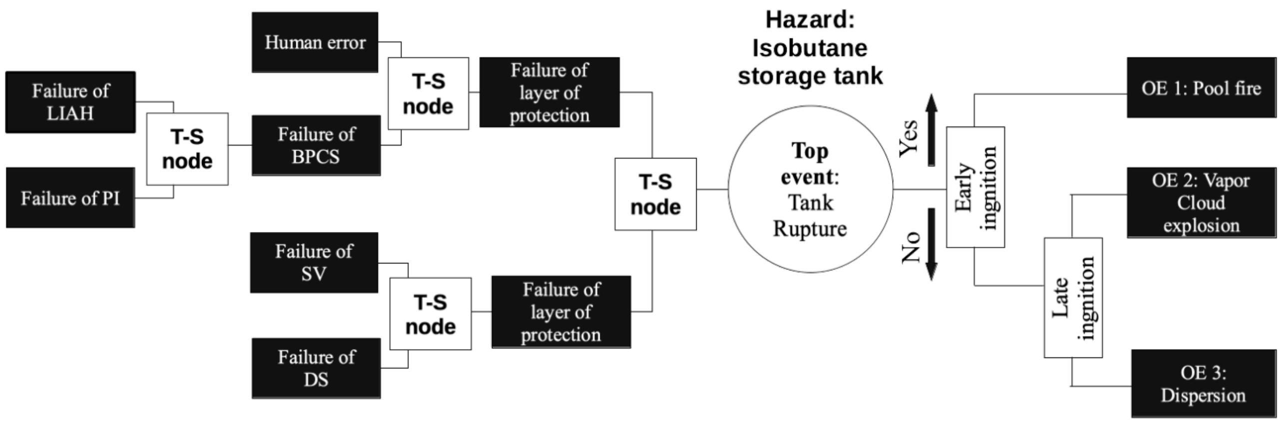


Figure 4 Fuzzy Bowtie (Takagi-Sugeno inference) structure

3.3 Definition of Fuzzy Sets

The fuzzy numbers parameters are given in Table 1. In this study, fuzzy trapezoidal numbers are proposed inspired by the related work [4]. As to facilitate dealing with the parameter adjustment, it was used the logarithmic calculation of the frequencies. Figure 5 shows the fuzzy sets depicted in the graph highlighting the smooth transition from one set to another.

Table 1 Frequency fuzzy numbers parameters used in the bowtie right side

Variable	Fuzzy set	Fuzzy trapezoidal number
'OR' NODE 'AND' NODE	Impossible (I)	[5.12, 5.60, 8, 8]
	Very Low (VL)	[4.12, 4.60, 5.12, 5.6]
	Low (L)	[3.12, 3.60, 4.12, 4.6]
	Moderate (M)	[2.12, 2.60, 3.12, 3.60]
	Fairly High (FH)	[1.12, 1.60, 2.12, 2.60]
	High (H)	[0.12, 0.6, 1.12, 1.60]
	Very High (VH)	[0, 0, 0.12, 0.60]

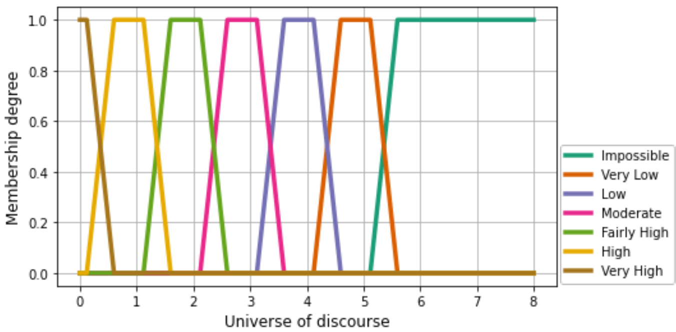


Figure 5 Trapezoidal functions graph from the defined fuzzy sets

3.4 Basic Events Inputs

The inputs used by Markowski et al. (2007) were replicated (Table 2). The crisp values were considered the mean values of the fuzzy trapezoidal set of each linguistic term.

