Fuzzy-based Prioritization of Health, Safety, and Environmental Risks: The Case of a Large Gas Refinery

Auob Mirsaeidi*[*1], Hossein Moradi[1], Maryam Zekri[2]

1) Department of Natural Resources, Isfahan University of Technology, Isfahan, Iran
2) Department of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan, Iran

**Author for Correspondence: amsaeidi90@gmail.com*

Received: 1 Apr. 2016, Revised: 11 Aug. 2016, Accepted: 15 Oct. 2016

ABSTRACT
The main objective of this study was to develop a fuzzy–based framework for the prioritization of health, safety and environment related risks posed against employees, working conditions, and process equipment in large gas refineries. The First Refinery at Pars Special Economic Energy Zone in South of Iran was taken as a case study. For this purpose, health, safety and environment related risks were determined based on the three criteria of impact severity, occurrence probability, and detect-ability using a questionnaire of 33 identified failures. The values obtained were processed by a so-called 'contribution coefficient'. The results were then subjected to fuzzification and fuzzy rules were defined to calculate the risk level indices as the model outputs, which was then employed to facilitate the management decision-making process by prioritizing the management options. The prioritization values were then classified in six categories in the order of risk severity. Results revealed that failure in a combustion furnace had the highest rank while failure in the slug catcher ranked the lowest among the risk sources. It was also found that about 0.4% of the identified risks prioritized as "intolerable", 79% as "major", 20% as "tolerable", and 0.7% as "minor". Thus, most of the risks (more than 79%) associated with the refinery has the potential of significant risks. The results indicated that the risk of the pollutant emissions from the combustion furnaces is the highest. Exposures to harmful physical, chemical, psychological, and ergonomic substances are the other risks, respectively.

Key words: Failures, Fuzzy Logic, Process Operations, Gas Refinery

LIST OF ABBREVIATIONS
HSE-MS (Health, Safety and Environment Management System**)**
OP (Occurrence Probability)
DA (Detect-ability)
IS (Impact Severity)
FTA (Fault Tree Analysis)
ETA (Event Tree Analysis)
RBM (Risk Based Maintenance)
QADS (Assessment of Domino Scenarios)
PSEEZ (Pars Special Economic Energy Zone)
RL (Risks Levels)

INTRODUCTION
Industrial environments, due to having the dangerous processes may lead to loss of life, injury, social and economic disruption or destruction of the environment. So, for these high-risk environments a structure called Health, safety and environmental management system (HSE- MS) was introduced as the important management approach in 1985. Actually this system was a reaction to probabilistic accident [1, 2].
There is close relationship between health, safety and environment; all these factors can affect people and their behavior [3]. Fig. 1 illustrates the relationship between the HSE components (independent variables) and performance indicators (dependent variables). Each HSE Components indicates a set of system aspects which are interrelated and assumed to have impact on together and on the performance indicators.
Therefore, at an organizational level, injurious factors in the workplace could cause human failure and safety issues which would result in environmental risks [4, 5].

HSE management system to reduce or minimize accidents in industrial environment uses a process called risk assessment. Risk assessment is vital demands for any industry to characterize their risks for staff, environment and loss of money. It is a systematic way of identifying which features of the workplace or work activities that could potentially cause harm, and then deciding what action to take to make them safe. In general, risk assessment is a complex process that entails the consideration of many qualitative parameters which are difficult to quantify [6].

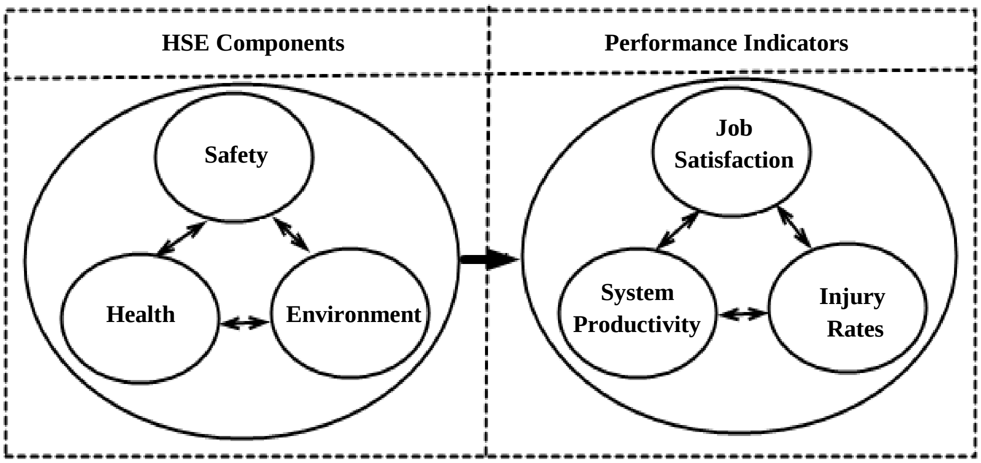

Fig. 1. The relationship between HSE components and their impact on performance components.

The main objective underlying risk assessment programs is to provide the major portion of the information required for supporting the risk management program (that includes identification, selection, and implementation of appropriate measures to control the risk).

Risk assessment is based on the three input variables including: occurrence probability (OP), detect-ability (DA), and impact severity (IS). Any measure aimed at reducing the risk (s) requires one or all of these three variables to be reduced [7]. The reliability of risk assessment results greatly relies on the accuracy of the model used and the verifiability of the risk data [8].

Risk assessment methods are classified in three categories including: (a) the qualitative techniques such as; check-lists, HAZOP and what-if analysis, (b) the hybrid techniques such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Risk Based Maintenance (RBM), and (c) the quantitative techniques such as QRA, Quantitative Assessment of Domino Scenarios (QADS) and Weighted Risk Analysis (WRA) techniques [9, 10].

Because the traditional approaches cannot be to provide adequate answers to deal with this issue and using of them may mask other aspects of incomplete and imprecise knowledge and can lead to a Wrong impression of accuracy and precision for the decisions [11]. Moreover, in most cases, no adequate information is typically available for the reliable estimation of the frequency distribution or other characteristics of the risk factors [12, 13] and risk assessors are often faced with situations where the risk data are either incomplete or associated with a high level of uncertainty. It is, therefore, essential to develop a novel method of risk assessment that is capable of identifying the critical uncertainty [14]. To overcome these uncertainties, probabilistic risk analysis such fuzzy expert systems have been developed for states in which measured data about the precision and reliability of a system are restricted and expert knowledge is the only source of information available [15].

Fuzzy logic can be exploited to give better simulations of complex processes and vague or qualitative information. The concept of membership function in fuzzy theory will be useful for illustrating and understanding qualitative, ambiguous, or uncertain information [16]. Linguistic rules used in the structure of risk factors carry such vague information that can be best expressed by fuzzy logic. Fuzzy expert systems are transforming these rules to their mathematics equal. These systems have the capacity of developing the functionality of engineering systems and sets with linguistic terms in data analyzing, processing or decision-making [17]. Other advantages of fuzzy logic are facility and flexibility, because fuzzy logic can manipulate imprecise problems and it can model any arbitrary and complicated function [18, 19]. Within the HSE literature, application of optimizing tools in the management systems is used in a few studies. Assessment and development of HSE management systems are mainly important in Process Industries. Study about these systems in the context of HSE is introduced by many researchers. In this paper, an optimization tool is applied to assess HSE risks in gas refineries. HSE management systems are evaluated by some researchers.

