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Original Article

Fuzzy FMECA analysis of radioactive gas recovery system in the SPES experimental facility

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ABSTRACT

Selective Production of Exotic Species is an innovative plant for advanced nuclear physic studies. A radioactive beam, generated by using an UCx target-ion source system, is ionized, selected and accelerated for experimental objects. Very high vacuum conditions and appropriate safety systems to storage exhaust gases are required to avoid radiological risk for operators and people. In this paper, Failure Mode, Effects, and Criticality Analysis of a preliminary design of high activity gas recovery system is performed by using a modified Fuzzy Risk Priority Number to rank the most critical components in terms of failures and human errors. Comparisons between fuzzy approach and classic application allow to show that Fuzzy Risk Priority Number is able to enhance the focus of risk assessments and to improve the safety of complex and innovative systems such as those under consideration.

1. Introduction

Selective Production of Exotic Species (SPES) project [1–3] is a facility designed by Istituto Nazionale di Fisica Nucleare (INFN), Laboratori Nationali di Legnaro, Italy, with two main goals:

- provide an accelerator system to perform forefront research in nuclear physics and astrophysics by studying nuclei far from stability
- develop an accelerator based interdisciplinary research centre.

The activities will allow to improve knowledge on production of radionuclides of medical interest or, more generally, to investigate materials for future nuclear reactors.

The major differences of SPES with respect to similar plants is the production of neutron-rich radioactive nuclei with mass in the range 80–160 b y using protons that induce fissions on a direct target of Uranium Carbide (UCx) at a rate of 10^{13} fission/s [4–7].

Attention to neutron-rich isotopes is justified by the fact that this vast territory has been little explored, at exceptions of some decay and in beam spectroscopy following fission.

Each experiment will run through a long period of time in order to determine good characteristic of radioactive beams used for experimental purposes. This implies that the exhaust gases of the vacuum system should be filtered and stored safely in an appropriate system called high activity gas recovery system (HA-GRS).

It should be noted that radioactive gases produced in SPES target are β and γ emitters and direct discharge of this gas mixture into the atmosphere isn't allowed due to radiation risks for the environment.

After a sufficient storage time (various months), nuclear decay events reduce the concentration of the emitters, so it becomes possible to release gas to the chimney in a controlled way. Design of HA-GRS should ensure to manage different and complex operational steps, where high levels of safety are required.

Currently, the safety team is involved in research activities of HA-GRS devices that are suitable for use in safety instrumented functions (SIF) [8]. The main aim is to define a detailed design, foreseen at the end of this year. The last stages are installation and commissioning of the whole system.

In this field, failure mode effect and criticality analysis (FMECA) is a powerful tool to identify potential failures of components and to assess the risk associated with failure modes.

FMECA determines the critical ranking of failure modes using the risk priority numbers (RPN) as product of evaluation criteria like occurrence (O), detection (D), severity (S). Parameter O

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describes the probability that a failure event occurs; D examines the probability to detect the failure mode before it happens; S measures the severity of consequences of failure mode.

RPN method may not be realistic in some applications [9]. Moreover, precise ranking values of O, S and D are often difficult to elicit from the experts which may prefer linguistic-valued judgments rather than quantitative ones [10,11]. Finally, equal importance attributed to these parameters could lead to inaccurate risk ranking of failure modes [11].

In addition, in case of experimental facility or, more generally, complex systems, a critical aspect to identify risks associated to multiple operational steps is related to extensive use of one-of-a-kind devices for which experiences in failure modes and reliability data collections are limited. Consequently, it is a mandatory step for the safety analyst resorting to more than one expert judgement.

As a response to these issues, it is proposed to use fuzzy risk priority number (FRPN) [11], modified by employing the Evidence Theory [12] in construction of weights for linguistic classifications of O, S and D and in assignment of relative importance among these parameters. The aim is to reduce the uncertainty that exists among multiple alternatives elicited from various opinions [13–16].

Methodologies to determine the weight of risk factors mainly include the subjective weighting method, the objective weighting method, and the comprehensive weighting method [17]. However, the proposed approach allows to take into account interpretative processes performed by experts on data related to risk assessments of failure modes and, at the same time, to give consideration to a number of deficiencies in conventional RPN calculation highlighted in literature [9–11,18–24]. This is performed both for component failures and human error.

By using this tool, two main operating conditions of HA-GRS have been examined: storage operation and discharge operation. FMECA analyses of maintenance procedures are also addressed to identify HA-GRS malfunctions due to operator errors (human factor).

