**Fuzzy Process Safety Analysis for Process Industries**

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**ABSTRACT**

Fuzzy logic deals with uncertainty and imprecision, and is an efficient tool for problems where knowledge uncertainty may occur. Such situations arise frequently in a process safety analysis of different industrial processes. The lack of detailed data on failure rates, uncertainties in available data, imprecision and vagueness and other deficiency in a safety analysis may lead to uncertainty in results, thus producing an underestimated or overestimated process risk index.

This paper explores the application of the fuzzy sets theory for risk assessment basically used in all process safety analysis. The traditional part and fuzzy part of process risk assessment were selected and the application of Fuzzy Logic System (FLS) was made applying either the fuzzy rules or the fuzzy arithmetic. Using FLS concept, the consequence analysis, important for emergency management, is presented and the BLEVE calculation illustrates the effect of fuzzy arithmetic application. The preliminary tests confirmed that the final results on the range of distance to radiation threshold values are more precisely and realistic determined.

**Key words**: process safety analysis, uncertainty, fuzzy set, fuzzy logic, consequence analysis

## 1. Introduction

Chemical process industry plays a vital role in daily life although its public image is rather negative. Major accidents, when they do happen, result in numerous losses resulting in bad publicity and stricter regulations, e.g. Seveso Directives. However, several current developments point to a significantly brighter future. These developments relate to practising inherently safer design, and application of the more reliable safety systems. All those developments must be assessing in terms of the process risk. Such an exercises called Process Safety Analysis (PSA) enable decisions concerning the selection of appropriate technical and organization safety measures in order to meet risk acceptance criteria [1].

Traditional PSA requires numbers of input data for the models used for probability assessment as well for consequences analysis. However, the variability of data and assumptions used for those mathematical models form uncertainty and complexity. In such way, risk analysis results of PSA may not be considered as exact, precise and creditable output data. Therefore, it is important to look for the methods that may reduce the level of uncertainty in the description of process hazard risks. One of the promising methods for reduction of the uncertainties in process safety assessment seems to be fuzzy logic [2,3]. The present paper gives some results on the application of the fuzzy logic in the classical process safety analysis.

## 2. Traditional risk assessment model

Traditional risk assessment model presents Fig. 1.

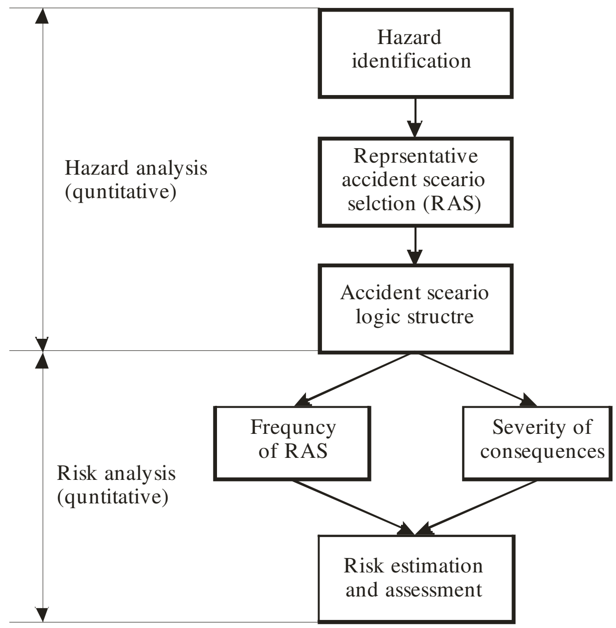


Fig. 1. Framework for process risk analysis.

There are two main phases:

1. The qualitative hazard analysis.
2. The semi-quantitative or quantitative risk analysis.

The first phase includes hazard identification and risk ranking in order to select the list of representative accident scenario (RAS). Several methods can be applied here including Hazard and Operability studies (HAZOP), Preliminary Hazard Analysis (PrHA), Failure Mode and Effect Analysis (FMEA), and others [1]. Those scenarios are subsequently examined by constructing of the fault tree (FT) and event tree (ET), in order to provide "bow-tie" model for each scenario. This is starting point to the second quantitative phase.