Bernardo *et al.* (2009) Stated that the extent of environmental management systems are really Depended on the quality and other standardized management systems which implemented in organizations [20]. Azadeh *et al.* (2014a, 2014b) evaluated HSE systems of a gas transmission unit by Data Envelopment Analysis and also used Fuzzy Data Envelopment Analysis to decrease uncertainty existing in qualitative indicators and human risk failures [21, 22]. Gurcanli and Mungen (2009) and Beriha *et al.* (2012) provided a method for assessment of the risks that workers expose in construction sites using a fuzzy rule-based safety analysis to deal with uncertain and insufficient data. Using this method, historical accident data, judgments of experts, and the current safety level of a construction site merged together [23, 24]. Ciarapica and Giacchetta (2009) demonstrated the flexibility and advantages of the neuro-fuzzy network for occupational injury study. They analyzed injury data for developing classification schemes according to the trend in injury and subsequently, carried out a sensitivity analysis concerning the frequency of the injury [25]. Azadeh *et al.* (2008) have developed a fuzzy expert system for performance assessment of health, safety, environment (HSE) and ergonomics system factors in a gas refinery. It is demonstrated that use of fuzzy expert systems can reduce human failure, create expert knowledge and interpret large amount of vague data in an efficient manner [26]. Dejoy *et al.* (2004) stated employee's attitudes play a vital role in safety issues. They also demonstrated that industrial accidents not only affect human capital but also generate financial losses due to disruptions in industrial processes, damages to Working process [27].

In the present study, a framework is presented based on fuzzy logic for the assessment of HSE risks and to prove its implementation to the quantitative characterization of the expert's opinion to the risk associated with the First Refinery at PSEEZ. The main objective of fuzzy modeling of health, safety and environment (HSE) risks is assisting the risk management process for the improvement of HSE conditions at workplace, by identifying, assessing and controlling risks to an acceptable level by using corrective or preventive actions. It helps determine risks factors with the highest priorities. Moreover, the overall advantage of using this method in modeling of HSE risks is reduced time and cost. To this end, in this study, a new method of classifying risks factors is developed. It will be able to use a fuzzy logic approach for accurate and precise prediction of accident in an uncertain environment when sufficient data are not available.

MATERIAL AND METHODS

Study Area

Pars Special Economic Energy Zone (PSEEZ) is located at approximately 105 km south of Pars Gas Field in the east of Bushehr Province along the coastlines of the Persian Gulf. The First Refinery is one of the 5 presently active of a total number of 24 modules provisioned for this zone. The refinery supplies 25 MCM of treated gas on a daily basis into the national network. Also, two condensate stabilization units supply 40,000 barrels of condensate to storage tanks to be exported. The H2S be separated at the sweetening units transferred to the sulfur recovery units which produce a daily quantity of 200 tons of granulated sulfur which is transported by truck to automate sulfur storage. After the condensate from natural gas entering the refinery is removed, the remaining parts then treated in two operational units as shown in Fig. 2 [28].

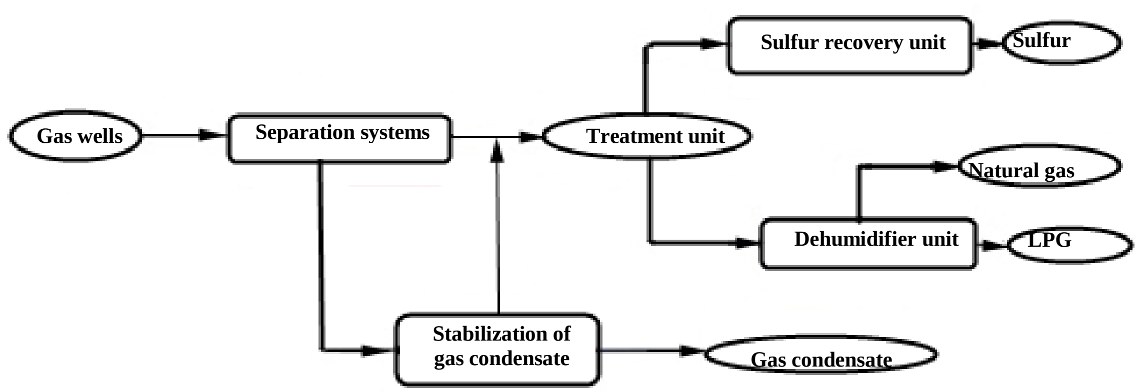

Fig. 2. Flowchart of the natural gas treatment at the First Refinery at PSEEZ.

Much of the capability of fuzzy logic lies in its ability to display ambiguous data, a capacity that much resembles human reasoning when dealing with inexact information or uncertainty in decision-making. This theory by introducing expert knowledge into the system, human reasoning can be usefully exploited for solving engineering problems and it provides a means for dealing with vague and uncertain information generated by any system [29, 30]. The fuzzy logic method used in this study is presented in Fig. 3 and a detailed description of its steps is given below.

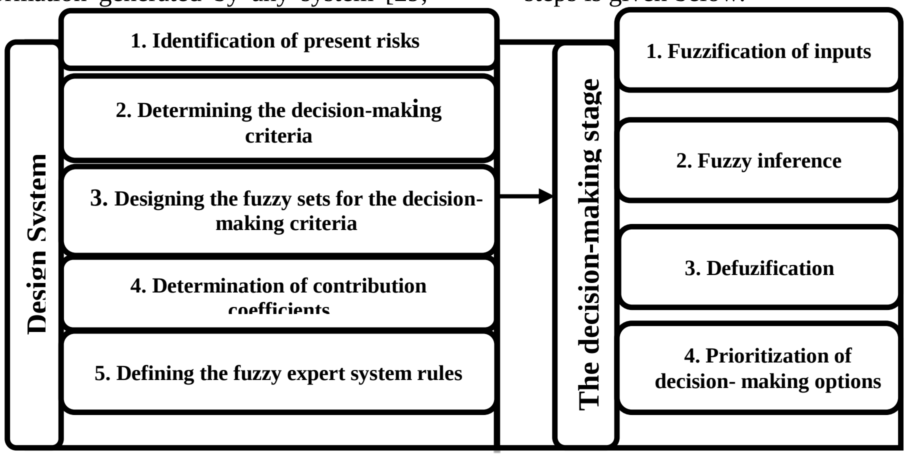

Fig. 3. Fuzzy risk assessment system.

System Design

Identification of Present Risks

Risk assessment begins with the identification of process-related risks and potentially dangerous events, impacts, and their likely consequences. Indeed, the success of any project depends on the identification and detection of the associated risks at all the system levels. It is one of the most vital steps toward the perfection of a project safety [31]. In addition to Field investigations and detailed literature review, all efforts were made in this study to design a comprehensive and exhaustive questionnaire that could disclose and maximally benefit from the experience and knowledge gained by experts, engineers, and operators working in the industry. For this purpose, over 100 main risks were identified. Field investigations and expert views were then used to select 33 main risks from among the initial 100, which were exploited in designing the questionnaire.

Determining the Decision-Making Criteria

The process of selecting system criteria is based on the following two activities:

(i) Investigation of the criteria used in previous studies; and

(ii) Investigation of the HSE criteria deemed successful by managers and experts.