Critical analysis of the results has allowed to provide recommendations able to improve safety requirements for equipment and procedures, reducing the occurrence of accidental conditions. These suggestions will be used in revised design of HA-GRS system.

This paper is organized as follows. Section 2 describes fuzzy RPN approach in FMECA, evidence theory application in FRPN tool and improvements proposed for elicitation procedure used to refine failure modes ranking, both for component failures and human factor. A numerical example is shown. Section 3 introduces description of HA-GRS system and results of FRPN analysis. Section 4 reports our conclusions.

2. Use of FRPN in FMECA and evidence theory application

Failure Mode and Effects Analysis (FMEA) [17] and FMECA [18–20] are methodologies designed to identify potential failure modes of components, assess risks associated with those failure modes, rank the issues in terms of importance and, finally, carry out corrective actions to address the most significant issues.

In this methodology, widely used in numerous industrial applications [17–24], index RPN permits to rank the importance of each failure by using the product of three ratings:

$$RPN = O \times D \times S \tag{1}$$

where, O, D, and S, measured on a 10-point scale (high value means more critical risk), are: O is related to the occurrence frequency of the component failure mode, D is the probability of not detecting this failure, and S is the level of damage that it can do on the system, process and the environment.

Despite its wide use, traditional RPN has been criticized due to various shortcomings [9–11,20,22,24] such as: risk factors O, D, and S are difficult to be precisely evaluated; different evaluation of O, S and D may lead to identical RPN even if there are different risk implications; the methodology is unable to properly deal with human errors.

To improve traditional FMECA application, a fuzzy logic methodology of RPN (i.e. FRPN) is proposed in Ref. [11] to address the following issues: provide a linguistic support to experts that must give three values for the risk factors; consider human errors in FMECA; and solve the issue that different O, D, and S combinations lead to same RPN value.

The methodology infers fuzzy conclusions from fuzzy facts by using the following steps [11]:

- O, S, and D, used as inputs, and FRPN, used as output, are classified into fuzzy linguistic distributions (e.g. Very Low, Low, Moderate, …), by using triangular and trapezoidal fuzzy sets. A weight is attributed to each linguistic variable by assuming linear hypothesis. Moreover, the relative contribution (i.e., relative importance) of *O, D,* and *S* to proportionate their contribution in FRPN ranking is assigned by resorting to expert opinions. All these data are required to build fuzzy inference system (FIS), i.e. well-defined rule base consisting of *if*–*then*rules for FRPN calculations
- fuzzy *if-then* inference system is evaluated by using “min-max inferencing” method [25] to process fuzzy inputs and to produce a fuzzy output;
- defuzzification process based on centre of gravity (COG) method is used to evaluate a FRPN crisp value.

Linguistic terms of risk factors O, D, S and FRPN are shown in Tab.s (1) through (4) [11].

Weights of linguistic variables related to O, S, D, and FRPN are evaluated by assuming linear hypothesis as follows:

$$W_O, W_D, W_S, W_{FRPN} = i/k \quad i = 1, 2, \ldots, k \tag{2}$$

where k is the number of language variables that define *O, D, S* and *FRPN*.

Relative importance R_O, R_D, R_S of risk factors *O, D,* and *S* (see Table 5) are given by the analyst that defines values, non-negative and sum of 1, based on the needs of the safety analysis.

However, linear hypothesis of weights for linguistic labels describing risk factor scales not always can apply. In the case in point here, component failures can result in environmental radioactive contaminations with consequences that can lead to a growing range of severity scale, moreover component irradiation effects can modify their performances and, consequently, affect relationships between score ranking and failure occurrence probability. In addition, detection scoring, based on probabilistic information, describes the ability of the process to identify potential failures by means of inspection, periodic testing or the like, use of suitable measurement and detection instruments with or without real-time feedback, etc. However, irradiation conditions or use of one-of-a-kind devices can change or limit detection methods' effectiveness and so it could be necessary to modify association between detection scores and detection probability information.

Moreover, equal importance among O, D and S could lead to inaccurate risk ranking of final failure modes. As is well known, component reliability data reported in literature does not take into account the increase in failure rates due to the aging/failure acceleration during irradiation processes. In this case, it is reasonable that the impact of risk factor O in FRPN calculations should be more

Table 1
Linguistic terms of risk factor, *O*, and related weights W_O.