This is usually performed by the Quantitative Risk Assessment (QRA) or semi quantitative risk assessment, e.g. LOPA. Within QRA or LOPA, two components are needed to be determined. The first one concerns the frequency of particular accident scenario, which is determined based upon previous established logic structures of the fault and event trees. They identify the different combinations of basic, intermediate and top events for fault tree and conditional, safety function and outcome undesirable events for event tree. After qualitative examination of structure (MCS) the quantitative analysis of fault tree and event tree take place. The calculation requires providing the failure rate data for all inputs events identified in fault and event trees. Both those analytical tools are based on traditional Boolean mathematical models using the classical two-valued logic where all variables are assumed to

have sharply defined boundaries. Usually, as a result of that analysis a single-valued frequency, which characterizes a particular accident scenario, is obtained.
The second parallel component of QRA concerns the assessment of possible severity of consequences of those RAS. It can be accomplished in several ways, e.g. by the effects and consequences analysis or for certain cases by the subjective reasoning and expert judgement. Both components that is frequency and severity of consequences are combined together to get risk contours map (in QRA) or category of risk (in LOPA).
The output from the risk analysis usually provide point estimate of risk, which may be change to the other single-valued risk after introducing a new input data. In such way, these point estimates belong to a risk distribution that reflects the uncertainties in the data and models applied in the PSA.
As can be concluded, the assessment of safety assurance cannot be based on the single-valued risk and the same, plant cannot be classified into the dichotomy safe/unsafe only. This is because the process plant is never safe or unsafe on an absolute basis. It has always a certain level of hazards, which cannot be completely eliminated as well as due to numbers of uncertainties it always has a certain level of “unsafeness”. This eliminates the Boolean approach, which sharply says: plant is safe or plant is unsafe. Therefore, there is need to apply some other mathematical method that will tell, “how much is process plant safe”, that is method which introduce the “matter of degree”. This is fuzzy logic, which may deal with typical risk assessment uncertainty caused mainly by fuzziness, vagueness and ambiguity.

## 3. Uncertainty in process risk assessment

Uncertainty in process risk analysis applies to imperfect prediction of future accident scenario risk related to unwanted release of dangerous substance encountered in chemical processes. The Process Safety Analysis (PSA) realizes that prediction. Taking into account Fig.1 there are four main components to be analysed:

- identification of accident scenario (RAS),
- the frequency of the RAS, and
- severity of consequences of those scenarios,
- risk estimation and assessment.

Each component has its own specific functions in PSA and the same there are different uncertainties sources related to above mentioned components.
In terms of PSA, consisting of some separate steps of analysis with different qualitative-quantitative approaches in each step, it is convenient to distinguish three types of uncertainties:

1. completeness uncertainty,
2. modelling uncertainty,
3. parameter uncertainty.

**The completeness uncertainty** refers to the question whether all significant phenomena and all relationships have been considered. This uncertainty is difficult to quantify but this type is a major contributor in hazard analysis. **Modelling uncertainties** refers to inadequacies and deficiency in various models used to assess accident scenario probabilities and its consequences. Availability of these models may enable the interpretation of different degrees of belief in each model. This is a major type of uncertainty in consequence assessment. This is a subjective uncertainty or knowledge elicited from experts, which is often incomplete, imprecise and fragmentary. The imprecision and inaccuracies in the parameters which are used as an input to PSA are called **parameter uncertainty**. Such uncertainty is inherent because the available data are usually incomplete and the inference process needs to be based on incomplete knowledge. However, there is an opinion that parameter uncertainty is the easiest to quantify. This type may exist in each step of PSA. It is not easy to separate all these types. Table 1 gives a summary of the sources and types of the uncertainties in PSA.

