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Fuzzy logic-based approach for identifying the risk importance of human error

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ABSTRACT

In the system reliability and safety assessment, the focuses are not only the risks caused by hardware or software, but also the risks caused by "human error". There are uncertainties in the traditional human error risk assessment (e.g. HECA) due to the uncertainties and imprecisions in Human Error Probability (HEP), Error-Effect Probability (EEP) and Error Consequence Severity (ECS). While fuzzy logic can deal with uncertainty and imprecision. It is an efficient tool for solving problems where knowledge uncertainty may occur. The purpose of this paper is to develop a new Fuzzy Human Error Risk Assessment Methodology (FHERAM) for determining Human Error Risk Importance (HERI) as a function of HEP, EEP and ECS. The modeling technique is based on the concept of fuzzy logic, which offers a convenient way of representing the relationships between the inputs (i.e. HEP, EEP, and ECS) and outputs (i.e. HERI) of a risk assessment system in the form of IF–THEN rules. It is implemented on fuzzy logic toolbox of MATLAB using Mamdani techniques. A case example is presented to demonstrate the proposed approach. Results show that the method is more realistic than the traditional ones, and it is practicable and valuable.

1. Introduction

The reliability and safety assessment of operational systems should not only focus on hardware failure but also include human error. A study by Trager (1985) showed that 50–70% of the risk at nuclear power facilities was because of human errors. In a large-scale and complex industrial system, human is prone to produce various errors by the effects of error-forcing conditions. If a potential human error has a high occurrence probability or potential severe effects, this error is termed critical human error. To prevent and reduce human errors, it is important to identify these potentially critical human error modes by human error risk assessment.

A variety of human error identification (HEI) techniques have been developed for identifying critical human errors. Kirwan (1998) outlined and reviewed 38 approaches of human error identification, categorizing them into many types of error identification approach. These also include first generation and second-generation human reliability analysis (HRA) methods. The "first generation" method of HRA, like technique for human error rate prediction (THERP) (Swain and Guttmann, 1983), accident sequence evaluation program (ASEP) (Swain, 1987), which is a simplified version of the THERP, and human cognition reliability (HCR) (Hannaman et al., 1985), success likelihood index methodology (SLIM) (Embrey, 1984), and the human error assessment and reduction technique (HEART) (Williams, 1992), are based on a fact that human has inherent deficiencies just like mechanical or electrical components. In first generation human reliability analysis, operator actions are broken into sub-tasks up to a defined degree of resolution. Most of the basic human error probabilities (HEPs) are given by expert judgments and then they are modified by the factors representing the effects of the environment in the scope of uncertainty. Those factors are called Performance Shaping Factors (PSFs) or Performance Influencing Factors (PIFs). The second-generation method like cognitive reliability and error analysis method (CREAM) (Hollnagel, 1998), a technique for human error analysis (ATHEANA) (Cooper et al., 1996), SPAR-H (Gertman et al., 2005) and MDTA (Kim et al., 2005, 2008) are based on the cognitive model of human decisions and actions. They attempt to identify Errors of Commission (EOC) and incorporate contextual factors into their qualitative and quantitative analyses. All these methods are well suited for supporting basic or generic Quantitative Risk Assessment (QRA). They provide the probabilities of human errors and thus meet the primary requirement of reliability analysis. However, all these methods focus strongly towards quantification, in terms of success/failure of action performance, with lesser attention paid to the effects of individual human error on system. These result in limitations in the discovery of real critical human error modes, and do not satisfy the objective of system safety or risk assessment.

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Some researchers have studied the above issues. For instance, Whittingham and Reed (1989) developed the Human Error Mode Effect and Criticality Analysis (HEMECA) to identify the prioritization of human error modes on the baisis of the principle of hardware-oriented failure mode and effect analysis (FMEA). Yu et al. (1999) also developed the Human Error Criticality Analysis (HECA) method. It is used to identify the potentially critical human errors and tasks in the human operation system by constructing human error criticality matrix. Its horizontal axis and vertical axis are respectively the criticality index number (i.e. the HEP multiplied by the EEP) of human error modes and safety or cost severity classification. It considered not only the HEP, but also the Error-Effect Probability (EEP) and Error Consequence Severity (ECS). These three indices are integrated into the human error risk assessment model to assess the risk prioritization of human errors or tasks. However, the above methods do not take the relative weights of the HEP, EEP and ECS into account. They cannot define the risk importance (i.e. risk magnitude or risk criticality) of human errors for the lack of the classification of Risk Criticality Level (RCL). In addition, Gertman et al. (2001) and Lee et al. (2004) used Conditional Core Damage Probabilities (CCDPs) to measure human error contribution to risk in operating events by statistical analysis of event reports. However, This kind of method do not considers the effects of individual human error on system, and requires a lot of event reports.

Human error risk assessment is a process to determine the risk magnitude of each human error mode to assist decision-making. The reliability of results of risk assessment highly relies on the correctness of the risk model, the availability and accuracy of the risk data. However, risk assessors often face the circumstances where the risk data are incomplete or accompanied by high uncertainty. For example, one of the major criticisms of current HRA techniques is the need for expert judgment to evaluate HEP (Kim, 2001; Mosleh and Chang, 2004). Additionally, in many circumstances, the effects of human error modes on system cannot be explicitly evaluated because of the complex structures and functions of the system, and the complex interactions between human and machines. Therefore, it is necessary to develop a new human error risk assessment method which can model the uncertainty to identify critical human errors. Under such conditions, fuzzy logic approaches are very practical. The fuzzy logic method can better simulate the complicated process and treat qualitative or imprecise or vague knowledge and information (Klir and Yuan, 1995). When the available information from the process is qualitative, inexact, vague or uncertain, the notion of the membership function utilized by fuzzy theory is then most adequate for depicting this knowledge. Therefore, the fuzzy logic methodology provides a tool for directly working with the linguistic terms used in making the risk factor assessment, and has currently had many applications in safety and risk analysis field such as system reliability and risk assessment (Bowles and Pelaez, 1995; Sii et al., 2001; Yadav et al., 2003; Guimaraes and Lapa, 2007; Markowski et al., 2009) and human reliability analysis (Onisawa, 1988; Cai et al., 1991; Auflick, 1999; Kim and Bishu, 2006; Kim et al., 2006; Konstandinidou, 2006; Marseguerra and Zio Enrico Librizzi, 2007; Zioa et al., 2009), etc. The problem is that they neither consider the risks caused by human error nor the effects of human errors on system. Thus this paper proposes a fuzzy logic-based comprehensive framework to assess the risk of human error and determine the risk importance of human error.

The paper is organized as follows. Section 2 briefly introduces the basic components of fuzzy logic system. Section 3 describes a comprehensive methodology of assessing the risk of human error in human operational system, which includes three stages: the preliminary phase, the measure phase of risk indices and the fuzzy inference phase. Section 4 presents a case example to demonstrate the proposed approach. Section 5 presents some concluding remarks.