Occurrence, Linguistic classification	W_O, weight by [11]	W_O, weight by expert opinion
Very Low, VL	0.20	0.414
Low, L	0.40	0.503
Medium, M	0.60	0.679
High, H	0.80	0.910
Very High, H	1.00	1.000

Table 2
Linguistic terms of risk factor, *D*, and related weights W_D.

Detection, Linguistic classification	W_D, weight by [11]	W_D, weight by expert opinion
Non Detection, ND	1.00	1.000
Very Remote, VR	0.83	0.970
Remote, R	0.67	0.722
Moderate, M	0.50	0.650
High, H	0.33	0.217
High, VH	0.17	0.175

Table 3
Linguistic terms of risk factor, *S*, and related weights W_S.

Severity, Linguistic classification	W_S, weight by [11]	W_S, weight by expert opinion
No Effect, N	0.10	0.289
Very Minor, VM	0.20	0.324
Minor, MR	0.30	0.397
Very Low, VL	0.40	0.431
Low, L	0.50	0.494
Moderate, M	0.60	0.621
High, H	0.70	0.782
Very High, VH	0.80	0.910
Hazardous With Warning, HWW	0.90	0.965
Hazardous Without Warning, HWOW	1.00	1.000

Table 4
Linguistic terms of *FRPN* and related weights W_{FRPN}.

FRPN, Linguistic classification	W_{FRPN}, weight by [11]	W_{FRPN}, weight by expert opinion
Unnecessary, U	0.10	0.316
Minor, MI	0.20	0.322
Very Low, VL	0.30	0.479
Low, L	0.40	0.485
Moderate, M	0.50	0.648
High, H	0.60	0.658
Very High, VH	0.70	0.821
Extremely High, EH	0.80	0.837
Necessary, N	0.90	0.995
Absolutely Necessary, AN	1.00	1.000

Table 5
Weights of relative importance R_O, R_D, R_S for component failure and fault due to human factor.

relative importance	weight by [11]	weight by expert opinion for component failure	weight by expert opinion for human error
R_O	0.30	0.335	0.461
R_D	0.30	0.255	0.163
R_S	0.40	0.410	0.376

important than risk factor D. But which is the more appropriate value to attribute to importance of risk factor O for determining FRPN?

It follows that is essential to have different expert opinions, i.e.: resort to expert judgment elicitation to a large degree; aggregate their multiple point of views; reduce objectively the uncertainties associated with their estimates.

To give an answer to above issues in a more focused and effective manner, it is proposed to improve FRPN by resorting to evidence theory in construction of weights for linguistic distributions of O, S and D and in assignment of relative importance among these parameters. This is performed both for component failures and human error.

The aim is to take into account the interpretations by experts of data related to risk assessments in failure modes of component/human factor, and at the same time to carry out a new strategy to reduce uncertainties that exist among alternative points of view [13–16].

2.1. Preliminaries of the evidence theory

Evidence theory, referred also as Dempster-Shafer theory (DST), is an approach devoted to the representation of an uncertain environment which entails assigning a "lower probability" [26] or a "degree of belief" [27] to every event, or proposition. The notion of belief degrees, or belief functions of subsets of a frame of discernment, aims to present evidence theory as an extension of probability theory [28].

In this theory, each evidence of the "evidence system" contains different potential decisions, called "focal elements", and the probability that the "focal element" is a good decision is denoted as Basic Probability Assignment (BPA), known also as belief mass.

Let us consider Ω a frame of discernment, or a set of possible answers to some questions (e.g. Very Low is the chance to detect a potential failure mode), and A_i a subset of Ω (i.e. A_i is a set of focal elements of the evidence containing a number of n mutually exclusive and exhaustive propositions).

Belief mass functions maps m from 2^{Ω} to interval [0,1] are defined by:

$$m(A_i) \rightarrow [0,\ 1]\ satisfying\ m(\varnothing) \rightarrow 0 \sum_{A_i \subseteq \Omega} m(A_i) = 1 \tag{3}$$

To solve the problem more than one in information measurement, and consequently to handle uncertainty, Shannon proposed the concept of "information entropy" (i.e. entropy as a measure of the disorder, in an analogous way to thermodynamic entropy) [27].