Table 1. Sources and types of uncertainties in PSA

| Step of PSA | Main goal | Main tool | Types of uncertainty | | |
|---|---|---|---|---|---|
| | | | Completeness | Modelling | Parameter |
| Hazard analysis | Identification and logic structure of accident scenario (RAS) | HAZOP PHA Fault Tree (FT) Event Tree (ET) | Inability to identify of all contributions to risk and all RAS as well errors in screening of hazards | Wrong interaction between different contributors and variables in accident scenario models | Imprecision or vagueness in characteristic properties of contributors and variables |
| Consequence assessment | Health, property and environmental consequences | Consequen-ce models | Incorrectness in identification of all types of the consequences as well as of all interactions among consequences | Complexity phenomena and inadequacy and imprecision of the models for source terms, dispersion and physical effects | Lack or inadequacy or vagueness in values for model variables |
| Frequency | Frequency of RAS | FTA and ETA (“bow-tie model”) | Wrong selection of events, safety function and number of accident outcome cases | Wrong analysis of FT and ET leading to inadequate Minimum Cut Set (MCS) | Lack of real time data for equipment failure rates and human errors |
| Risk estimation | Risk indexes or risk category | QRA QRAS LOPA | Limited assumptions in: external conditions, in number of accident outcome cases and incorrectness in interpretation of results | Inadequacy in selection of appropriate risk measures as well as of risk acceptance criteria | Lack of real time data weather conditions, ignition sources and population |

There are many different approaches to uncertainty analysis: classical statistic, probabilistic, sensitivity analysis and possibility approach [4-5]. In science, it is traditional to deal with uncertainty through the use of probability theory. This approach is frequently used for variability uncertainty connected with stochastic variability of different parameters or measurable quantity used for different PSA methods. It does not work with knowledge uncertainty especially encountered in the frequency analysis (FTA and ETA) and consequence assessment. Knowledge uncertainty is generally more difficult to handle than physical variability.

One of the current uncertainty theories devoted to the handling of incomplete information more precise and the simplest from mathematical point of view, is the possibility theory [6-8]. This theory, which emerged from the fuzzy sets developed by Zadeh [2] considers expert information on a particular linguistic variable, e.g. frequency rate of particular basic event with possibility being matter of degree from 0 to 1. As a result of application of fuzzy logic system (FLS) applied to a certain step in the PSA, the output variable (e.g. risk representing safety assurance level) is obtained and represented by a certain fuzzy set what allows to answer the question of safety: **“how safe is the plant?”** This is a completely opposite approach to the typical risk evaluation method where the received risk level answers only to the question: **“is the plant safe?” As we said before, the a**nswers “no” or “yes” are unrealistic because of, e.g. the presence of inherent risk in each chemical plant. Therefore, we feel that the process safety analysis is a “fuzzy issue” and therefore the fuzzy sets theory can be effectively included into process risk analysis to reduce substantially knowledge uncertainty.

## 4. Fuzzy logic basic

Fuzzy logic is the general name of “fuzzy set analysis” and “possibility theory,” which can work with uncertainty and imprecision and is an efficient tool for applications where no sharp boundaries (or problem definitions) are possible.
Fuzzy set A, defined on collection of objects called universal set X, represent a class of objects with a continuum of grades of membership. Such a set is characterized by the membership (characteristic) function, $\mu_A(x)$ which assigns to each object a grade of membership ranging between zero (non membership) and one (total membership). In that way a fizzy set is set of pair: $A = \{(x, \mu_A(x)); x \in X\}$, where $\mu_A : X \rightarrow [0,1]$ is membership function describing degree of belonging for x in A. Fig. 2 illustrates the differences between classical set and fuzzy set for “”safe state”.

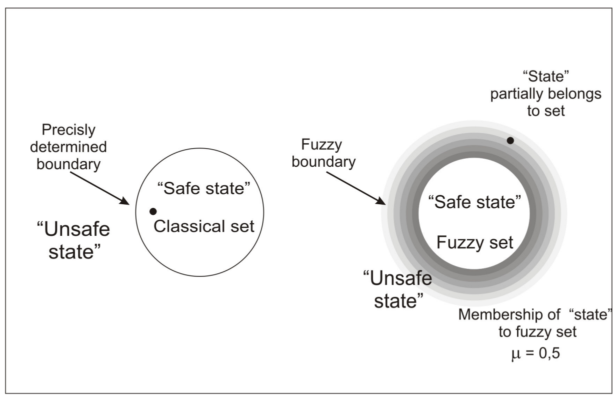


Fig. 2. Classical set and fuzzy set for “safe” and “unsafe” state.