2. Short description of fuzzy inference system

Fuzzy logic was originally introduced by Zadeh (1965) as a mathematical way to represent vagueness in everyday life. In contrast to classical logical systems, fuzzy logic considers modes of reasoning that are approximate rather than exact. Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. The fundamental difference between fuzzy logic and conventional modeling techniques is on the definition of sets. Traditional set theory is based on bivalent logic where a number or object is either a member of a set or it is not. Contrary to that, fuzzy logic allows a number or object to be a member of more than one set, and most importantly it introduces the notion of partial membership (Klir and Yuan, 1995). The general fuzzy inference process is shown in Fig. 1, which consists of four components. Namely, fuzzy rule base, fuzzy inference process, fuzzification process, and defuzzification process (Yadav et al., 2003). The following is a brief introduction.

2.1. Fuzzy rule base

Fuzzy rule base is the most basic unit of the fuzzy logic system. All other components of the fuzzy logic system are used to implement these rules in a reasonable and efficient manner. Fuzzy rule base consists of a set of fuzzy IF–THEN rules and the fuzzy inference engine uses these fuzzy IF–THEN rules to determine a mapping from fuzzy sets in the input universe of discourse $U(U \in R^n)$ to fuzzy sets in the output universe of discourse $V(V \in R)$ based on fuzzy logic principles (Guimaraes and Lapa, 2007). The fuzzy IF–THEN rules are of the following form:

$$R^{(l)}: IF \quad x_1 \text{ is } A_1^l \quad \text{and} \quad \cdots x_n \text{ is } A_n^l, \; THEN \quad \text{is } B^l \tag{1}$$

where $A_i^l (i = 1, 2, \ldots, n)$ and B^l are fuzzy sets, $x = (x_1, \ldots, x_n)^T \in U$ and $y \in V$ are input and output linguistic variables. Respectively, l represents the number of the rules, and $l = 1, 2, \ldots M$.

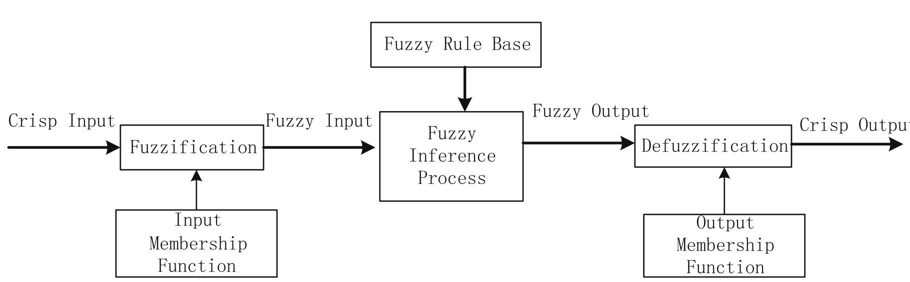

Fig. 1. The general structure of a typical fuzzy logic system.

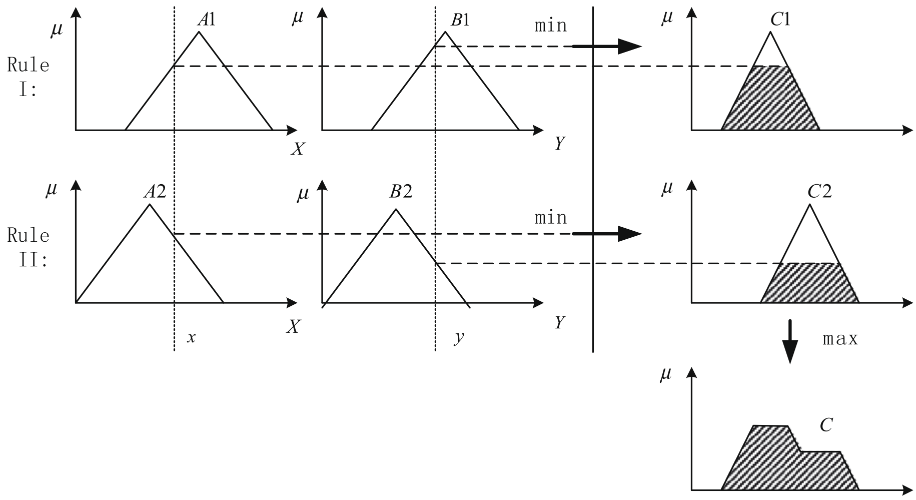

Fig. 2. Mamdani fuzzy inference system for two inputs and single output.

2.2. Fuzzy inference process

The fuzzy inference process combines the rules in the fuzzy rule base and then carries out a mapping from fuzzy set A in universe of discourse U to fuzzy set B in universe of discourse V using fuzzy logic principle in the fuzzy inference engine. By the treatment of fuzzy inference engine, the output B^l can be obtained by the following formula (Wang, 1995):

$$\mu_{B^l}(y) = \max_{l=1}^{M}[\sup \min(\mu_{A^l}(x), \mu_{A_1^l}(x_1), \ldots, \mu_{A_n^l}(x_n), \mu_{B^l}(y))] \tag{2}$$

There are many fuzzy inference methods. This paper uses the Min–Max fuzzy inference method proposed by Mamdani. The Mamdani fuzzy inference principle with two inputs and single output is shown in Fig. 2 (Yadav et al., 2003).

2.3. Fuzzification

The inputs of fuzzy logic system are real-valued variables or linguistic variables, but fuzzy inference engine can only deal with fuzzy set signal. It cannot directly treat real-domain signal. So the real-domain signals must be fuzzified for the operation of fuzzy inference. Fuzzification is the process of decomposing a system input variables into one or more fuzzy sets, thus producing a number of fuzzy perceptions of the input, and carrying out a mapping from real-domain variables x^* ($x^* \in U \subset R^n$) to the corresponding fuzzy set A^l.

2.4. Defuzzification

Defuzzification is the process of weighting and averaging the outputs from all the individual fuzzy rules into one single output decision or signal. The output signal eventually exiting the system is a precise, defuzzified, crisp value (Yadav et al., 2003). In general, there are some methods of Defuzzification, but the centroid of area is the most frequently used method. Its equation is as follows:

$$Z = \frac{\int_Z \mu_B(Z)Z\,dZ}{\int \mu_B(Z)dZ} \tag{3}$$

where $\mu_B(Z)$ represents the aggregated output membership function and Z crisp value of output.

3. Risk assessment model of human error

This paper constructs risk assessment model of human error on the basis of fuzzy approximate inference as shown in Fig. 3. It includes the following stages: (1) The preliminary phase. (2) The measurement phase of risk indices of human error. (3) Fuzzy inference phase.

3.1. Preliminary analysis phase

The preliminary analysis phase consists of the determination of specific analysis object, collection of information, identification of critical task, task analysis and identification of potential human error. Firstly, the determination of specific analysis object is to select most valued object and determine the analysis boundary of object. This paper generally selects a most unexpected occurrence accident as analysis object in a nuclear power plant. Then it collects and analyzes information related to specific object involving the status of the plant, the historical data, documents, the operation procedures, the data about interviewing with experienced experts and operators, the structure and function maps of the selected target system and so on. The identification of critical task is to discriminate those tasks that possibly harm persons, making the significant loss of property, process, system and environment. Then task analysis is to decompose a task into task units. Hierarchical Task Analysis (HTA) is generally used to build a sequence of events. Finally, the most potential human error is identified according to the collection of the above collected information.