Shannon entropy, E_s, can be used to calculate the uncertainty of BPA elements of A_i as follows [29–32]:

$$E_s = -\sum_{i=1}^{n} m(A_i) log_2[m(A_i)] \tag{4}$$

An extension of Shannon entropy is Deng entropy [30], that uses the BPAs and the cardinality of A_i to calculate the uncertainty as follows:

$$E_d = -\sum_{i=1}^{n} m(A_i) log_2\left[\frac{m(A_i)}{2^{|A_i|}-1}\right] \tag{5}$$

where $|A_i|$ is the cardinality of the set A_i.

Note that, Deng entropy, E_d, of Eq. (5) degenerates into Shannon entropy, E_s, of Eq. (4) when the cardinality of A_i is equal to 1.

Deng relative entropy [31,32] allows to measure the different degree among more BPA, and, between two belief mass functions m_1 and m_2, it is defined as follows:

$$D_d(m_1,\ m_2) = \sum_{i=1}^{n} m_1(A_i) log_2\left[\frac{m_1(A_i)}{m_2(A_i)}\right] \tag{6}$$

By using Shannon entropy, Lin in Ref. [33] proposed the belief Jensen–Shannon (*BJS*) divergence to measure the different between two BPA [34–36]:

$$BJS(m_1,\ m_2) = \frac{1}{2}\left[D_d\left(m_1, \frac{m_1+m_2}{2}\right) + D_d\left(m_2, \frac{m_1+m_2}{2}\right)\right] \tag{7}$$

where D_d is evaluated by Eq. (6).

Eq. (7) can be written as follows:

$$BJS(m_1, m_2) = \frac{1}{2}\sum_i m_1(A_i) log_2\left[\frac{2\, m_1(A_i)}{m_1(A_i)+m_2(A_i)}\right] + \frac{1}{2}\sum_i m_2(A_i) log_2\left[\frac{2\, m_2(A_i)}{m_1(A_i)+m_2(A_i)}\right] \tag{8}$$

Notice that when BPA assignments tend to zero, Eq. (8) cannot be calculated. Consequently, it is assumed $m_1(A_i) = m_2(A_i) = 10^{-12}$ when this condition occurs [34,37]. This doesn't affect the results as shown in Ref. [37].

To improve advantages of belief divergence to measure differences among data from multi-sources and belief entropy to quantify the system information volume, Wang and Xiao in Ref. [35] proposed to integrate the credibility and the information volume to allocate the weight on the original evidence. The new combination rule allows merging knowledge from different sources as coherent evidence and to resolve conflicts among sources. The authors highlight that, if an evidence is highly similar to the average BPA, it means that the evidence is more reliable because supported by most of the other evidences, so it has high credibility.

Consequently, according Eq. (8), *BJS* is evaluated between each belief function m_j and the arithmetic average of BPA, m_{av}, as follows:

$$BJS\,(m_j,\ m_{av}) = \frac{1}{2}\sum_{i=1}^{n} m_j log_2\left[\frac{2\, m_j}{m_j+m_{av}}\right] + \frac{1}{2}\sum_{i=1}^{n} m_{av} log_2\left[\frac{2\, m_{av}}{m_j+m_{av}}\right] \quad j=1, 2, \ldots m \tag{9}$$

where m is the number of mass functions for each evidence.

Similarities of evidences are negatively correlated with their divergences, so if the divergence between two evidences is higher, they have lower similarity. On the basis of this, the divergence between belief mass m_j and m_{av} can be converted into their similarity as follows:

$$Sim(m_j,\ m_{av}) = e^{-BJS(m_j,\ m_{av})} \tag{10}$$

Credibility weight, *wCR*, is determined by normalizing the similarity evaluated by Eq. (10):

$$wCR_j = \frac{Sim\,(m_j,\ m_{av})}{\sum_{j=1}^{m} Sim\,(m_j,\ m_{av})} \tag{11}$$

Information volume of mass function m_j is evaluated as follows [34]:

$$IV_j = e^{E_{dj}} \tag{12}$$

where E_{dj} is the belief entropy of A_i, calculated by Eq. (5).

Information volume weight, wIV_j, is obtained by normalizing IV_j:

$$wIV_j = \frac{IV_j}{\sum_{j=1}^{m} IV_j} \tag{13}$$

Based on credibility and information volume weight of evidence, the new weight is adjusted and normalized, next modified evidence $m*$ is calculated as follows:

$$w_j = (wCR_j)(wIV_j) \tag{14}$$

$$w_j^* = \frac{w_j}{\sum_{j=1}^{m} w_j} \tag{15}$$

$$m^*(A_i) = \sum_{j=1}^{m} w_j^* \, m_j(A_i) \tag{16}$$

Finally, for decision making, the pignistic probability transform has been shown to be a good method of using BPA to make decisions [38,39].