Based on these investigations, the system input and output are determined and the components of occurrence probability (OP), detect-ability (DA), and impact severity (IS) are selected as inputs to the system while the HSE risks levels (RL) are determined as the output of the expert system designed.

Designing the Fuzzy Sets for the Decision-Making Criteria

In order to design the foundations of the fuzzy expert system, five fuzzy sets including “Low”, “Very Low”, “Moderate”, “High”, and “Very High” were designed for each of the main decision criteria to make a total number of15 fuzzy sets (table 1, 2 , 3 and Fig. 4). The fuzzy set thus obtained for each of the variables is as follows:

OP: { Very low, Low, Moderate, High, Very High}

DA: {Very High, High, Moderate, Low, Very Low}

IS: {Negligible, Marginal, Moderate, Severe, Catastrophic}

Determination of Contribution Coefficients

Considering the fact that each expert has his/her own contribution to the final results and given the fact that such factors as experience and education need to be emphasized in experts’ contributions, the responses made any experts were further processed using a specific contribution coefficient (W). For example, if the questionnaire was administered among n expert respondents, the with expert respondent would have a contribution coefficient of w_i, where:

$$w_1+w_2+\ldots+w_n = 1 \text{ and } 1>w_i>0.$$

Table 1: Linguistic terms used for OP.

Linguistic variable	Description of the OP	Failure value
Very Low	Occurrence probability is very low	0-2
Low	There is an occurrence probability but its frequency is low.	1-4
Moderate	Occurrence probability of the failure is at least once a year.	3-7
High	The failure is sure to occur at least once a year.	6-9
Very High	The failure is sure to occur at least a few times a year.	8-10

Table 2: Linguistic terms used for DA.

Linguistic variable	Description of DA	Failure value
Very High	Process-related risks are identified and alerted.	0-2
High	Risks are detected by tracking and auditing the current status, visual inspection, and/or daily monitoring.	1-4
Moderate	Risks are completely identified and monitored empirically using reliable instruments.	3-7
Low	There is little likelihood that risks could be detected using the presently available monitoring and instruments.	6-9
Very Low	There is no monitoring system in place or it is not capable of detecting potential risks.	8-10

Table 3: Linguistic terms used for IS.

Linguistic variable	Description of IS	Failure value
Negligible	The failure has no effect on the performance of the system or the operator.	0-2
Marginal	The failure has no effect on system performance but leads to small problems for the operator.	1-4
Moderate	The failure causes a negligible but significant level of failure in the system and a high degree of trouble for the operator.	3-7
Severe	The failure causes a significant destruction in system performance and minor injuries to the operator.	6-9
Catastrophic	The failure causes destruction in the whole system and severe injuries to the operator.	8-10

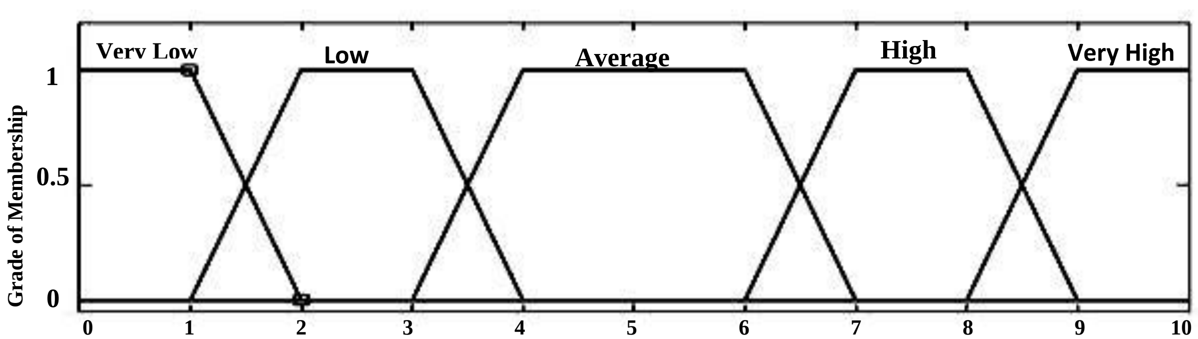

Fig. 4: Definition of the fuzzy set for OP, DA and IS.

Defining the Fuzzy Expert System Rules

The Decision-Making Stage

Fuzzification of the Input

Fuzzification of system input accounts for the first processing stage by the fuzzy expert system. It is in this stage that the membership degree of each input in the corresponding fuzzy set and the membership degree of input variables proportional to the corresponding membership functions is determined [33]. The fuzzification stage designed in this study consists of two steps as described below.

The inference core of an expert system consists of a set of if-then rules. In the fuzzy expert system, the rules are expressed by a series of linguistic expressions. The rules of the expert system then evaluate the favorable status against the option under study and determine the conformity of the favorable status to that of the option in question using a relevant linguistic expression [32]. For the fuzzy expert system used in this study, 125 (5×5×5) rules were defined, each being affected by five impact levels of each criterion. Table 5 presents some of these rules for illustration.

Fuzzification of Inputs Variables

For the fuzzification of the input data, each was assigned to one category using linguistic variables. As already mentioned, the categorization of input and output data was accomplished based on previous studies reported in the literature and according to the approach outlined in the Section on modeling algorithm. Then, the values assigned by the experts (0 to 10) for each of the three risk components were multiplied by the contribution coefficient obtained for each expert and the summation of the values thus obtained were taken as the processed value for the relevant component. For example, if the failure for HE1 is evaluated by an expert as in Table 6 below, and if the contribution coefficient assigned to the expert is designated by CC, then the normalized value for each of the three main risk components is calculated as the product of this coefficient and the value for the relevant component. Normalized values assigned by all the expert respondents to each component are then summed up as in Relations (1) to (3) below to obtain the processed value for the component in question.

Table 4: Some of the rules employed in the fuzzy expert system in this study.

Rule No.	Description
R1	IF OP is very low and IS is negligible but DA is very high, THEN RL is minor.
R2	IF OP is very low and IS is marginal but DA is very high, THEN RL is minor.
R75	IF OP is very high but IS is catastrophic and DA is moderate, THEN RL is intolerable.
R90	IF OP is average and IS is catastrophic but DA is low, THEN RL is intolerable.
R106	IF OP is low, IS is negligible, and DA is very low, THEN, RL is tolerable.
R121	IF OP is very high but IS is negligible and DA is very low, THEN RL is tolerable.
R125	IF OP is very high and IS is catastrophic but DA is very low, THEN RL is intolerable.

Table 5: Assessment value for a given risk assigned by an expert respondent.