3.2. Measurement phase of risk indices of human error

3.2.1. Identification of the risk indices of human error

The risk importance of human error is determined according to the three risk indices, namely, the probability of human error occurrence, human Error-Effect Probability and the consequence criticality of human error (Yu et al., 1999). Provided that the relative weight between risk indices of human error is not considered, the following formula is used to express the risk criticality of human error:

$$C_{HER} = \alpha \times \beta \times \gamma \tag{4}$$

where α represents the probability of human error occurrence, β human Error-Effect Probability, which is the conditional probability that the error effect will result in the identified severity classification given that certain human error mode has occurred, γ represents the consequence criticality of human error and C_{HER} the risk criticality of human error.

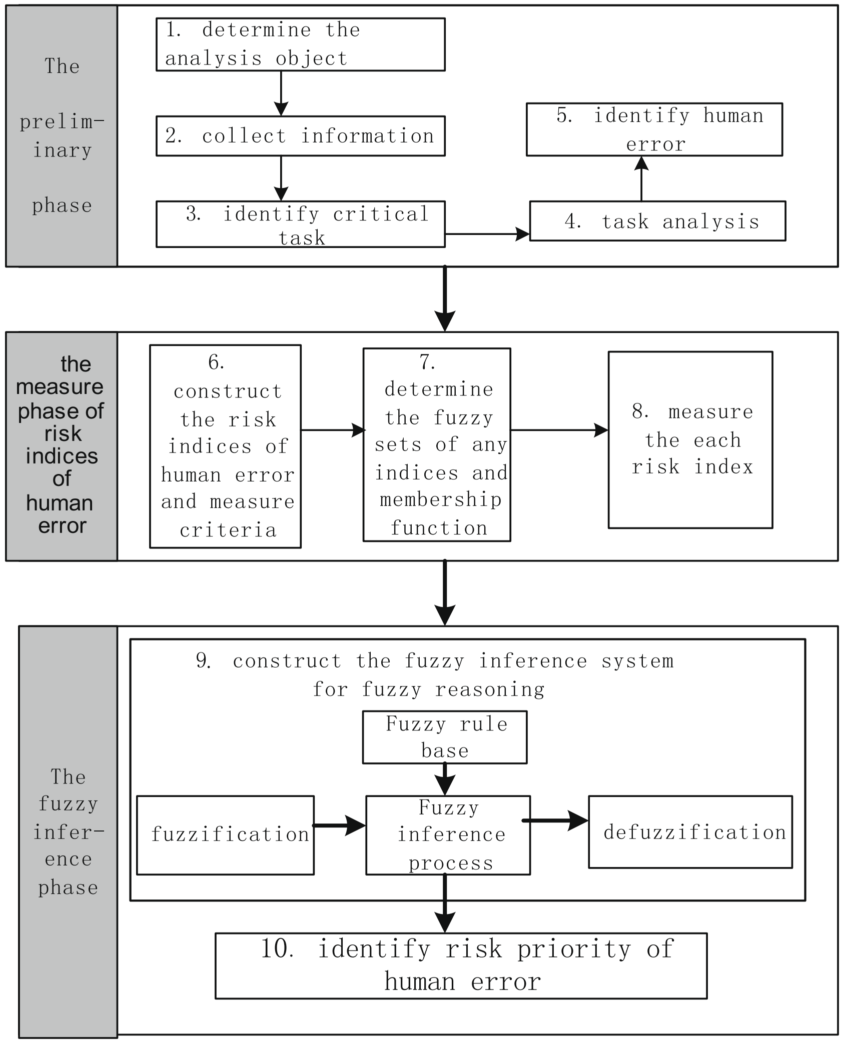

Fig. 3. Risk assessment model of human error based on fuzzy inference.

3.2.2. Definition of fuzzy subsets or linguistic variables and membership function for each of the risk index

To capture the uncertainty associated with both input (risk indices) and output (risk criticality) attributes, and imprecise knowledge about the relationship between input and output variables, fuzzy set theory provides a fundamental basis to map the approximate relationship between fuzzy variables. The input and output attributes are treated as fuzzy numbers (sets) and uncertainty is characterized by membership function. In this study, the membership function of each fuzzy set is assumed to be triangular. According to CREAM (Hollnagel, 1998) and discussion of experts, the probability of human error is described in linguistic term set:

$$HEP = \{Very\ Low,\ Low,\ Moderate,\ High,\ Very\ High\}$$

as shown in Table 1.

The fuzzy sets of the probability of human error (α) and membership functions are graphed in Fig. 4. It presents the above fuzzy sets using the logarithm of the probability in the x-axes for better output representation.

Similarly, the fuzzy sets of Error-Effect Probability (β) are assigned to four qualitative levels according to the MIL-STD-1629A (MIL-STD-1629A, 1980) as shown in Table 1. The average values of β are used to determine the fuzzy sets as cut-off points of fuzzy set interval. For the severity classification in this study, we categorize the severity classification into five levels in terms of loss degree of system, which are given in Table 1. Figs. 5 and 6 present the fuzzy sets of Error-Effect Probability and the consequence severity of human error separately.

3.2.3. Measurement of risk indices of each human error

Analysts and experts are required to measure risk indices of each human error on the basis of their knowledge and expertise. The experts or analysts can provide a precise numerical value (e.g. 0.1), a range of numerical values (e.g. 0.1–0.2), a linguistic term (e.g. high) or a triangular fuzzy number (e.g. (0.1–0.3)). If adequate information is obtained and the risk index is quantitative measurable, an expert or analyst is likely to provide a precise numerical value, e.g. "the occurrence probability of the ith human error mode is 1×10^{-3}. However, expert sometimes find that it is difficult to give numerical value due to uncertainties of the risk index and insufficient knowledge and information and then a linguistic term or a fuzzy number can be used. In this way, we can treat inaccurate measurement results in order to obtain precise value to input the constructed fuzzy inference system through the defuzzification method. The defuzzification method of triangular center of gravity is used to calculate the crisp values. Its formula is as follows (Zeng et al., 2006):

$$F_i = \frac{(u_i - l_i) + (m_i - l_i)}{3} + l_i \tag{5}$$

Table 1
linguistic terms of the risk indices of human error.