It converts each belief function into a pignistic probability distribution BetP [38] as follows:

$$BetP(A_i) = \sum_{A_i \subseteq \Omega} \frac{m^*(A_i)}{|A_i|} \tag{17}$$

In this paper, to construct a decision rule for predicting the system of weights for linguistic variables and assignment of relative importance in FRPN calculation, Eq. (17) is used.

2.2. Evidence theory application in FRPN

Eq.s (9) through (17) are proposed as rules to be used to treat elicited knowledge from experts in FRPN application.

A flowchart of the proposed approach is reported in Fig. (1). The method consists of the following main steps.

The expert-opinion process necessitates identifying and recruiting qualified experts, soliciting their opinions in a structured and efficient manner, retrieving a best estimate, and, perhaps most importantly, quantifying the uncertainties associated with such an estimate.

Elicitation procedure is done with one expert at a time, so that an expert's judgment would not be adversely influenced by other experts.

As suggested in Ref. [16], an advisor-expert is involved to support the selection of experts and elicitation questions.

Ad hoc questionnaire was assigned to each expert and, in order to evaluate its experience in the field in question, experts were asked to answer questions regarding some major system-level failure causes (e.g. faults of critical component in acceleration systems; question about radiological risk; potential origins and development of certain kinds of errors and failures in design and use).

Five subject matter experts were selected to perform the analysis described in this paper.

All selected experts were asked to quantitatively state their opinions on weights of linguistic variables, or their combinations, for *O, S, D*, and *FRPN* and assignment of relative importance R_O, R_D, and R_S, in accordance with conditions Eq. (3).

Note that the application of relative importance of risk factors in RPN and FRPN calculation procedures has been limited to failure modes of components [9,40–42], neglecting the importance to address also human factors as a key factor in the development of mitigating strategies towards a significant reduction of accidental events.

To overcome this shortcoming, the proposed approach has included relative importance R_O, R_D, and R_S connected to human roles in risk assessment.

Tab.s (6) through (11) report belief systems defined by using the above described elicitation process.

In particular, Tab.s (6) through (9) report BPA distributions related to linguistic variables for *O*, *D*, *S* and *FRPN*. Tables (10) and (11) show BPA distributions of relative importance R_O, R_D, and R_S for technical failure and human factor, respectively.

It is important to underline that BPA scoring results for component failures by experts, reported in Table (10), show a tendency to enhance the belief system construction especially on risk factors O and S, while for human error, reported in Table (11), this direction is taken to emphasize the risk factor O.

In the subsequent step, credibility degree and information volume are combined, as described in section 2.1.

Finally, belief functions are converted into pignistic probability distributions to get the final decision about weights for linguistic variables of *O, S, D*, and *FRPN* and relative importance R_O, R_D, and R_S. Tables (1) and (4) report weights obtained for language variables of *O*, *S*, *D*, and *FRPN*. In these tables, data used in Ref. [11] and obtained by Eq. (2), are also shown. Table (5) reports results of relative importance R_O, R_D, and R_S for technical failures and human faults. Fig.s (2) through 6 show these results in graphical form.

Note that, R_O, R_D, and R_S is calculated by using Eq. (17), whereas weights for *O*, *S*, *D*, and *FRPN* are evaluated in terms of *BetP* that is normalized respect the maximum value to obtain results in the interval [0,1], as requested by FIS system for FRPN evaluations [11].

Analyzing results shown in Fig.s (2) and (5), linguistic terms of risk factors *O* and *FRPN* have weights higher than linear trend. Similar results are achieved for S linguistic distributions reported in Fig. (4), except for linguistic terms Very Low (VL), Low (L), and Moderate (M) that are close to the linear hypothesis.

It is worth noting that for risk factors *O*, *S*, and *FRPN*, with linguistic variable characterized by meaning of low-impact, weights are about double (e.g., see occurrence *O* with linguistic attribution "Very Low" of Fig. 2, $W_O = 0.414$ obtained by expert judgment compared to $W_O = 0.2$), or more than double in case of *S*.

This derives from the fact that, for the definition of BPA in belief systems, more experts, among those interviewed, have preferred to attribute importance also to linguistic categorizations considered of low level, pointing out some aspects such as lack of shared technical knowledge in innovative aspects of the facility under consideration, and "low-risk" isn't "no-risk", especially in nuclear field.