The fuzzy sets undergo similar mathematical operations like in classical set theory that is intersection, union, and complement and the the foundations of fuzzy arithmetic are already well established [9].
The use of fuzzy logic (FL) in different aspects of safety and reliability analysis has been undertaken in a number of papers [10 - 14].
Fuzzy modeling is realized by the Fuzzy Logic System (FLS), which maps crisp inputs into crisp outputs. The FLS structure is shown in Fig 3.

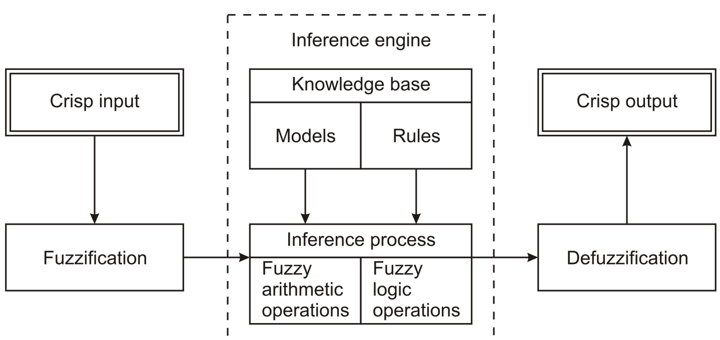


Fig. 3. The structure of a typical fuzzy logic system (FLS)

Fuzzy logic system (FLS) consists of the following components:

1. The fuzzifier decomposes system input variables with crisp numbers and maps the crisp numbers into fuzzy sets. It means that fuzzification is the formation of fuzzy set $\overline{A}$ in some relevant universe of discourse $X$ { $x_1,x_2,x_3,\ldots$} with assignments of the membership function μ(x) to particular linguistic variable, to be represented by the order pair (x, μ(x)).
2. The inference engine of the FLS maps input fuzzy sets, by means of a knowledge base, into fuzzy output sets. It follows "if-then-else" rules established on the basis of human knowledge and/or mathematical calculus specifically used in analysis of particular operation. Each rule consists of a condition and an action, where the condition is interpreted from the input fuzzy set and the output is determined from the output fuzzy set. Each calculus represents mathematical algorithms describing certain analysis, e.g. consequence or frequency analysis. In other words, fuzzy inference is a method that interprets the values in the input vector and, based on a set of rules, assigns values to the output vector.
3. The defuzzification is a process of weighting and averaging the outputs from all of the individual fuzzy rules or calculus into one single output precise, defuzzified, crisp value.

In such a way by means of FLS one is able to maps imprecise, uncertain input parameters of the particular model into output of this model that is exactly determined. This property was built-in a typical risk assessment procedure forming fuzzy risk assessment model (fRA).

## 5. Fuzzy risk assessment model (fRA)

Traditional risk assessment model shown in Fig. 1. was modified by use of FLS for each appropriate element to received fuzzy Risk Assessment (fRA) model which is shown in Fig 4. It consists of combination of traditional part, where methods within the Process Hazard Analysis (PHA) are used, and "fuzzy part" where Fuzzy logic Systems (FLS) are applied to all elements of risk analysis. The new element called fuzzy Risk Correction Index (fRCI) was introduced in order to take into account the effect of quality of the process safety analysis on overall risk index [ 15] .

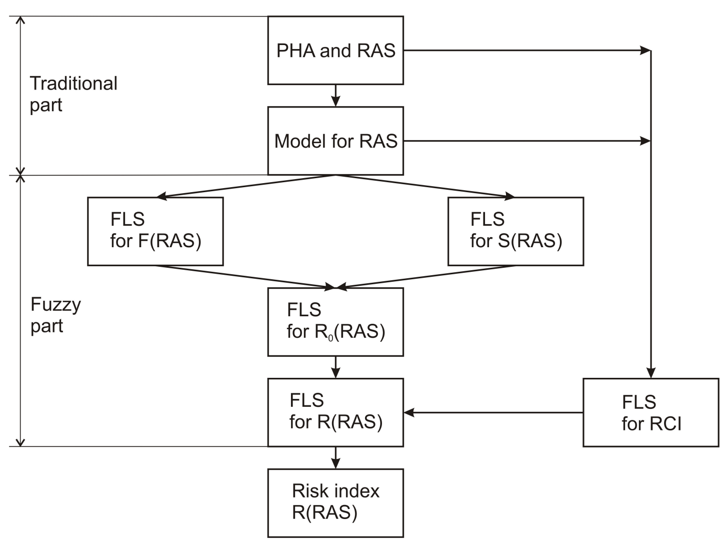


Fig. 5. Fuzzy Risk Assessment model (fRA)