Failure type	Expert's name	Impact severity	Occurrence probability	Detect-ability
HE1	E1	IS	OP	DA

$$P_{IS} = \sum_{i=1}^{n} IS.CC \quad (1)$$

$$P_{OP} = \sum_{i=1}^{n} OP.CC \quad (2)$$

$$P_{DA} = \sum_{i=1}^{n} DA.CC \quad (3)$$

For the purposes of this study, the trapezoidal membership functions expressed by Eq. 4 were used. The minimum and maximum values of the trapezoid were considered to vary from 0 to 1 as shown in Fig. 5, where the parameters a and d represent the set of points of the base or that of the left and right bases, the parameters b and c represent the set of points on the shoulder or the upper side of the trapezoid, and x and y are the spatial coordinates of the reference points.

$$trapmf = [abcd] \quad (4)$$

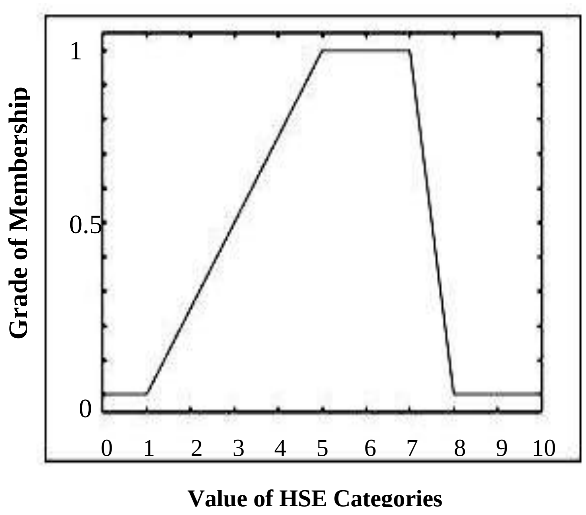

Fig. 5. Example of a trapezoidal membership function.

Finally, Eq. 5 is used for the fuzzification of the trapezoidal membership functions.

$$f(x,a,b,c,d) = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \quad (5)$$

Fuzzification of Output Variables

The output variable in this study, which is the risk level index, is expressed by the four qualitative linguistic terms of minor, tolerable, high, and intolerable as shown in Table 7. As already mentioned, it is clear from Fig. 6 that the quantitative description of the risk is expressed by a trapezoidal membership function.

Fuzzy Inference

The fuzzy inference process accomplished in accordance with the rules defined for the system is the most important process performed by a fuzzy expert system. In this stage, fuzzy sets are created for each criterion to determine the compliance of each option for each criterion [34]. The principles of fuzzy logic in this process contribute to the development of an output fuzzy set through the combination of the IF–THEN fuzzy rules. These steps have been depicted clearly in Fig. 7.

Defuzzification and Prioritization of Decision-Making Options

Defuzzification involves the weighting and normalization of all the outputs resulting from the whole set of fuzzy rules exclusively pertinent to a single decision or an output signal, which should be ultimately turned into an exact, non-fuzzy, and explicit value. In this study, the commonly used method of gravity center was employed to defuzzify the output. Once the level of each risk has been evaluated and its significance accordingly defuzzified, the risks are prioritized and a series of mitigation measures are introduced that will either reduce the risk or prevent unexpected events so that the decision-making process is facilitated.

Table 6: Linguistic terms of the RL.

Linguistic variable	Description of RL	Failure value
Minor	Acceptable risk	0.0-0.3
Tolerable	Risk to be reduced commensurate with the cost	0.2-0.6
Major	Measures required for reducing the risk to a reasonable level.	0.5-0.9
Intolerable	Risk should be reduced.	0.8-1.0

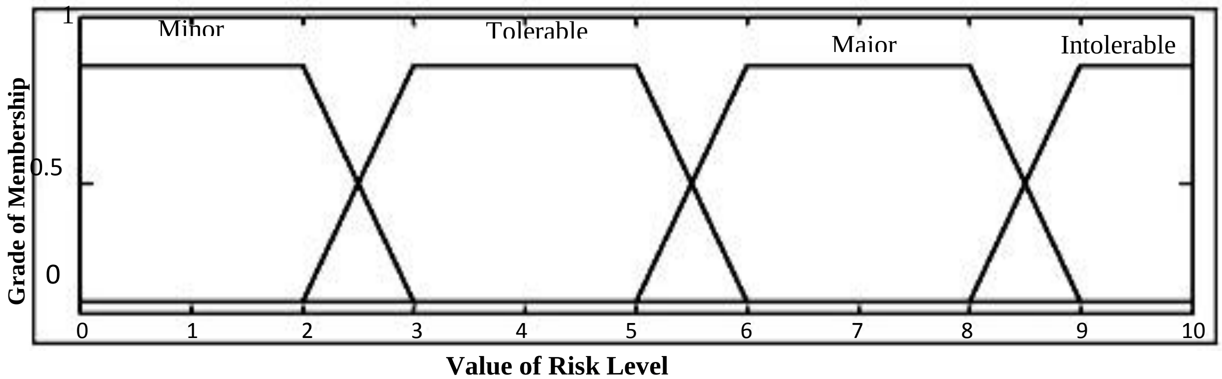

Fig. 6. The fuzzy sets of the RL.

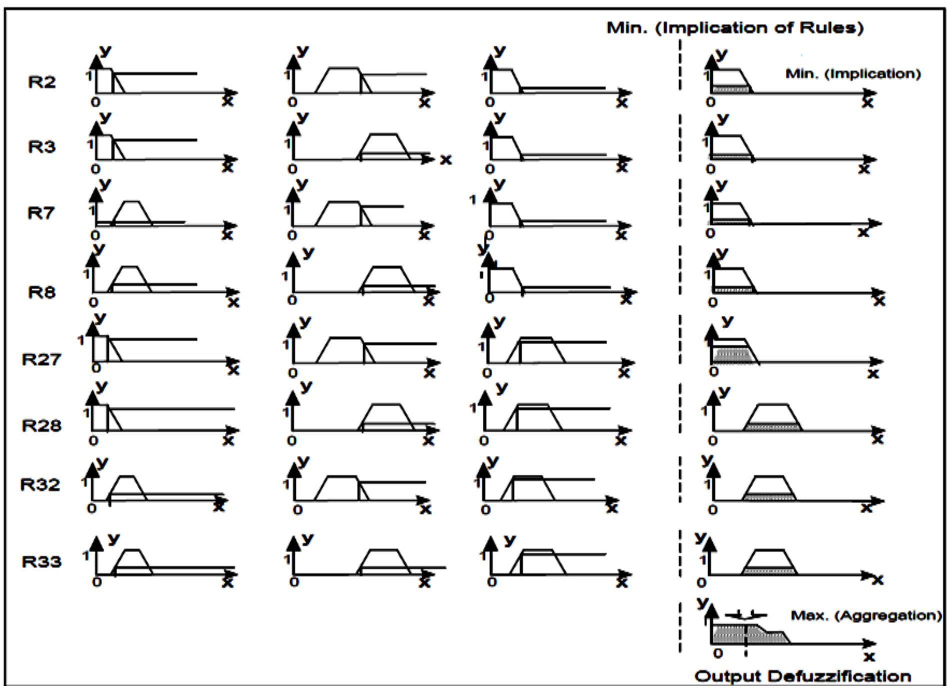

Fig. 7. The fuzzy inference process.

RESULTS AND DISCUSSION

Field investigations and expert views helped to identified 100 initial risks and then select 33 main risks which were then divided into the three health, safety, and environmental risks as reported in Table 7**.**

Defuzzification process resulted in calculating the risk levels together with the membership function for each risk (table 8). Once the level of each risk has been evaluated and its significance accordingly defuzzified, the priorities of the risks in the study area are presented according to their order of importance (Fig. 8 and table 9). Obviously, risks with higher levels in the fuzzy model are prioritized higher and waiting for urgent mitigation measures. Tables 8 and 9 showed that about 0.4% of the risks faced with at the First Refinery at PSEEZ are prioritized as *intolerable* (EN1), 79% as *major* (such as HE1, HE2, SA1, etc.), and 20% as *tolerable* (such as SA2, SA11, SA15, etc.), and only about 0.7% prioritized *minor* level (SA16). These results indicate that a major portion of the risks (about 79%) is above the "*major*" level and that immediate measures are, therefore, needed within the environmental management scheme of the refinery to control and reduce them to acceptable levels.