Level	Linguistic terms	Human Error Probability	Linguistic terms	Error-Effect Probability	Consequence criticality	Cost loss level percentage
1	Very low	$5\times10^{-6}\leqslant\alpha<1\times10^{-3}$	Almost no effect	$0\leqslant\beta<0.05$	Very low	$0\leqslant\gamma<0.25$
2	Low	$1\times10^{-4}<\alpha<1\times10^{-2}$	Possible effect	$0<\beta<0.55$	Low	$0<\gamma<0.5$
3	Moderate	$1\times10^{-3}<\alpha<1\times10^{-1}$	Probable effect	$0.05<\beta<1$	Moderate	$0.25<\gamma<0.75$
4	High	$1\times10^{-2}<\alpha<0.5$	Absolute effect	$0.55<\beta\leqslant1$	High	$0.5<\gamma<1$
5	Very high	$1\times10^{-1}<\alpha\leqslant1$			Very high	$0.75<\gamma\leqslant1$

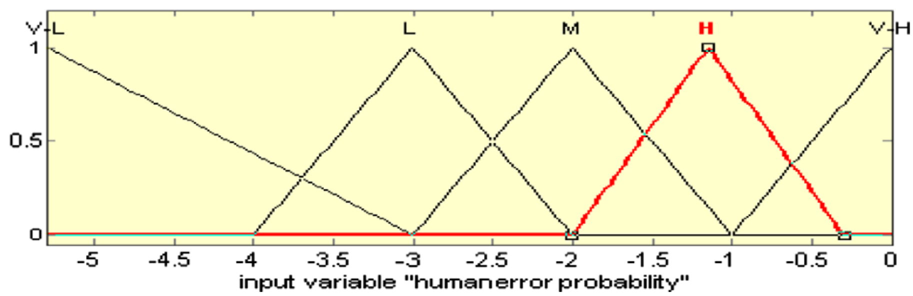

Fig. 4. Fuzzy set definition for the index of Human Error Probability.

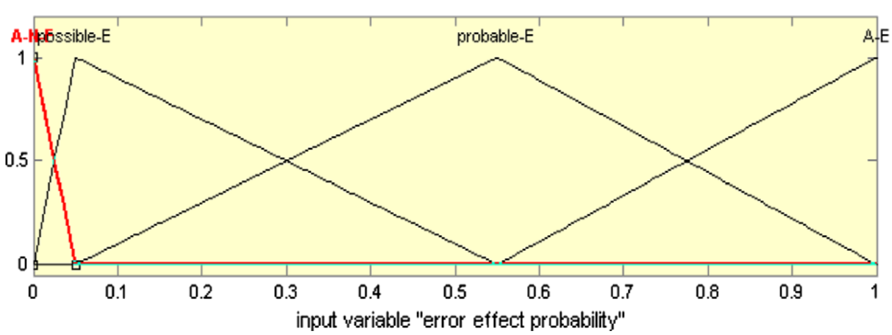

Fig. 5. Fuzzy set definition for the index of Error-Effect Probability.

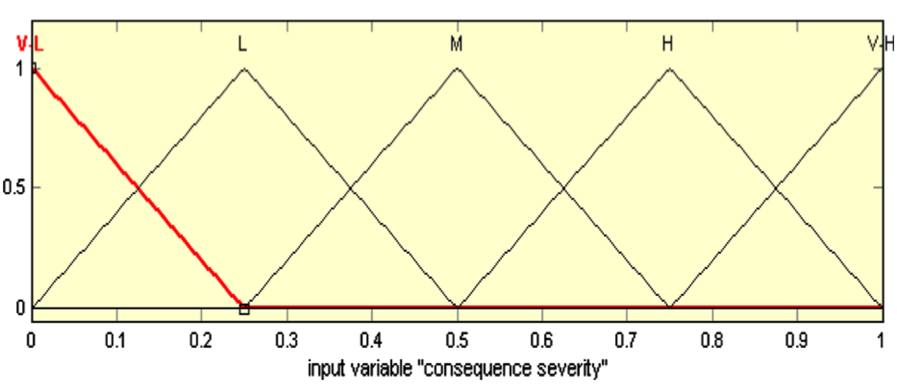

Fig. 6. Fuzzy set definition for the index of consequence severity of human error.

where $F_i (i = 1, 2, \ldots)$ is a crisp value transformed from fuzzy membership function, l_i, m_i, u_i are respectively the lower bound, the mean bound, and the upper bound of a fuzzy triangular set.

For instance, if the consequence severity classification of a human error is evaluated as "*very low*", and the triangular fuzzy number corresponding to the fuzzy set "*very low*" is (0, 0, 0.25), then the precise value 0.083 is obtained by Eq. (5).

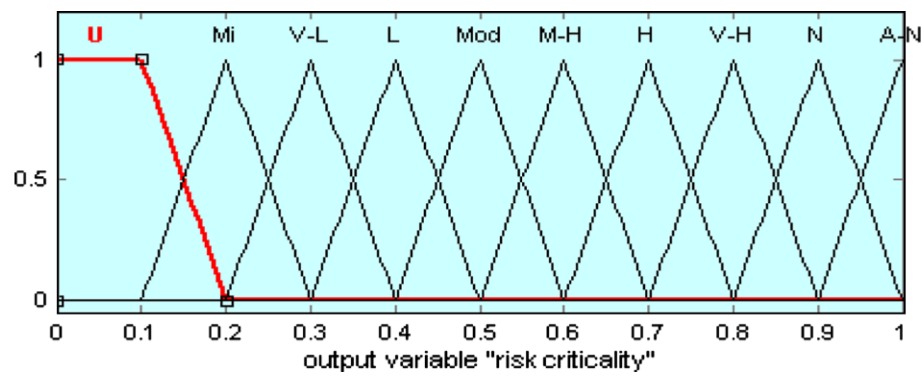

Fig. 7. Fuzzy set definition for the risk criticality of human error.

3.3. Fuzzy inference phase

3.3.1. Construction of the fuzzy inference system

According to Section 2, fuzzy inference system is made up of four basic components, namely the units of fuzzification, fuzzy rule base, fuzzy inference engine and defuzzification, which can be constructed by using the fuzzy logic toolbox simulator of Matlab (Wen et al., 2002). However, the fuzzy sets of inputs (risk indices of human error) and output (risk severity) variables and fuzzy rules for fuzzy inference should be determined before building the fuzzy inference system.

3.3.1.1. Determination of fuzzy sets of output variable. According to discussion of experts and the literature (Guimaraes and Lapa, 2007), the risk criticality of human error is described in linguistic term set:

$$RS = \left\{ \begin{matrix} Unnecessary, \ Minor, \ Very \text{ Low}, \ Low, \ \text{moderate}, \\ Moderate\ High, \ High, \ Very\ High, N \quad and \quad A-n \end{matrix} \right\}$$

It is graphically represented in Fig. 7.