Fuzzy part applies the principle of Fuzzy Logic System for each element of the RA in different mapping ways; either applies the fuzzy rules or applies the fuzzy algebra. There are five of FLS as follow:

1. FLS for the calculation of fuzzy probability $F_{RAS}$ uses arithmetical operation on fuzzy numbers follows the fuzzy algebra. As a result the fuzzy probability of outcome event for particular RAS is obtained (fLOPA).
2. FLS for the calculation of severity of consequences, $S_{RAS}$ using fuzzy rules provided by fLOPA.
3. FLS for the evaluation of fuzzy risk index $R_0$(RAS), using fuzzy inference provided by fuzzy risk matrix.
4. FLS for the evaluation of risk correction index RCI, using fuzzy rules presented in Table 2.
5. FLS for the evaluation of final risk index R(RAS), using fuzzy rules, presented in Table 3.

After defuzzification the outcome risk index is obtained which presents the range of values that belong to the particular set with a certain membership function.

The development of fuzzy sets and rules for first three elements were presented in our previous papers [14, 16,17] and Fig. 6 presents the fuzzy risk matrix used for evaluation of fuzzy risk index and its with  comparison with the traditional risk matrix.

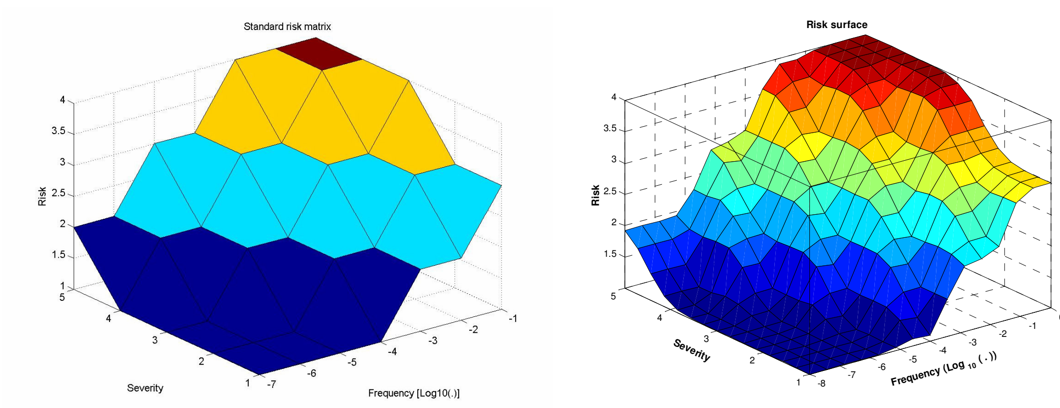


Fig. 6. Traditional risk matrix and fuzzy risk matrix

FLS for the calculation of severity of consequences, $S_{RAS}$ using fuzzy rules  applied to the consequence models is shown below.

## 6. Fuzzy logic system  for severity of the consequence

Emergency management is based on proper prediction of  the severity of consequence of accidental releases of the chemicals. This is a very complex task. A detailed consequence analysis contains number of consequence models including: release models, physical models and vulnerability models [18, 19]. The scheme of consequence analysis is shown in Fig. 7.