Table7: Potential health, safety, and environmental risks identified.

Risk type	Risk code	Description
Health (HE)	HE1	Exposure to harmful physical substances (noise, vibration, light, radiation, heat, and cold).
	HE2	Exposure to chemical substances (chemical gases and vapors, disinfectants, and drugs).
	HE3	Exposure to harmful biological substances (bacteria, viruses, fungi, etc.).
	HE4	Exposure to harmful psychological substances (stress, workload, shift work).
	HE5	Exposure to harmful ergonomic substances (monotonous and repetitive work, unsuitable body posture during working, and unsuitable work equipment)
Safety (SA)	SA1	Exposure to high voltage current
	SA2	Fall into windows, channels, and slug catchers
	SA3	Falling from plantars and elevated corridors
	SA4	Amputations, fractures, or injuries in the head and face caused by collisions, blows, hits, and flying objects
	SA5	Explosion of boilers and pressurized systems or control valve overflows
	SA6	Explosion due to eruption of energy or excess pressure on tanks leading to tank explosion and gas emissions
	SA7	Defective leak detectors
	SA8	Failure of temperature and pressure control devices
	SA9	Blockage in gas condensate lines
	SA10	Blockage in air outlet valves and throttle valves
	SA11	Malfunctioning of the safety/pressure valves
	SA12	Fires due to electric sparks
	SA13	Fires caused by tank failure and chemical leakage
	SA14	Fires caused by failure in gas transmission lines
	SA15	Failure in the filtering system (pig receiver & pig launcher)
	SA16	Failure in the slug catcher system
	SA17	Failure in the pressure breaking system (powered valves)
	SA18	Failure in the separator system
	SA19	Failure in the cooling system (Air Cooler)
	SA20	Failure in compressors, pumps, and condensers
Environmental (EN)	EN1	Pollutant emissions from the combustion furnaces (CO2, CO, NOx, SOx, and PM)
	EN2	Pollutant emissions from fellers.
	EN3	Emission of volatile pollutants due to leakage from equipment, tanks, fractures, cracks, and joints.
	EN4	Soil and groundwater contamination due to leakage of various hydrocarbons from the main gas pipe lines and pipe fittings
	EN5	Hydrocarbon pollution of seawater due to discharge of process water into the environment
	EN6	Pollution of seawater with chlorine compounds due to coolant discharge into the environment.
	EN7	Noise pollution at the refinery due to compressors, fellering, and other equipment
	EN8	Noise pollution in the surrounding are

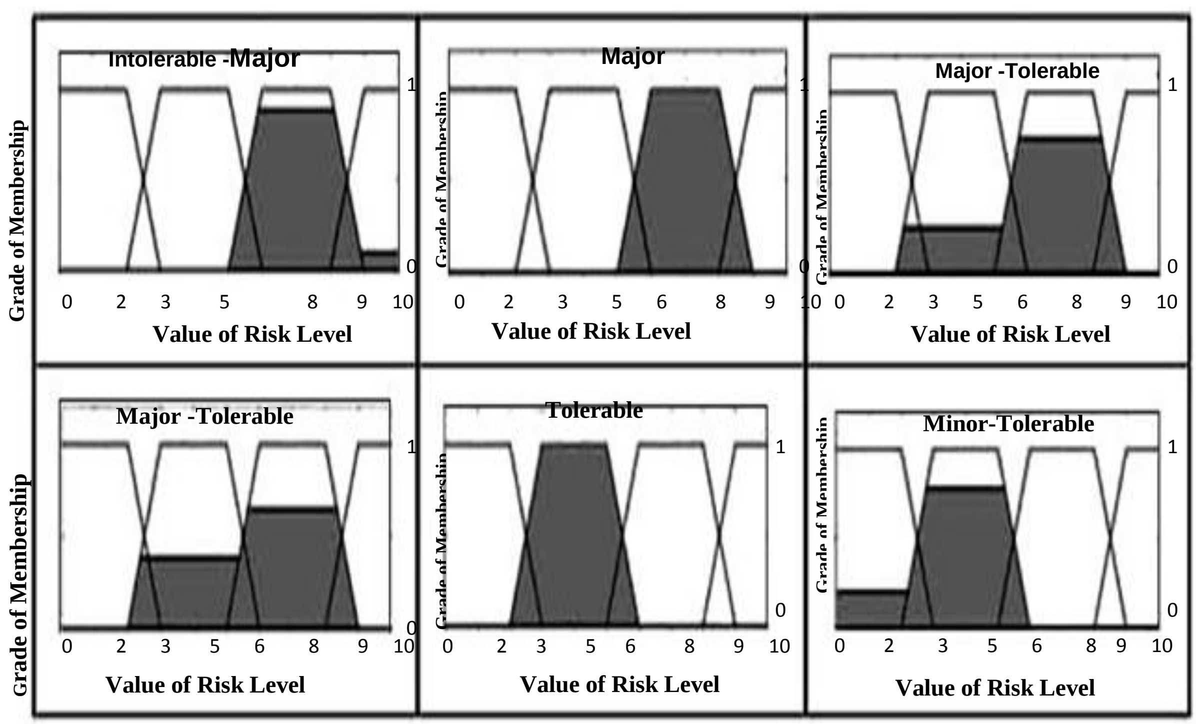

Table 8: Ultimate risks levels and the membership function for each risk. Safety Science

Failure type	OP	IS	DA	RL	Membership functions of the RL			
					Minor	Tolerable	Major	Intolerable
HE1	6.17	6.84	3.25	0.72	-	-	100%	
HE2	4.85	6.07	5.26	0.70	-	-	100%	
HE3	3.52	4.78	4.00	0.56	-	40%	60%	
HE4	4.69	5.91	5.01	0.70	-	-	100%	
HE5	5.06	6.57	4.11	0.70	-	-	100%	
SA1	5.13	5.51	4.86	0.70	-	-	100%	
SA2	3.15	5.36	2.99	0.45	-	100%	-	
SA3	4.27	6.62	4.71	0.70	-	-	100%	
SA4	3.51	5.85	5.02	0.56	-	40%	60%	
SA5	4.43	6.21	5.26	0.70	-	-	100%	
SA6	4.43	6.25	4.98	0.70	-	-	100%	
SA7	5.19	5.89	5.12	0.70	-	-	100%	
SA8	3.62	5.10	5.22	0.58	-	25%	75%	
SA9	4.19	5.51	4.64	0.70	-	-	100%	
SA10	4.98	5.68	5.11	0.70	-	-	100%	
SA11	3.08	6.10	3.35	0.44	-	100%	-	
SA12	5.65	6.35	4.97	0.70	-	-	100%	
SA13	5.33	7.07	4.50	0.70	-	-	100%	
SA14	5.44	6.10	5.18	0.70	-	-	100%	
SA15	3.20	5.00	4.96	0.46	-	100%	-	
SA16	1.47	3.38	3.51	0.29	20%	80%	-	
SA17	5.90	6.06	5.32	0.70	-	-	100%	
SA18	5.29	5.80	5.38	0.70	-	-	100%	
SA19	5.20	6.08	5.23	0.70	-	-	100%	
SA20	4.88	5.79	5.47	0.70	-	-	100%	10%
EN1	7.29	8.69	4.78	0.81	-	-	90%	
EN2	5.35	6.54	4.83	0.70	-	-	100%	
EN3	5.23	6.40	4.62	0.70	-	-	100%	
EN4	6.27	7.52	3.85	0.72	-	-	100%	
EN5	7.29	7.02	4.46	0.70	-	-	100%	
EN6	6.68	6.54	6.27	0.73	-	-	100%	
EN7	5.97	6.67	5.45	0.70	-	-	100%	
EN8	3.46	6.52	4.80	0.56	-	40%	60%	

Table 9: Prioritization of the HSE risks of the First Refinery at PSEEZ.