3.3.1.2. Development of fuzzy rule base of combinating the input sets with the output sets. The membership function derived from the experts is used to generate the fuzzy rule base. The fuzzy IF–THEN rules are developed on the basis of the experts' ideas and the available information derived from human error analysis. Considering the relative weights of three risk factors (for example, the weights of HEP, EEP and ECS separately correspond to 0.4, 0.2, 0.4) and the multiple fuzzy sets of each input parameter and using the logical AND operation as the building mode, 100 ($5 \times 4 \times 5$) rules are developed. Some of the rules are given below:

- Rule 1. If (human_error_probability is V-L) and (error_effect_probability is A-N-E) and (consequence_severity is V-L) then (risk_criticality is U).
- Rule 2. If (human_error_probability is V-L) and (error_effect_probability is possible-E) and (consequence_severity is V-L) then (risk_criticality is U).
- Rule11. If (human_error_probability is L) and (error_effect_probability is possible-E) and (consequence_severity is V-L) then (risk_criticality is V-L).
- Rule 12. If (human_error_probability is L) and (error_effect_probability is probable-E) and (consequence_severity is V-L) then (risk_criticality is V-L).
- Rule 21. If (human_error_probability is L) and (error_effect_probability is A-E) and (consequence_severity is V-L) then (risk_criticality is L).
- Rule 22. If (human_error_probability is M) and (error_effect_probability is A-N-E) and (consequence_severity is M) then (risk_criticality is L).
- Rule 31. If (human_error_probability is L) and (error_effect_probability is possible-E) and (consequence_severity is M) then (risk_criticality is Mod).
- Rule 32. If (human_error_probability is L) and (error_effect_probability is probable-E) and (consequence_severity is M) then (risk_criticality is Mod).
- Rule 41. If (human_error_probability is V-H) and (error_effect_probability is A-N-E) and (consequence_severity is V-L) then (risk_criticality is Mod).
- Rule 42. If (human_error_probability is V-L) and (error_effect_probability is possible-E) and (consequence_severity is V-H) then (risk_criticality is M-H).
- Rule 51. If (human_error_probability is M) and (error_effect_probability is probable-E) and (consequence_severity is M) then (risk_criticality is M-H).
- Rule 52. If (human_error_probability is M) and (error_effect_probability is A-E) and (consequence_severity is L) then (risk_criticality is M-H).
- Rule 61. If (human_error_probability is L) and (error_effect_probability is possible-E) and (consequence_severity is V-H) then (risk_criticality is H).
- Rule 62. If (human_error_probability is L) and (error_effect_probability is probable-E) and (consequence_severity is V-H) then (risk_criticality is H).
- Rule 71. If (human_error_probability is V-H) and (error_effect_probability is A-E) and (consequence_severity is L) then (risk_criticality is H).
- Rule 72. If (human_error_probability is V-H) and (error_effect_probability is A-N-E) and (consequence_severity is M) then (risk_criticality is H).
- Rule 81. If (human_error_probability is H) and (error_effect_probability is possible-E) and (consequence_severity is H) then (risk_criticality is V-H).
- Rule 82. If (human_error_probability is H) and (error_effect_probability is probable-E) and (consequence_severity is H) then (risk_criticality is V-H).
- Rule 91. If (human_error_probability is H) and (error_effect_probability is A-E) and (consequence_severity is V-H) then (risk_criticality is N).
- Rule 92. If (human_error_probability is V-H) and (error_effect_probability is A-N-E) and (consequence_severity is V-H) then (risk_criticality is N).

These fuzzy IF–THEN rules build a fuzzy system that concerts fuzzy input into fuzzy output. Fig. 8 shows fuzzy mapping or functions between two inputs and output in a three-dimensional input–output space. The Rule Viewer of the Matlab that opens during the simulation can be used to access the “Membership Function Editor” and the “Rule Editor” to edit membership functions of input–output variables and fuzzy rules related inputs to

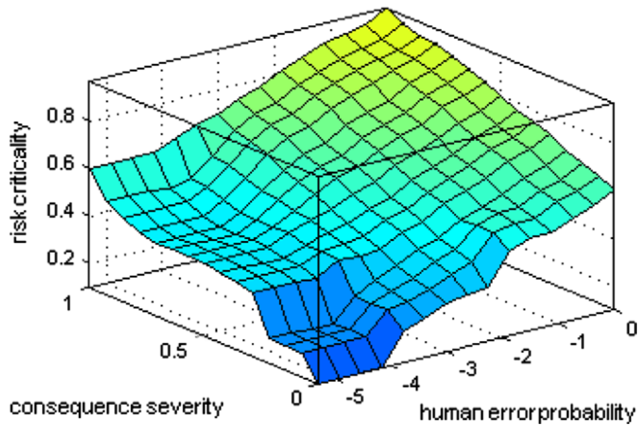

Fig. 8. Fuzzy function defined by IF–THEN rules between two inputs and output.

output. The fuzzy inference system for human error risk assessment is developed as shown in Fig. 9.

3.3.2. Identification of risk importance of human error

The output is audited by expert group on the basis of their knowledge and experience. If they find some unreasonable results in the output, the output modification is necessary in some situations for securing a reliable decision. For instance, system structure has been changed and the impact of certain risk index has not been adequately measured. Therefore, experts and analysts should gather more information related to targeted object, review the risk assessment process and reevaluate and modify the risk parameters to simulate to reach a reliable result. According to the (modified) output, the assessment of risk criticality must be carried out to determine the risk importance of human error. The final result of risk assessment provides safety management with reliable data for risk respond decision-making.

4. Case study

After an initiating event in a nuclear power plant, operators should respond to the emergency accident and the errors might take place because of the effects of context on human activities. A case of steam generator tube rupture (SGTR) accident in a PWR nuclear power plant (Zhang, 2006) is used to demonstrate the proposed identification method of fuzzy logic-based risk importance of human error.

4.1. Preliminary analysis phase

4.1.1. Determination of object and collection of relevant information

SGTR accident is defined as a kind of accident that one or two heat transfer tube ruptures take place in a steam generator, and it is characterized by the destruction of the integrity of pressure boundary of the primary loop and the primary coolant leak through the damaged steam generator to the secondary loop (Fig. 10). Therefore, it is necessary to timely isolate the damaged steam generator to prevent leakage of the radioactive substance. The reactor units will be taken to the cold shutdown situation for maintaining the damaged steam generator through a series of operations such as cooling, depressurizing, high pressure safety injection, feed and bleed. After determining the object of analysis, the relevant information is collected including: the final safety analysis reports, the flow chart of pipeline systems, electrical system diagrams and instrument system diagrams and so on.

4.1.2. Identification of critical task and task analysis

It is the analysis object that the damaged SG is isolated successfully after the occurrence of the steam generator rube rupture (SGTR) accident. The results of an Hierarchical Task Analysis (HTA) created for the isolation of the damaged SG task are shown in Table 2. They are on the baisis of the experts' thoughts, the collection of relevant information and principle of HTA.