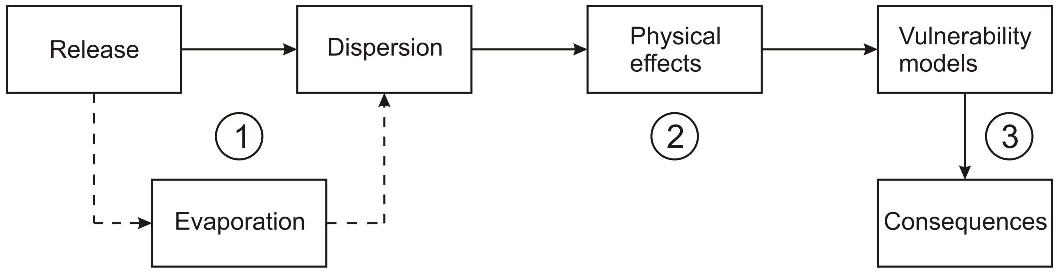


Fig. 7. Consequence analysis for accidental releases of chemicals.

Those models are interfaced allowing for transfer of data from a previous model to a subsequent model in the chain representing an accident scenario (RAS). Each model, containing separate sub-models for certain applications, must be calculated separately and has its own assumptions and different types of uncertainties. For example an objective uncertainty can occur for certain variables, like condition of released material (temperature, pressure) and meteorological conditions (wind speed and direction) used in released models, subjective uncertainties refers to the accuracy of the theoretical models used for the simulation particular physical effects or vulnerability models, and so on.

Models vary in degree of complexity and detail, and have common tendency to describe highly idealized situation. In such a way uncertainty of the first model will progress from one model to the next. This uncertainty propagation of the different types through the consequence analysis will require an application of some an integration methods with different techniques, depending on the expressed types of uncertainty [20].

In such a way the final result of consequence analysis quantifying the health, safety, environmental or economic impact of particular accident scenario may be overestimated or underestimated with further serious consequence for a decision making process.

Whereas the research on uncertainty problem concerning a frequency analysis is widely undertaken in literature, the same issue for consequence analysis is rather limited [13,14,20].

Similarly to arguments we used before, the fuzzy logic could be successfully used in the consequence analysis. All vague input problems and subjective assumptions, encountered in consequence analysis, can be transformed in more precise output data by means of the fuzzy set theory.

Because of the complexity each separate consequence model is considered as a separate fuzzy logic system FLS and the calculation is performed for that FLS according to the appropriate model algorithms. Each model can be represented in the general form as follows:

$$Y = f(\overline{S}, \overline{P})$$

where $S$ is the vector of state variables, $P$ is the vector of parameters, and $Y$ - output specific function of the model. State variables define the type of scenario, like type of substance, vessel temperature and pressure, etc, while vector parameters are uncertain in the time of calculation, although in the time of scenario can have an exact value, e.g. the size of the release hole. Therefore there is a need to select these parameters that are especially uncertain and take them into account in fuzzy modeling.

FLS applied to consequence analysis can be performed into two methods:

1. simplified method based on the categorization of the severity of consequences into separate categories using an expert opinion providing the size of released materials; further process applies assigning of fuzzy set for that size of release (fuzzification) and this is input data for risk matrix assessment [19],
2. parameter method used for particular consequence model, e.g. BLEVE model.

The use of parameter method is shown in Fig 8. As can be seen this is a typical FLS applied for given consequence model. Before the fuzzification the sensitivity analysis takes place to identify potential major contributors (parameters, P) to overall output. After fuzzification further calculation uses an appropriate formula of each consequence model where a fuzzy arithmetic replaces the classical mathematical operation. It allows obtaining the crisp exact output value of the consequence model Y.