Risk priority	Risk type
1	EN1
2	HE1, HE2, HE4, HE5, SA1, SA3, SA5, SA6, SA7, SA9, SA10, SA12, SA13, SA14, SA17, SA18, SA19, SA20, EN2, EN3, EN4, EN5, EN6, EN7
3	SA8
4	HE3, SA4, EN8
5	SA2, SA11, SA15
6	SA16

Further details are presented in Figs.10 to 14. Where, Fig. 9 presents a 3D diagram in which *HSE risk levels* (the “y” axis) is plotted versus two components of *impact severity* (“x” axis) and *occurrence probability* (“z” axis). Clearly, about 70% of the weight assigned to the rules belongs to low and marginal risks (Light and dark blue colors in Fig. 9). In other words, only 30% of the total weight of the risks levels is assigned to risks that need more urgent consideration and for which mitigation measures need to be taken in order to reduce them to acceptable levels (Light and dark green colors in Fig. 9), because from the 33 identified risks only 9 cases of them (30 percent) from the perspective of experts Have been placed in the high and critical Risk levels. The following diagrams (Figs. 10, 11, and 13) of the impact of each variable on the ultimate calculated RL the contribution of each of the three risk components to the ultimate RL.

Based on the three main model parameters and their individual contributions to the ultimate RL, the effects of the components on the risk level are individually illustrated in Figs. 10 to 12. In overall, special importance should be attached to OP due to the likelihood of a wide variety of events in the study area and the risky nature of the specific operations that gives rise to chain incidents leading to environmental disasters. As can be seen in Fi.10, a slight increase in the OP has an increasing effect on the ultimate risk.

It is clear that impact severity has a delayed effect on the ultimate RL such that its increased level does not directly lead to increased ultimate risk but that it often causes step like increments in a delayed manner. This may be attributed to the fact that no accurate estimate of the losses in occupational environment, employees, or process equipment can be made until a potential event is actually realized on the ground. Fig. 11 depicts the effect of IS on the ultimate RL.

Unlike the other two factors, DA is inversely related to risk level. As can be seen in Fig. 12, even a slight effect on DA leads to a major failure to timely detect incidents which, in turn, leads to exponentially increasing risk levels. It may, therefore, be concluded that risk probability is most affected by the ability to detect and predict potential risks. Naturally, this may be considered as the most important output of the risk assessment fuzzy model because technical, engineering, and management control systems could have more emphasize on failure detect-ability. Enhanced potential for failure detection will evidently lead to reduced risk levels. Finally, this will help reduce challenges facing the industry and the environment so that the economic, social, and environmental consequences are prevented in a timely manner.

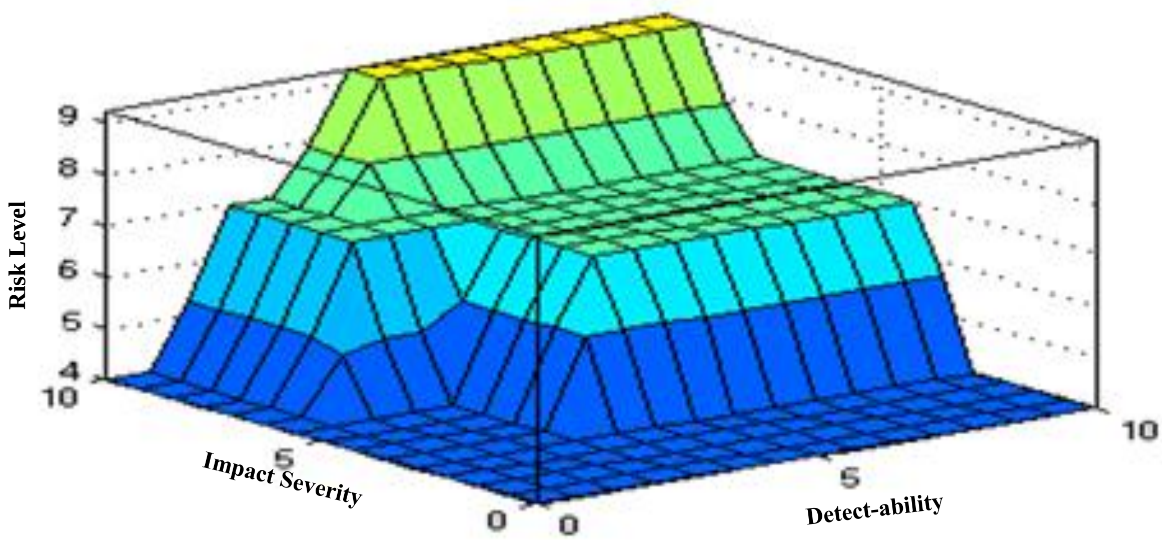

Fig. 9. Three dimensional diagram of the risks plotted versus Impact Severity and Occurrence Probability.

Fig. 13 shows the aggregation of three components mentioned above. The aggregation of the three components creates a diagram similar to that of the effects of OP factors on RL, which represents the high influence of OP in balancing RL. Therefore, the temporal component can be used in the absence of the other two components to estimate the RL.

The HSE assessment system developed in this research presents a method for quantifying HSE categories and provides a sort of prioritization. This framework has the potential to consider statistical uncertainty inherent in the risk management system. It is also applicable in different conditions and different processes of the industries. Moreover, this method can be easily modified and expanded to be incorporated in other possible HSE components.

In order to compare the results obtained by the proposed model and the outputs of other researchers; the presented result are consistent with a number of studies such as A. Pinto1 et al. (2010). Their findings indicate that, Fuzzy approaches for human-centered problems seem to be quite flexible; hence in this work we introduce a preliminary version of a qualitative method for risk assessment by using the fuzzy logic concepts and techniques [6].

The other researchers have tried to a framework as simple as possible that the approach be easily applicable. Juglaret *et al.,* (2011) and Amir-Heidari *et al.* (2016) also have reported simple and logical structure with a strong philosophical and mathematical framework which, to the best of our knowledge, there is no similar research previously [35, 36]. Therefore, our general two-stage innovative framework which is based on fuzzy risk assessment can be used by any kind of organization or company for measuring qualitative performances, including HSE performance. In this line, Markowski and Mannan (2008) and Sa'idi *et al.* (2014) showed that different studies indicated that the traditional risk matrix model does not fit the practical data but the fuzzy model fitted the data very well [37, 38].

In the present study, fuzzy probabilistic rules were extracted from association rules. The introduced methodology prevents from losing information while using Confidential information and non-quantitative (i.e., probabilities) in investigating HSE process.