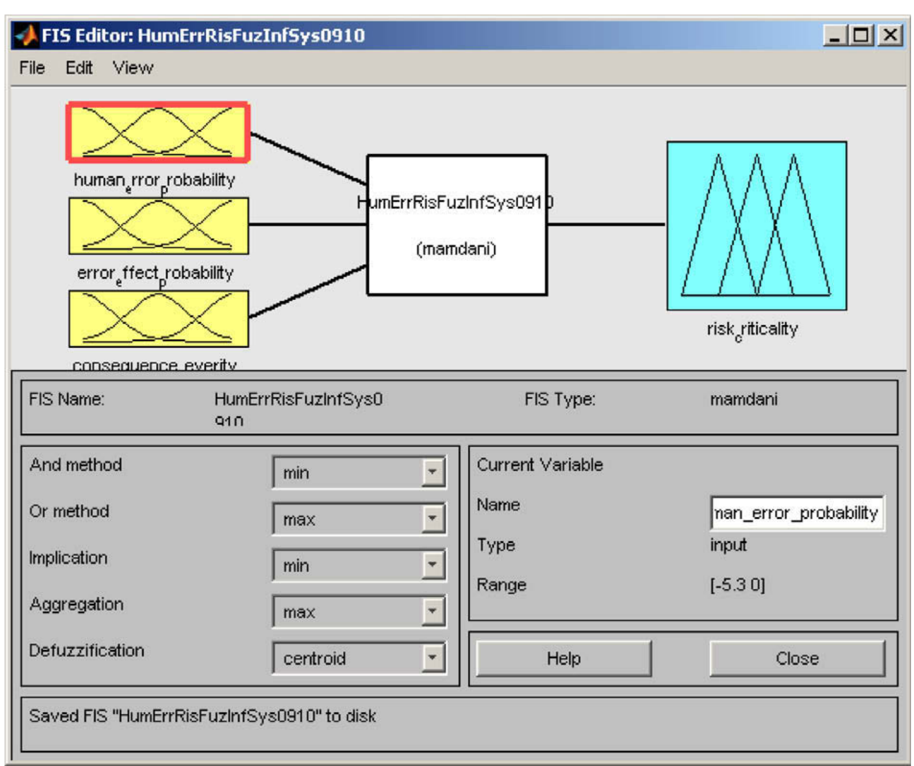

Fig. 9. Fuzzy inference system for risk assessment of human error.

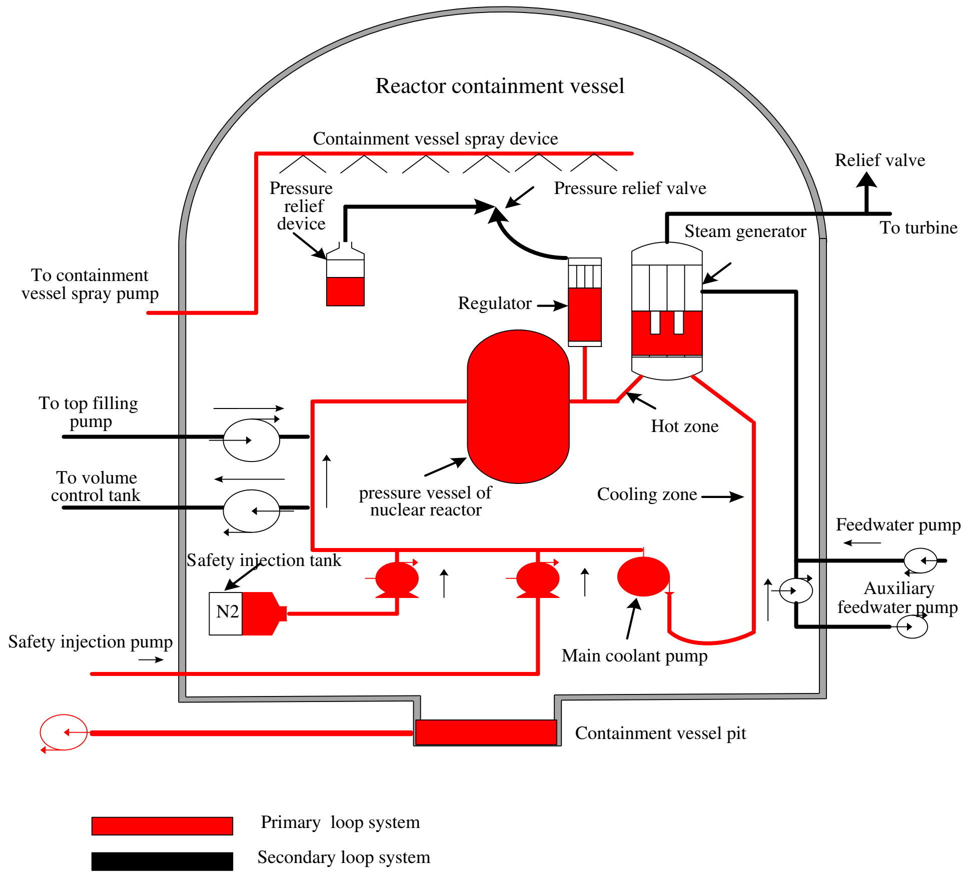

Fig. 10. The system diagram of primary loop and secondary loop in a nuclear power plant.

4.1.3. Identification of potential human error

Many human error identification techniques can be used to identify the potential human error, such as THERP, CREAM, HEART et al. CREAM is adopted to analyze the case example because of the consideration of the effect of context on human and human cognitive and action errors in CREAM. The detailed description of human error identification procedures can be found in CREAM (Hollnagel, 1998). The results of human error analysis on the basis of CREAM are shown in Table 2.

4.2. Measurement phase of risk indices of human error

The risk indices of human error involve the occurrence probability of human error, Error-Effect Probability and the consequence severity, which can be measured separately for each error.

4.2.1. Measurement of Human Error Probability

The failure probability of human is determined by the detailed following steps (Hollnagel, 1998): (1) Determining the basic or nominal Cognitive Failure Probability (CFP) for each of the likely cognitive function failures; (2) assessing of the effects of Common Performance Conditions (CPCs) on the nominal CFP values; (3) adjusting CFP to obtain adjusted CFP.

On the basis of the steps in CREAM, the analytical results are obtained in Table 2. For example, the cognitive activity is "observe" in the sub-task 1.1 named "observed abnormal state or alarm signal" as shown in Table 2. The corresponding cognitive function is also "observe". Its potential error mode is "O3" according to the special context analysis and the basic error probability of "O3" is 0.007. The value of weighting factor is 0.128 according to CPCs analysis in special context, as shown in Table 3. Therefore, adjusted probability of "O3" is 0.000896.

4.2.2. Measurement of Error-Effect Probability

Error-Effect Probability is the conditional probability that the error effect will result in the identified severity classification given that the *i*th human error has occurred. If certain human error has occurred, it will lead to certain degree of the loss of system with any truth. The level of truth (or the certain level of confidence) of the determined ranking of severity is the Error-Effect Probability, the range of which is from 0 to 1. For example, the potential error mode is "O3" in sub-task 1.1, which leads to the loss of system evaluated as "very low" (V-L), the Error-Effect Probability is 1. This means we absolutely believe the loss of system is V-L caused by the error mode O3. Similarly other analytical results are obtained as shown in Table 2 (i.e. the column of EEP).

4.2.3. Measurement of consequence severity of human error

Human error impacts hardware system, system function, personnel safety, environment and the like. The classification of severity can be synthetically considered from the standpoint of safety, reliability, maintainability, quality, cost, and so forth. For the severity classification in this study, we focus our attention on cost criteria. And for cost factor, we categorize the severity classification into five levels (five fuzzy sets), which are given in Table 1. This paper assumes that the effects of cognitive errors exist and is reflected in process, such as diagnostic errors will certainly affect the operational errors.

Based on the system analysis and experts' ideas, the measurement results of severity index of each human error are shown in Table 2.

Table 2
The steps in isolation of the damaged SG and the results of risk assessment.