Table 2 System inputs: Crisp values and linguistic terms

	LIAH	PI	HE	DS	SV
Input values	1	1	2	2	2
Linguistic terms [4]	H	H	FH	FH	FH

3.5 Python Program

The application was developed in Python language using the Fuzzylab library [6], a library based on the Octave fuzzy logic toolkit. Also, two more libraries were used to support the analysis of the results: Matplotlib and Numpy.

4. DISCUSSION

4.1 Formulation of rule base

Once the linguistic terms and their fuzzy sets were defined, the rules were formulated based on the relation between the events. These relations were obtained by previous specialist knowledge. It was generated forty-nine rules to describe the system. Table 3 shows an example of 'OR' rules.

Table 3 Rules examples used for Takagi-Sugeno Inference in node 1.

Rule		Event failure frequency 1		Event failure frequency 2		Failure frequency result
1		Very Low		Very Low		Very Low
2		Low		Low		Low
3		Very Low		Low		Low
4		Low		Very Low		Low
5		Moderate		Moderate		Moderate
.	**IF**	.	**AND**	.	**THEN**	.
.		.		.		.
.		.		.		.
43		High		High		High
44		Very Low		High		High
45		High		Very Low		High
46		Low		High		High

4.2 Adjustment of Zero-order Takagi-Sugeno consequent parameters

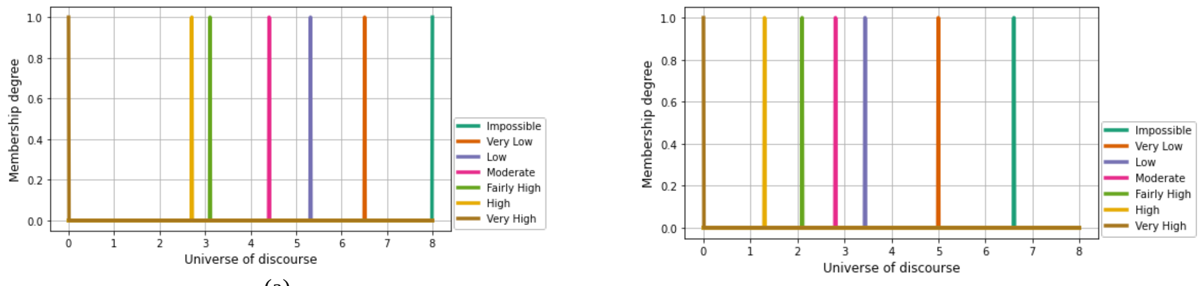
This work used Takagi-Sugeno zero-order inference, which required adjusting the consequent parameters, representing the linguist term assigned in the rules. The final values can be seen in Table 4.

Figure 5 illustrated these parameters as singleton functions, reinforcing that zero-order Takagi-Sugeno inference could be considered as a particular case of the Mamdani inference method.

Table 4 Frequency fuzzy numbers parameters used in the bowtie right side

‘AND’ node	
Impossible (I)	8.0
Very Low (VL)	6.5
Low (L)	5.3
Moderate (M)	4.4
Fairly High (FH)	3.1
High (H)	2.7
Very High (VH)	0.0

‘OR’ node	
Impossible (I)	6.6
Very Low (VL)	5.0
Low (L)	3.4
Moderate (M)	2.8
Fairly High (FH)	2.1
High (H)	1.3
Very High (VH)	0.0