These results are consistent with assessments of relative importance R_O, R_D, and R_S reported in Fig. (6) (see also Table 5). In fact, the proposed approach leads to values of relative importance that stress risk factor *S*. For human errors, there is a tendency to emphasize also risk factor *O*.

Human errors in innovative and advanced systems are difficult to predict because such systems are often characterized by high volume of information, criticality of decisions and actions, and complexity of interactions [43–52]. So it is to be expected a special attention by experts about problems related to human error occurrence probability.

To help the reader to understand the procedure of calculations described in section 2.1, a numerical example relevant to R_O, R_D, R_S calculation for technical failure are described in detail below.

The belief structure used for calculations is reported in Table (10).

Step 1: arithmetical average of BPA is calculated for each belief mass function of set $A_i = \{(R_O);(R_D);(R_S);(R_O, R_D);(R_O, R_S);(R_D, R_S)\}$:

$m_{av}[(R_O)] = 0.207$
$m_{av}[(R_D)] = 0.167$
$m_{av}[(R_S)] = 0.287$
$m_{av}[(R_O, R_D)] = 0.080$
$m_{av}[(R_O, R_S)] = 0.160$
$m_{av}[(R_D, R_S)] = 0.10$

Step 2: BJS divergence measure between m_j and m_a is evaluated according to Eq. (9). Then, similarity degree of each evidence by Eq. (10) and weight of credibility by Eq. (11) are evaluated, respectively:

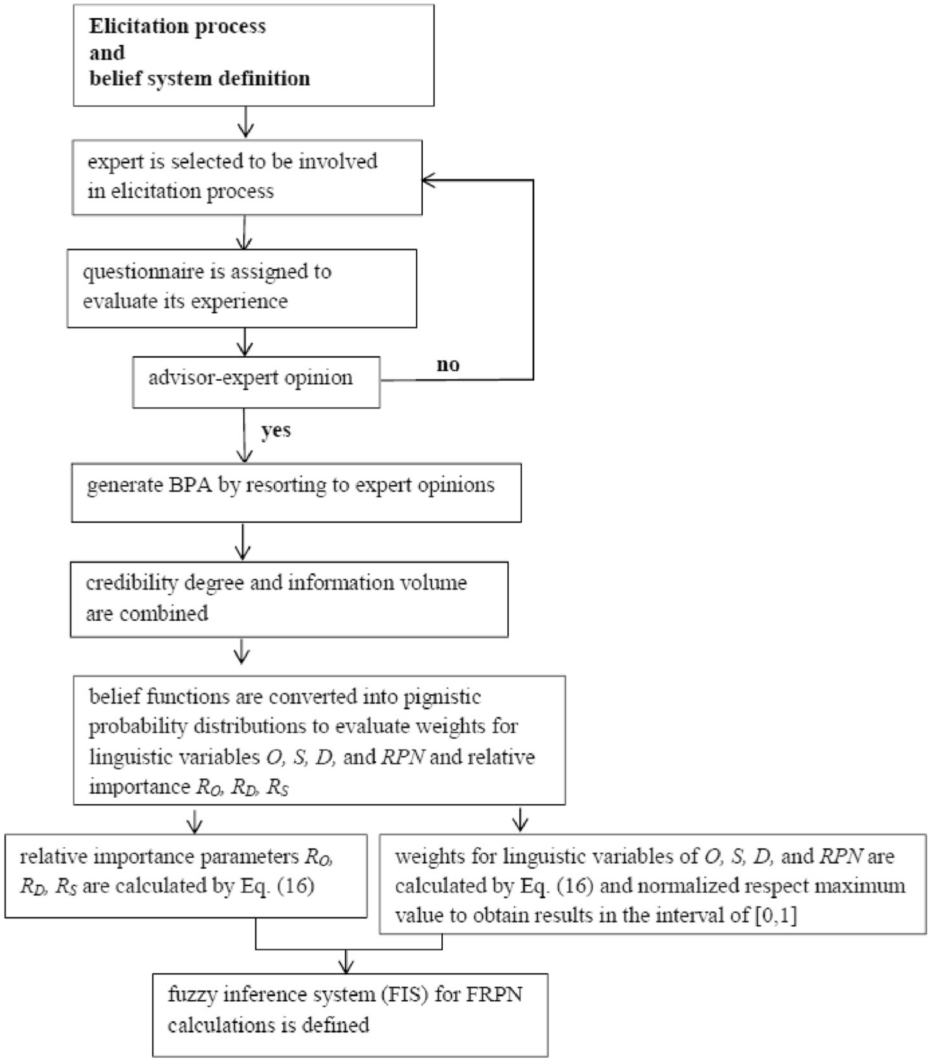

Fig. 1. Flow chart for the calculation process of weights for linguistic variables of *O*, *D*, *S*, and *FRPN* and for assignment of relative importance R_O, R_D, and R_S.