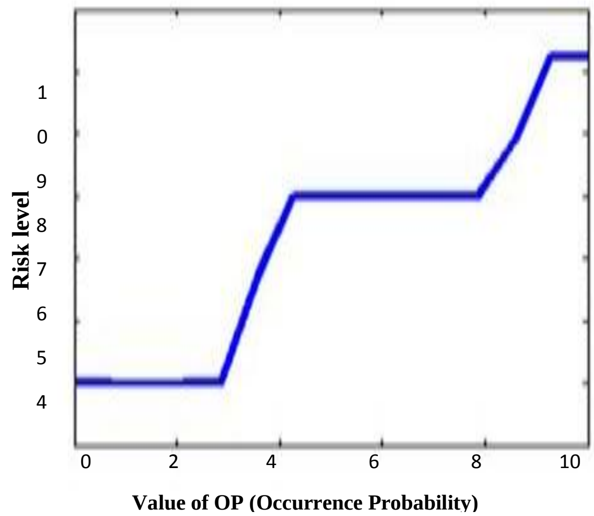

Fig. 10. Diagram of RL versus OP

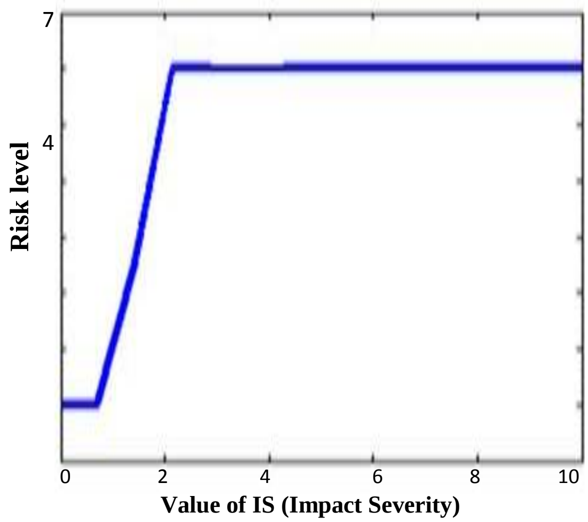

Fig. 11. Diagram of RL versus IS.

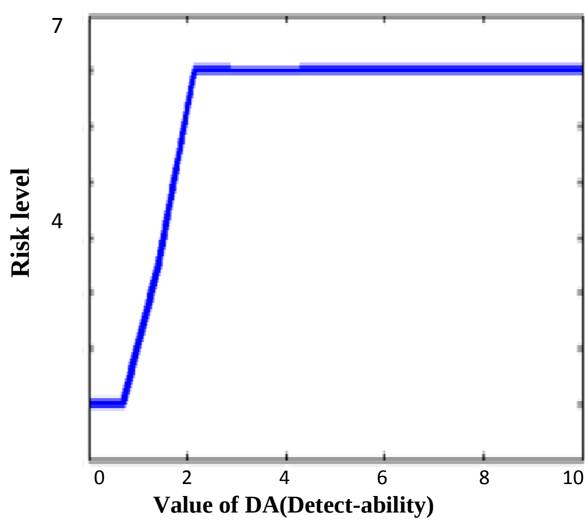

Fig. 12. Diagram of RL versus DA.

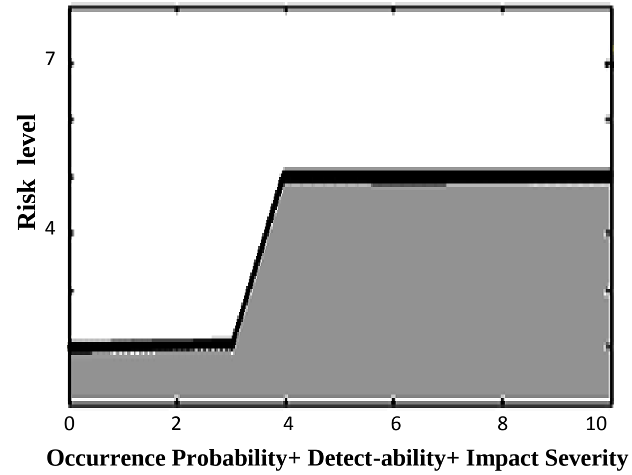

Fig. 13. Diagram of the aggregation of the three components of OP, IS, and DA.

CONCLUSION

In this paper, a fuzzy-based framework was developed for risk assessment of process operations in the large gas refineries. Therefore, 100 main risks were selected and 33 most important risks were identified through by using of the expert opinions and as partially were analyzed for risk assessment, then they were prioritized in the final structure.

The results showed that the risk of pollutant emissions from the combustion furnaces (CO_2, CO, NO_x, SO_x, and PM) is the highest. Exposure to harmful physical substances (noise, vibration, light, radiation, heat, and cold), exposure to chemical substances (chemical gases and vapors, disinfectants, and drugs), exposure to harmful psychological substances (stress, workload, shift work), exposure to harmful ergonomic substances (monotonous and repetitive work, unsuitable body posture during working, and unsuitable work equipment) are another risks for the First Refinery at Pars Special Economic Energy Zone in South of Iran, respectively.

This model is heavily dependent on the real conditions in these industries. In this model, data thus obtained were fuzzified and 125 rules were subsequently defined at the fuzzy inference step to convert the three input variables into the risk level indices. Thus, a novel method of risk assessment was developed based on elicited data and using a fuzzy logic approach. In many cases, HSE risk analysis is a complex task that is associated with a high level of uncertainty due to a wide variety of reasons such as complexity of human behavior and environment, inadequacy of the present knowledge, insufficient data, and subjective expert judgments. Therefore, the proposed model is a useful and applicable model to deal with uncertainties in which qualitative and fuzzy data can be compatibly used together. The model considers the weights of the three risk components (i.e., occurrence probability, detect-ability, and impact severity) in the process of creating a set of fuzzy rules. This is a new attempt of accounting for relative weights, which is consistent with objective reality. Lie *et al.* (2015) applied experts' weights and fuzzy logic to assess the performance HSE system and they concluded that this combination as well as the assessment result by degree of membership is more reasonable for HSE performance classification [39], which is our study major finding. Despite its advantages, the model has certain limitations. The continuous intervals of input and output variables artificially discretized leads to a set of discrete rules; as well as Weights are assigned to the risk factors solely on the basis of expert judgments rather than real measured data. This limitation calls for the collection of more data and the development of a more robust method (e.g., a fuzzy neural network) to reduce the associated uncertainties. It is obvious the prediction of various types of failures can help the managers to improve safety performance. Therefore, this model can be applied for assessing HSE risks of other industries. Albeit, the risk scales must be localized for any different conditions which may have a specific refinery.

ETHICAL ISSUES

Ethical issues such as plagiarism have not been observed.

CONFLICT OF INTEREST

The authors have declared that no competing interest exists.

ATHORS' CONTRIBUTION

The overall implementations of this study were the results of efforts by corresponding author. All authors participated in all aspects of the study, revising and approved the final manuscript.

FUNDING/ SUPPORTS

All the funding was paid by the authors.

ACKNOWLEDGEMENT

The authors would like to thank for the valuable comments and suggestion from the respected reviewers. Their valuable comments and suggestions have enhanced the strength and significance of our paper.

REFERENCES

[1] Azadeh M, Saberi M, Rouzbahman F. A neuro-fuzzy algorithm for assessment of health safety environment and ergonomics in a large petrochemical plant. Journal of Loss Prevention in the Process Industries. 2015; 34: 100-14.

[2] Constantin S. Industrial Health, Safety and Environmental Management; MV Wissenschaft; Muenster 2007.