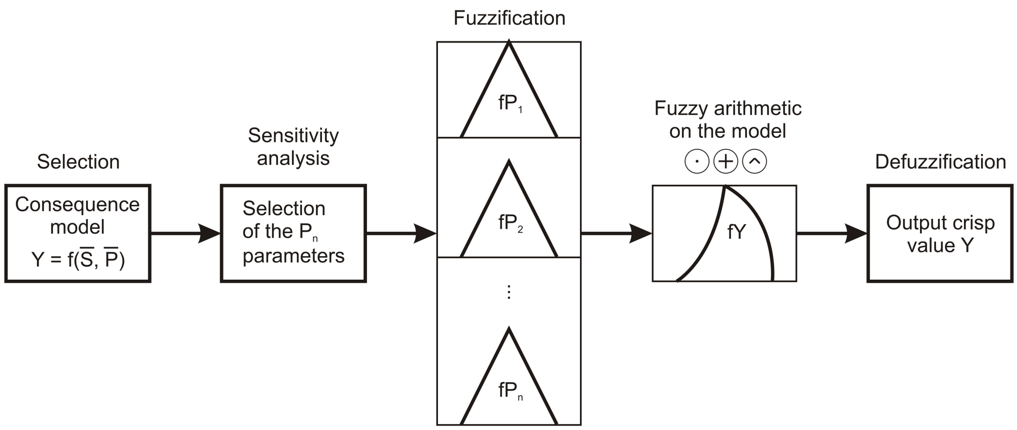


Fig. 8. Fuzzy logic system for consequence analysis.

An example of such application is shown in Fig. 9 on the BLEVE calculation for of the 600 $m^3$ tank with LPG with the help of PHAST program [21]. The results refer to three threshold values for thermal radiation 4, 12.5, 37.5 $kW/m^2$ and relate to specific consequences which may occur. Input fuzzy sets for the sensitive parameters were taken as a trapezoid shape.

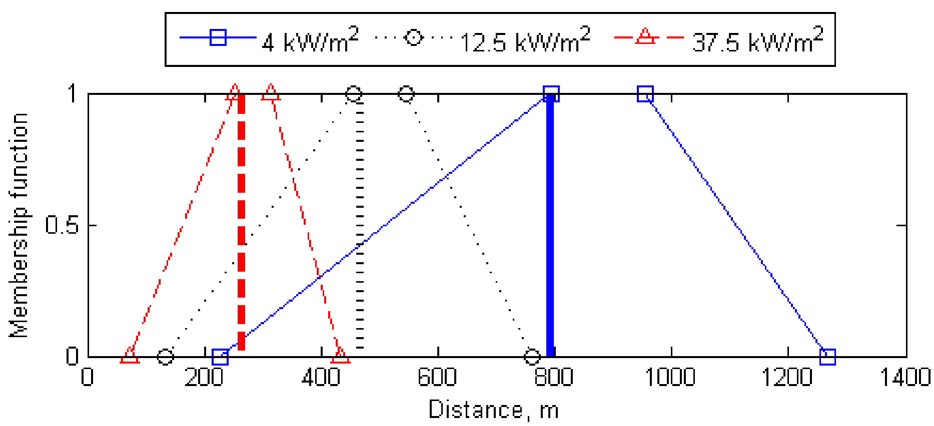


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Fig. 9. Range of distance for different radiation levels.

As can be seen the ranges of the hazard zones are widespread over the universe of discourse, especially for membership function $\alpha o = 0$. That reflects high uncertainty of the distance of hazard zones. It can be additionally noticed that the extent of intervals increases with the decrease of the threshold value of thermal radiation intensity. It is due to two reasons:

- firstly, to the exponential distribution of thermal radiation intensity in relation to the distance where for the distances close to the tank the thermal radiation intensity rapidly decreases and with the increase of the distance from the location of the failure the rate of thermal radiation intensity decrease is reduced;

- secondly, to so called effect of fuzzy results caused by the calculations on fuzzy numbers.

The comparison of fuzzy and non-fuzzy calculations are shown in Table 2. The results of non-fuzzy calculation over predict the hazardous zone distance by about 10 % for all radiation levels.

Table 2. Comparison non-fuzzy results with fuzzy results for BLEVE model

| Type of analysis | Range of distance to radiation level [m] | | |
|---|---|---|---|
| | 4 $kW/m^2$ | 12.5 $kW/m^2$ | 37.5 $kW/m^2$ |
| Non – fuzzy | 876 | 506 | 283 |
| Fuzzy | 793 | 467 | 264 |