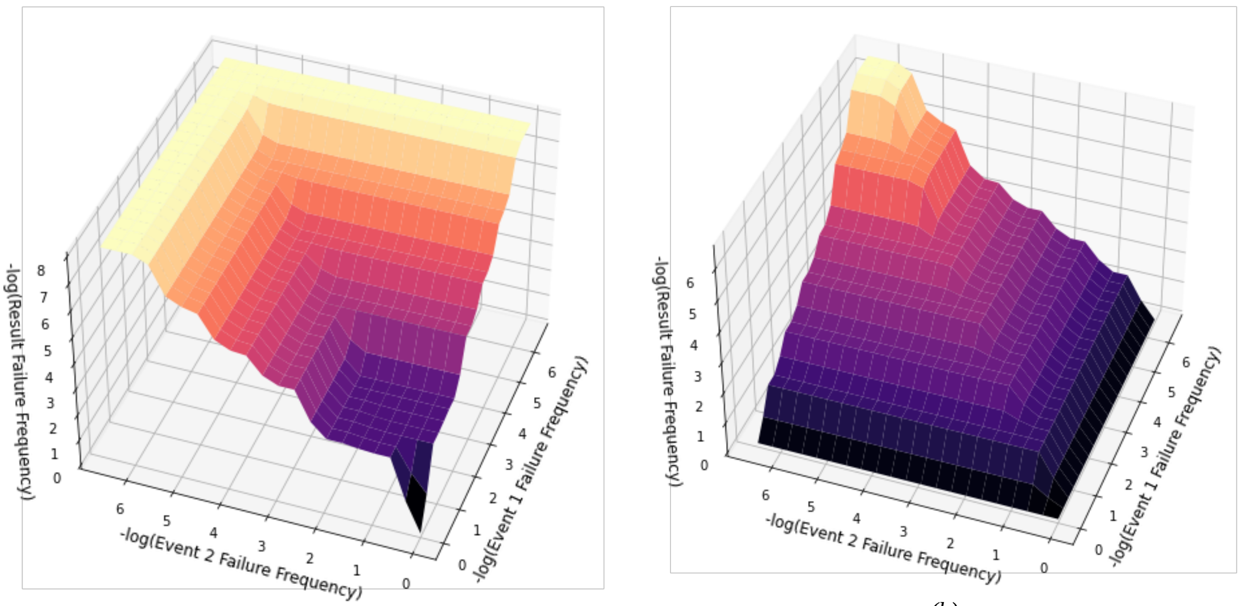


(a) (b)

Figure 5 (a) Zero-order T-S rules parameters for ‘AND’ node represented as singleton functions graph; (b) Zero-order T-S rules parameters for ‘OR’ node represented as singleton functions graph.

4.3 Response surface for ‘AND’ node and ‘OR’ node

Once the system was coded in Python and parameters defined, the program was run for various input frequencies between a range of zero to eight [0,8]. Thus, resulting in a response surface for ‘AND’ and ‘OR’ nodes (Figure 5). It demonstrates the behavior related to the results from the combination of two events frequency variation.



(a) *(b)*

Figure 5 (a) Response Surface for ‘AND’ node frequencies; (b) Response Surface for ‘OR’ node frequencies.

4.4 Comparison of zero-order Takagi-Sugeno inference and Markowski Fuzzy arithmetic operations

Table 5 shows the results of frequencies of top event and outcomes to arithmetic fuzzy bowtie and a fuzzy bowtie Takagi-Sugeno inference. It is important to emphasize that the safety functions frequency of failure in the event tree were considered for 'Early Ignition', 0.80 for 'YES', and 0.20 for 'NO'. And for 'Late Ignition', 0.60 for 'YES' and 0.20 for 'NO'.

The top event result for the two methods differed 2.82e-3 from each other, with Takagi-Sugeno fuzzy bowtie having the lower frequency. This difference is not relevant, given the magnitude of the value. All values of the outcomes, from the Takagi-Sugeno fuzzy bowtie, were higher when compared with the results of Markowski et al. (2007). This difference is related to the choice about not using fuzzy numbers to define the safety functions in the fuzzy bowtie system, the opposite of an arithmetic fuzzy bowtie system.

Table 5 Frequency fuzzy numbers parameters used in the bowtie right side

	TE	OE1	OE2	OE3
Fuzzy bowtie (Arithmetic fuzzy bowtie**)**	**4.40E-3**	**4.37E-4**	**4.98E-5**	**5.53E-6**
Fuzzy bowtie (Takagi-Sugeno inference**)**	**1.58E-3**	**1.27E-3**	**1.90E-4**	**1.27E-4**

5. CONCLUSION

A fuzzy bowtie using the zero-order Takagi-Sugeno inference method was coded in Python language. The values of the top event and outcomes frequencies were obtained to observe the system response, also comparing them with arithmetic fuzzy bowtie results. These observations showed that the system response is consistent with what was expected.

Other studies on inference methods, as pondered Mamdani and Mamdani, are being carried out. The following steps will be related to incorporating barriers in the structure, calculating the risk, and building a risk matrix using an inference method. Using Mamdani will indicate the degree of membership related to the results (78% High, 22% Moderate), allowing the specialists to understand better the information produced by the hybrid risk assessment method.

6. ACKNOWLEDGEMENT

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