[3] Azadeh A, Rouzbahman M, Mohammad Fam I, Saberi M. An adaptive neural network algorithm for assessment and improvement of job satisfaction with respect to HSE and ergonomics program: the case of a gas refinery. Journal of Loss Prevention in the Process Industries. 2011; 24: 361-70.

[4] Asadzadeh SM, Azadeh A, Negahban A, Sotoudeh A. Assessment and improvement of integrated HSE and macro ergonomics factors by fuzzy cognitive maps: The case of a large gas refinery. Journal of Loss Prevention in the Process Industries. 2013; 26: 1015-26.

[5] Bertolini M. Assessment of human reliability factors: a fuzzy cognitive maps approach. International Journal of Industrial Ergonomics. 2007; 37: 405-13.

[6] Pinto A, Nunes IL, Ribeiro RA. Qualitative model for risk assessment in construction industry: a fuzzy logic approach. In Doctoral Conference on Computing, Electrical and Industrial Systems; Springer Berlin Heidelberg. 2010 Feb 22: 105-11.

[7] Medina H, Arnaldos J, Casal J. Risk-Based Inspection and its Application to the Optimization of Chemical Plants. Chemical Engineering Transactions. 2011; 25: 201-06.

[8] Casal J. Evaluation of the effects and consequences of major accidents in industrial plants. Elsevier. Vol. 8: 2007.

[9] Marhavilas PK, Koulouriotis D, Gemeni V. Risk analysis and assessment methodologies in the work sites: on a review classification and comparative study of the scientific literature of the period 2000-2009. Journal of Loss Prevention in the Process Industries. 2011; 24(5): 477-23.

[10] Mohammadfam I, Zarei E. Safety risk modeling and major accidents analysis of hydrogen and natural gas releases: A comprehensive risk analysis framework. International Journal of Hydrogen Energy. 2015; 40(39): 13653-63.

[11] Ringen K, Englund A, Welch L, Weeks JL, Seegal JL. Why construction is different. Occupational Medicine. 1995; 10: 255–59.

[12] Chongfu H. Fuzzy risk assessment of urban natural hazards.Fuzzy sets and systems. 1996; 83(2): 271-82.

[13] Pitblado R, Bain B, Falck A, Litland K, Spitzenberger C. Frequency data and modification factors used in QRA studies. Journal of Loss Prevention in the Process Industries. 2001; 24: 249-58.

[14] Guimarães ACF, Lapa CMF. Fuzzy inference to risk assessment on nuclear engineering systems. Applied Soft Computing. 2007; 7(1): 17-28.
[15] Guikema SD. Natural disaster risk analysis for critical infrastructure systems: An approach based on statistical learning theory. Reliability Engineering & System Safety. 2009; 94(4): 855-60.
[16] Li PC, Chen GH, Dai LC, Li Z. Fuzzy logic-based approach for identifying the risk importance of human error. Safety Science. 2010; 48:902–913.
[17] Silva GC, Palhares RM, Caminhas WM. Immune inspired Fault Detection and Diagnosis: A fuzzy-based approach of the negative selection algorithm and participatory clustering. Expert Systems with Applications. 2012; 39(16): 12474-86.
[18] Haack S. Do we need fuzzy logic. International journal of man-machine studies. 1979; 11(4): 437-45.
[19] Zadeh L. Making computers think like people: the term fuzzy thinking is pejorative when applied to humans but fuzzy logic is an asset to machines in applications from expert systems to process control Spectrum. IEEE. 1984; 21(8): 26-32.
[20] Bernardo M, Casadesus M, Karapetrovic S, Heras I. How integrated are environmental quality and other standardized management systems: An empirical study. Journal of Cleaner Production. 2009; 17: 742-50.
[21] Azadeh A, Gaeini Z, Moradi B. Optimization of HSE in maintenance activities by integration of continuous improvement cycle and fuzzy multivariate approach: A gas refinery. Journal of Loss Prevention in the Process Industries. 2014a; 32: 415-27.
[22] Azadeh A, Madineh M, Motevali Haghighi S, Mirzaei Rad E. Continuous performance assessment and improvement of integrated HSE and maintenance systems by multivariate analysis in gas transmission units. Journal of Loss Prevention in the Process Industries. 2014b; 27: 32-41.
[23] Beriha GS, Patnaik B, Mahapatra SS, Padhee S. Assessment of safety performance in Indian industries using fuzzy approach. Expert Systems with Applications. 2012; 39(3): 3311-23.
[24] Gurcanli GM, Mungen U. An occupational safety risk analysis method at construction sites using fuzzy sets. International Journal of Industrial Ergonomics. 2009; 39(2): 371–87.
[25] Ciarapica FE, Giacchetta G. Classification and prediction of occupational injury risk using soft computing techniques: An Italian study. Safety Science. 2009; 47(1): 36–49.
[26] Azadeh A, Fam IM, Khoshnoud M, Nikafrouz M. Design and implementation of fuzzy expert system for performance assessment of an integrated health safety environment (HSE) and ergonomics system: The case of a gas refinery. Information Sciences. 2008; 178(22): 4280–00.
[27] Dejoy DM, Gershon RR, Schaffer BS. Safety climate: Assessing management and organization influences on safety. Professional Safety. 2004; 49(7): 50–57.
[28] http://wwwpseezir/fa/database/refinery
[29] Yadav OP, Singh N, Chinnam RB, Goel PS. A fuzzy logic based approach to reliability improvement estimation during product development. Reliability Engineering and System Safety. 2003; 80: 63–74.
[30] Zhang L. The Technique of Human Reliability Analysis of PSA. Atomic Energy Press, Beijing 2006 (in Chinese)
[31] Lin W, Stirling A. Fuzzy-based approach to qualitative railway risk assessment Proceedings of the Institution of Mechanical Engineers Part F. Journal of rail and rapid transit. 2006; 2202: 153-67.
[32] Siler W, Buckley JJ. Fuzzy expert systems and fuzzy reasoning. John Wiley & Sons, New Jersey, USA, 2005.
[33] Omid M, Lashgari M, Mobli H, Alimardani R, Mohtasebi S, Hesamifard R. Design of fuzzy logic control system incorporating human expert knowledge for combine harvester. Expert Systems with Applications. 2010; 37: 7080-85.
[34] Umar AA. Design for safety framework for offshore oil and gas platforms. Diss. University of Birmingham; 2010.
[35] Juglaret F, Rallo JM, Textoris R, Guarnieri F, Garbolino E. New Balanced Scorecard leading indicators to monitor performance variability in OHS management systems. InFourth resilience engineering symposium. Presses des Mines. 2011; 121-27
[36] Amir-Heidari P, Maknoon R, Taheri B, Bazyari M. A new framework for HSE performance measurement and monitoring. Safety Science, 2016 (In press).
[37] Markowski AS, Mannan MS. Fuzzy risk matrix. Journal of hazardous materials. 2008; 159(1): 152-57.
[38] Sa'idi E, Anvaripour B, Jaderi F, Nabhani N. Fuzzy risk modeling of process operations in the oil and gas refineries. Journal of Loss Prevention in the Process Industries. 2014; 31(30): 63-73.
[39] Li W, Liang W, Zhang L, Tang Q. Performance assessment system of health, safety and environment based on experts' weights and fuzzy comprehensive evaluation. Journal of Loss Prevention in the Process Industries. 2015; 35: 95-03.