## 7. Conclusions

1. Process Hazard Analysis (PHA), being a basis for decision making process in chemical industry is a very complex task, representing numbers of uncertainties connected with information shortages and other inaccuracies which may lead to important overlooks in the risk assessment of the process plants. There is no common approach to deal with that aspects.
2. One of the promising methods for reduction of the uncertainties in process safety assessment is fuzzy logic, which is the collective name for “fuzzy set analysis” and “possibility theory”. That allows using imprecise, vague and approximate data that are typically met in process safety analysis and after application of fuzzy logic system (FLS) the quite precise results may be obtained.
3. The fuzzy risk assessment model is presented which consists of a traditional part typical of qualitative hazard identification and the fuzzy part used for the quantitative assessment of risk components (frequency, severity of consequences and risk index). For fuzzy parts the FLS was applied to each component of risk analysis (in different way).
4. Application of fuzzy approach for BLEVE consequence analysis indicates that the output results are more precisely determined and indicate overestimation of hazardous zone using non-fuzzy traditional approach in comparison to fuzzy approach. This is important issue for emergency management.

## 8. References

1. Mannan, M.S. (2005) “Lees’s Loss Prevention for the Process Industries”,vol. I-III, 3rd edition, Elsevier Butterworth-Heinemann, Burlington, Massachusetts.
2. Zadeh, L. (1965),”Fuzzy Sets”, Information and Control, 8: 338-353.
3. Dubois D. and Prade H. “Fuzzy Sets and Systems-Theory and Applications”, Academic Press, 1980.
4. Quiech, J., & Cameron, J.T. (1994) “Uncertainty representation and propagation in quantified risk assessment using fuzzy sets”, Journal of Loss Prevention in the Process Industries, 7: 463-473.
5. Pate-Cornell, M.E. (1996), “Uncertainties in risk analysis: six level of treatment”, Reliability Engineering and System Safety, 54: 95-111.
6. Dubois, D., & Prade, H. (1988), “Possibility Theory – An approach to computerized processing of uncertainty”, New York: Plenum press.

7. Siler, W., & Buckley, J.J. (2005). Fuzzy expert system and Fuzzy reasoning. J. Wiley.
8. Dubois, D. (2006), “Possibility theory and statistical reasoning”, Computational. Statistics & Data Analysis, 51: 47-69
9. Yen J. and Langari R., “Fuzzy logic: Intelligence, Control and Information”, Prentice Hall PTR, Upper Saddle River, N.Y. 1999.
10. Karwowski, W., & Mital, A. (1986),” Potential Application of Fuzzy Sets in Industrial Safety Engineering”. Fuzzy Sets and Systems, vol. 19, 2: 105-120.
11. Gentile, M., Rogers, W. J., & Mannan M.S. (2003), “Development of an Inherent Safety Index Based on Fuzzy Logic”, AIChE, vol. 49, 4: 959-968.
12. Nilsen, T., & Aven. T. (2003) “Models and model uncertainty in the context of risk analysis”, Reliability Engineering and System Safety, 79: 309–317.
13. Solzano, E., & Cozzani, V. (2006), “A fuzzy set analysis to estimate loss intensity following blast wave interaction with process equipment”, Journal of Loss Prevention in the Process Industries, 19: 343-352.
14. Markowski, A.S. (2006), “Layer of Protection Analysis for the Process Industry” Lodz: PAN, ISBN 83-86-492-36-8.
15. Markowski, A.S., Mannan, M.S. „fRisk Assessment for process industry”, Congress CHISA, 2009
16. Markowski, A.S., Mannan, M.S., & Bigoszewska A., 2007, “Fuzzy Logic for Process Safety Analysis”, Texas A&M University, MKOPSC Symposium 2007
17. Markowski A.S. Mannan M.S. “Fuzzy Risk Matrix “, Journal of Hazardous Materials (2008), in print
18. AIChE. (1999), “Guidelines for Consequence Analysis of Chemical Releases”, AIChE CCPS. N.Y.
19. Casal, J. (2008) “Evaluation of the effects and consequences of major accidents in industrial plants”, Ind. Safety Series (vol.8). Elsevier
20. AIChE. (2000) “Guidelines for Chemical Process Quantitative Risk Analysis”, AIChE CCPS. N.Y.
21. Markowski, A.S, & Dobiech, J. (1999) „Modelling of hazard zones for BLEVE”, Proceedings of Chemical industry and Environment III (vol. 2., 2nd edition), 401-408. TU Lodz, ISBN:83-87198-68-15.