Task	Sub-tasks	Cognitive activity	Cognitive function	Potential error mode	Basic error probability	Weighting factor	Adjusted probability	Error effect	Ranking of Error-Effect Probability (exact value)	Ranking of consequence severity (exact value)	Risk importance
1. Shutdown or SI	1.1. Detect abnormal state or alarm signal	Observe	Observe	O3	0.007	0.128	0.000896 (3.0477)	Reflected in process	1	V-L (0.083)	0.433
	1.2. Identify the parameter states, alarm type and severity and quality	Identify	Interpret	I1	0.02	0.1	0.002 (−2.699)	Select the wrong procedure	1	V-H (0.9167)	0.798
	1.3. Confirm shutdown	Verify	Observe/ interpret	I1	0.02	0.1	0.002 (−2.699)	Reconfirm	Probable-*E*(0.5333)	L (0.25)	0.434
	1.4. Check the states of system/component to ensure them available	Verify	Observe/ interpret	O3	0.007	0.128	0.000896 (−3.0477)	Latent failure occurred	1	H (0.75)	0.697
2. Identify and isolate ruptured SG	2.1. Check RCPs	Observe	Observe	O3	0.007	0.256	0.001792 (−2.7467)	Reflected in process	Probable-*E*(0.5333)	M (0.5)	0.529
		Evaluate	Interpret/ plan	I1	0.02	0.2	0.004 (−2.3979)	Reflected in process	Probable-*E*(0.5333)	M (0.5)	0.558
	2.2. Identify the ruptured SG	Observe	Observe	O2	0.007	0.256	0.001792 (−2.7467)	Reflected in process	1	V-H (0.9167)	0.793
		Diagnose	Interpret/ plan	I2	0.01	0.2	0.002 (−2.699)	Leakage of radioactive materials	1	V-H (0.9167)	0.798
	2.3. Isolate the ruptured SG										
	2.3.1. Adjust the air relief valve of the ruptured SG to fixed value 7.0 Mpa	Monitor	Observe/ interpret	O3	0.007	0.256	0.001792 (−2.7467)	The main system pressure rise	1	H (0.75)	0.729
		Regulate	Observe/ execute	E1	0.003	0.2048	0.0006144 (−3.2115)	The main system pressure rise	1	H (0.75)	0.687
	2.3.2. confirm the state of air relief valve of the ruptured SG —shut	Verify	Observe/ interpret	O3	0.007	0.256	0.001792 (−2.7467)	Reflected in process	Probable-*E*(0.5333)	H (0.75)	0.629
	2.3.3. close The main steam isolation valves and bypass valves of the ruptured SG	Execute	Execute	E3	0.0005	0.2048	0.0001024 (−3.9897)	Leakage of radioactive materials	1	V-H (0.9167)	0.658
	2.3.4. Isolate the sewage from the ruptured SG	Execute	Execute	E3	0.0005	0.2048	0.0001024 (−3.9897)	Leakage of radioactive materials	1	V-H (0.9167)	0.658
	2.3.5. Close the drain valve located in front of the main steam isolation valves of ruptured SG	Execute	Execute	E3	0.0005	0.2048	0.0001024 (−3.9897)	Leakage of radioactive materials	1	V-H (0.9167)	0.658
	2.4. Confirm the success of isolation	Verify	Observe/ interpret	O2	0.007	0.256	0.001792 (−2.7467)	Reconfirm	Probable-*E*(0.5333)	V-L (0.083)	0.371

Table 3
Assessment of the effects of CPCs on cognitive function failures.

CPC name	Level	T 1.1 O3	T 1.2 O3	T1.3 I1	T1.4 I1
Adequacy of org.	Very efficient	1	1	1	1
Working conditions	Advantageous	0.8	0.8	0.8	0.8
Adequacy of MMI	Adequate	1	1	1	1
Procedures/plans	Appropriate	0.8	1	1	0.8
Number of goals	Matching current capacity	1	1	1	1
Available time	Adequate	0.5	0.5	0.5	0.5
Time of day	Day-time (adjusted)	1	1	1	1
Training and preparation	Adequate, high experience	0.8	0.5	0.5	0.8
Crew collaboration	Very efficient	0.5	0.5	0.5	0.5
Total influence of CPC		0.128	0.1	0.1	0.128

4.3. Fuzzy inference phase

The measurement results of risk indices of each human error are separately input into the built fuzzy inference system. The outputs are shown in Table 2. For example, the risk value of sub-task 1.1 (i.e. 0.433) is obtained when the Human Error Probability (−3.048), human Error-Effect Probability (i.e. 1.0) and consequence severity (i.e. 0.083) are inputted into the fuzzy inference system as shown in Fig. 11. According to Table 2, firstly, the most serious error modes are I1 in sub-task 1.2 and I2 in sub-task 2.2, their risk values are 0.798. This is mainly because the diagnosis is a knowledge-based action, the occurrence probability of diagnosis errors is high, if such errors occurred, the consequences are very serious. Secondly, the important error modes are O3 in the sub-task 2.3.1, its risk values reaches 0.729. Therefore, these errors should firstly be considered by the plant to take some measurements to prevent the occurrence of such serious human error. Next, the risk criticality or importance of human error followed by O3 in sub-task 1.4, and E1 in sub-task 2.3.1 and E3 in sub-tasks 2.3.3–2.3.5, and so on. According to the results related above, we can identify the risk importance of human error. Therefore, the plant can take some targeted measures according to this principle (the risk importance of human error) to reduce and prevent the occurrence of human error.

4.4. Comparative analysis of the results by CREAM, HECA and FHERAM

Human Error Probability (HEP) is used to assess the risk of human error by "CREAM", the traditional HECA uses the criticality index value of human error modes and safety or cost severity classification to construct human error criticality matrix, that is to say, it uses the product of three risk factors (i.e. α, β, γ) to define the risk importance of human error and critical human error modes. The Fuzzy Human Error Risk Assessment Method (FHERAM) is the proposed method in this paper to analyze the fuzzy risk importance of human error. The comparative results of three methods are shown in Table 4.

As shown in Table 4, through different methods the risk importance of human errors are different.

The most critical human error mode is I2 in the sub-task 2.1.2 according to CREAM. CREAM determines the risk importance of human errors only in terms of HEP. Its disadvantage is that it doesn't consider the impacts of human errors. Therefore, CREAM method doesn't really illustrate the risk importance of human errors.