$BJS(m_1,m_{av}) = 0.009;$	$Sim(m_1,m_{av}) = 0.991;$	$wCR_1 = 0.227$
$BJS(m_2,m_{av}) = 0.262;$	$Sim(m_2.m_{av}) = 0.770;$	$wCR_2 = 0.176$
$BJS(m_3,m_{av}) = 0.203;$	$Sim(m_3,m_{av}) = 0.817;$	$wCR_3 = 0.187$
$BJS(m_4,m_{av}) = 0.198;$	$Sim(m_4,m_{av}) = 0.820;$	$wCR_4 = 0.188$
$BJS(m_5,m_{av}) = 0.026;$	$Sim(m_5,m_{av}) = 0.974;$	$wCR_5 = 0.223$

Step 3: Belief entropy, information volume and its weight are calculated by using Eq. s (5), (12), (13), respectively. Note that n in Eq. (5) corresponds to the number of elements in set A_i, this is 6.

$E_{d1} = 3.16;$	$IV_1 = 23.47;$	$wIV_i = 0.278$
$E_{d2} = 3.19;$	$IV_2 = 24.29;$	$wIV_2 = 0.287$
$E_{d3} = 1.58;$	$IV_3 = 4.88;$	$wIV_3 = 0.058$
$E_{d4} = 1.49;$	$IV_4 = 4.42;$	$wIV_4 = 0.052$
$E_{d5} = 3.31;$	$IV_5 = 25.5;$	$wIV_5 = 0.325$

Step 4: new weight of each evidence is adjusted and normalized by using Eq. s (14) and (15), respectively:

$w_1 = 0.063;$	$w_1^* = 0.305$
$w_2 = 0.051;$	$w_2^* = 0.245$
$w_3 = 0.011;$	$w_3^* = 0.052$
$w_4 = 0.010;$	$w_4^* = 0.047$
$w_5 = 0.072;$	$w_5^* = 0.351$

Step 5: modified evidence is evaluated by Eq. (16):

$m^*(R_O) = 0.163$
$m^*(R_D) = 0.123$
$m^*(R_S) = 0.221$
$m^*(R_O, R_D) = 0.115$
$m^*(R_O, R_S) = 0.229$
$m^*(R_D, R_S) = 0.150$

Step 6: Pignistic transformation to represent the crisp value of final event is evaluated by using Eq. (17) (see Table 5).

Table 6
BPAs of belief system related to risk factor occurrence, *O*, obtained by resorting to expert judgment.

Belief mass	Evidence system for occurrence, O						
	(VL)	(L)	(M)	(H)	(VH)	(VL, L, M)	(H, VH)
m_1(expert1)	0.10	0.20	0.20	0.20	0.20	0.00	0.10
m_2(expert2)	0.00	0.00	0.00	0.00	0.00	0.30	0.70
m_3(expert3)	0.10	0.10	0.10	0.30	0.40	0.00	0.00
m_4(expert4)	0.00	0.00	0.20	0.30	0.50	0.00	0.00
m_5(expert5)	0.10	0.10	0.20	0.20	0.20	0.20	0.00

Table 7
BPAs of belief system related to risk factor detection, *D*, obtained by resorting to expert judgment.