The most critical human error mode is I2 in sub-task 2.2 according to HECA, next to it is O3 in sub-task 2.3.1.1 according to HECA and FHERAM as well. While the third critical human error mode between HECA and FHERAM is different while CREAM is I1 in sub-task 2.1.2 and FHERAM is O3 in sub-task 1.4. If both sub-task 2.1.2 and sub-task 1.4 fail, sub-task 2.1.2 (i.e. evaluate RCPs) mainly influence the decision-making of the shutdown of main pump, and sub-task 1.4 (i.e. Check the states of system/component) influences the availability of the whole system because of the potential fault in the system. Therefore, the effects of "O3" in

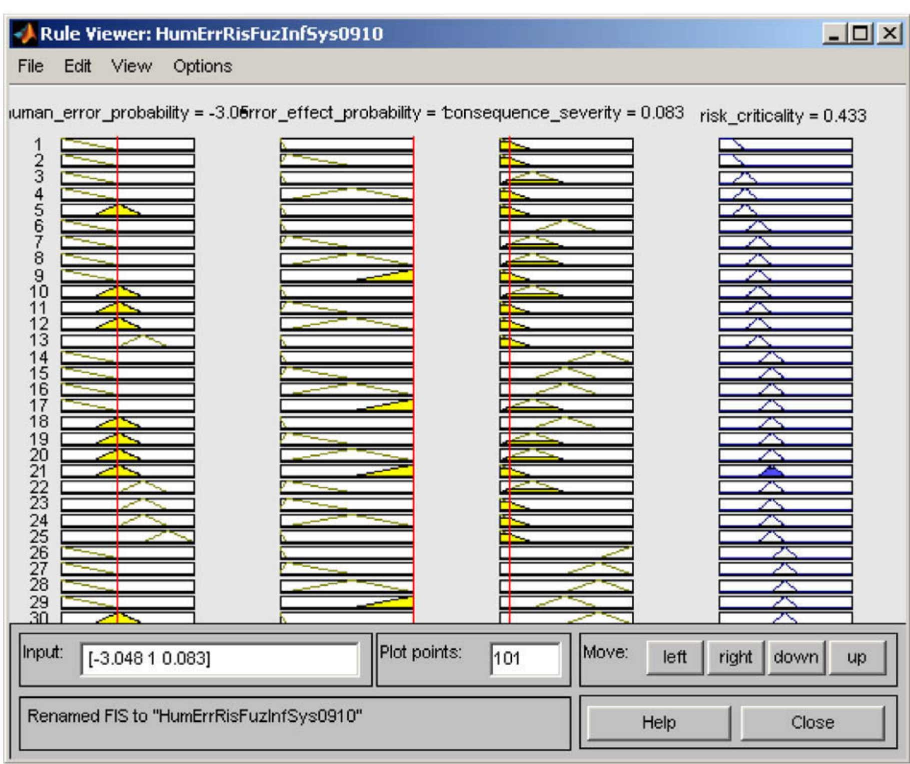

Fig. 11. IF–THEN rules for risk inference by changing the values of inputs.

Table 4
Comparison of analytical results of CREAM with HECA and FHERAM.

Task step	Error mode	α (CREAM)	β	γ	HECA	FRIHE	Ranking CREAM	Ranking HECA	Ranking FHERAM
1.1	O3	0.000896	1	V-L (0.083)	0.0000744	0.433	4	11	10
1.2	I1	0.002	1	V-H (0.9167)	0.0018334	0.798	2	1	1
1.3	I1	0.002	Probable-E(0.5333)	L (0.25)	0.0002667	0.434	2	8	9
1.4	O3	0.000896	1	H (0.75)	0.000672	0.697	4	5	3
2.1.1	O3	0.001792	Probable-E(0.5333)	M (0.5)	0.0004778	0.529	3	6	8
2.1.2	I1	0.004	Probable-E(0.5333)	M (0.5)	0.0010666	0.558	1	3	7
2.2	I2	0.002	1	V-H (0.9167)	0.0018334	0.798	2	1	1
2.3.1.1	O3	0.001792	1	H (0.75)	0.001344	0.729	3	2	2
2.3.1.2	E1	0.0006144	1	H (0.75)	0.0004608	0.687	5	7	4
2.3.2	O3	0.001792	Probable-E(0.5333)	H (0.75)	0.0007168	0.629	3	4	6
2.3.3	E3	0.0001024	1	V-H (0.9167)	0.0000939	0.658	6	9	5
2.3.4	E3	0.0001024	1	V-H (0.9167)	0.0000939	0.658	6	9	5
2.3.5	E3	0.0001024	1	V-H (0.9167)	0.0000939	0.658	6	9	5
2.4	O2	0.001792	Probable-E(0.5333)	V-L (0.083)	0.0000793	0.371	3	10	11

sub-task 1.4 on the system are more serious than one of I1 in sub-task 2.1.2. Although the HEP of I1 in sub-task 2.1.2 is higher than one of O3 in sub-task 1.4, the risk importance of the former is lower than the latter after integrating the impacts of human error into human error risk assessment and taking the risk-weighting factors into account. The main disadvantage of the traditional HECA is that it neglects the relative importance among α, β and γ. The three risk factors are assumed to have the same importance. This may not be appropriate when considering a practical application of HECA process. For example, considering two different human errors having values of 1×10^{-3}, 1, 0.25 and 1×10^{-3}, 0.5, 0.5, for α, β and γ respectively, both of the human errors have a total value of C_{HER} of 2.5×10^{-4}. However, the risk implication of these two human errors may not be the same. We generally think the latter of two human errors is critical than the former.

The proposed FHERAM in this paper addresses these shortcomings. It considers the relative importance among α, β and γ during the establishment of fuzzy rule base of FHERAM according to experts' ideas. And it can better treat the "fuzzy issues" in the process of human error risk assessment.

5. Conclusion and discussion

Human error is the main reason that leads to accident occurrence. Therefore, the pressing problem is how to identify the critical human error and the risk importance of human errors for purposely preventing the occurrence of human errors. This paper presents a new human error risk assessment method based on fuzzy logic to determine risk importance of human error. The conclusions are obtained as follows:

(1) In many situations, human error risk analysis is a complex task which is of great uncertainty due to the complexity of human behavior and environment, lack of information and knowledge, insufficient human error data and the subjective judgments of experts and so on.
(2) The proposed FHERAM can well model the uncertainty. The fuzzy, qualitative or imprecise information, as well as quantitative data can be used in the assessment and they are handled in a consistent manner.
(3) The proposed FHERAM not only considers the HEP, but also integrates the EEP and ECS into human error risk assessment model. From the point of the objective of probabilistic safety assessment (PSA), it actually reflects the real risk of human error because of the consideration of the effects of human error.
(4) It takes the weights of the three risk factors (i.e. HEP, EEP and ECS) of human error into account in the process of the establishment of fuzzy rule base. It is a new attempt of addressing the relative weight and would be in line with the objective reality.

Although the proposed method in this paper has some advantages related above, it still has some limitations: The continuous interval of input and output variables is artificially divided into the discrete one, which leads to a set of discrete rules; The design of membership functions is based on judgments from experts who are familiar with the underlying problems; The determination of weights of risk factors is based only on judgements of experienced experts, while not on the data. These non-systematic designs for dividing interval, developing membership functions, and developing fuzzy rule base are some main resources, which cause the uncertainty. Therefore, it is necessary to obtain more data (i.e. human error data) and develop a better method (i.e. fuzzy neural network model) to reduce this uncertainty.

Additionally, there are completeness uncertainty, modeling uncertainty and parameter uncertainty in human error risk assessment. For example, it does not analyze the effects of recovery factors (e.g., supervisor, alarm) on human error, which makes the results (i.e. HEP) a little conservative. Therefore, this leads to input parameter uncertainty, which is the major reason of the proposed method in this paper to address this issue.

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