Belief mass	Evidence system for detection, D								
	(ND)	(VR)	(R)	(M)	(H)	(VH)	(ND, VR)	(R, M)	(H, VH)
m_1(expert1)	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.30	0.20
m_2(expert2)	0.30	0.30	0.20	0.10	0.10	0.00	0.00	0.00	0.00
m_3(expert3)	0.40	0.30	0.20	0.10	0.00	0.00	0.00	0.00	0.00
m_4(expert4)	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.00
m_5(expert5)	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.40	0.10

$$R_O = BetP(R_O) = m^*(R_O) + \frac{m^*(R_O, R_D)}{2} + \frac{m^*(R_O, R_S)}{2} = 0.335$$
$$R_D = BetP(R_D) = 0.255$$
$$R_S = BetP\ (R_S) = 0.410$$

3. HA-GRS risk analysis and results

3.1. Fuzzy rule-based approach to evaluate a new FRPN

Let A be a collection of numbers or objects (fuzzy set), called the universe of discourse, whose elements are denoted by x; a fuzzy subset A in x is characterised by a membership function $f_A(x)$ that associates each element x with a real number in the interval [0, 1]. The function $f_A(x)$ represents the degree of membership of x in the fuzzy set A [25].

Degree of membership of variable x in fuzzy set A can be described by using the following relationships for triangular and trapezoidal distributions:

Table 10
BPAs of belief system related to relative importance R_O, R_D, R_S for component failure, obtained by resorting to expert judgment.

Belief mass	Evidence system for relative importance parameters, technical failures					
	(Ro)	(Rd)	(Rs)	(Ro, Rd)	(Ro, Rs)	(Rd, Rs)
m_1(expert1)	0.20	0.20	0.20	0.10	0.20	0.10
m_2(expert2)	0.00	0.00	0.20	0.20	0.40	0.20
m_3(expert3)	0.33	0.33	0.33	0.00	0.00	0.00
m_4(expert4)	0.30	0.20	0.50	0.00	0.00	0.00
m_5(expert5)	0.20	0.10	0.20	0.10	0.20	0.20

Table 11
BPAs of belief system related to relative importance R_O, R_D, R_S for failures due to human factor, obtained by resorting to expert judgment.

Belief mass	Evidence system for relative importance parameters, failure due to human factor					
	(Ro)	(Rd)	(Rs)	(Ro, Rd)	(Ro, Rs)	(Rd, Rs)
m_1(expert1)	0.50	0.10	0.40	0.00	0.00	0.00
m_2(expert2)	0.60	0.00	0.00	0.00	0.20	0.20
m_3(expert3)	0.30	0.30	0.30	0.00	0.00	0.00
m_4(expert4)	0.50	0.00	0.30	0.00	0.10	0.10
m_5(expert5)	0.00	0.00	0.00	0.00	0.50	0.50

$$f_A(x) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{x-c}{b-c} & b < x \le c \\ 0 & otherwise \end{cases} \quad f_A(x) = \begin{cases} \dfrac{x-a}{b-a} & a \le x \le b \\ 1 & b < x \le c \\ \dfrac{x-d}{c-d} & c < x \le d \\ 0 & otherwise \end{cases} \tag{18}$$

For brevity, triangular and trapezoidal fuzzy numbers are often denoted as *f(a;b;c)* and *f(a;b;c;d)*.

Using triangular and trapezoidal functions as linguistic data, inputs of risk factors O, S and D are break-down into fuzzy functions of Tab.s (12) through (14) and output FRPN into fuzzy sets reported in Table (15). These fuzzy linguistic functions are therefore used in

Table 8
BPAs of belief system related to risk factor severity, *S*, obtained by resorting to expert judgment.

Belief mass	Evidence system for severity, S														
	(N)	(VMR)	(MR)	(VL)	(L)	(M)	(H)	(VH)	(HWW)	(HWOW)	(N, VMR)	(MR,VL)	(L, M)	(H, VH)	(HWW, HWOW)
m1(expert1)	0.01	0.03	0.05	0.07	0.10	0.10	0.10	0.10	0.10	0.12	0.00	0.00	0.00	0.10	0.12
m2(expert2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.20	0.20	0.20	0.30
m3(expert3)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.00	0.00	0.00	0.00	0.00
m4(expert4)	0.00	0.00	0.00	0.00	0.10	0.10	0.20	0.20	0.20	0.20	0.00	0.00	0.00	0.00	0.00
m5(expert5)	0.00	0.00	0.00	0.00	0.00	0.10	0.10	0.20	0.20	0.20	0.10	0.10	0.00	0.00	0.00

Table 9
BPAs of belief system related to *FRPN* obtained by resorting to expert judgment.

Belief mass	Evidence system for risk priority number, FRPN														
	(U)	(MI)	(VL)	(L)	(M)	(H)	(VH)	(EH)	(N)	(AN)	(U, MI)	(VL, L)	(M, H)	(VH, EH)	(N, AN)
m1(expert1)	0.03	0.05	0.08	0.10	0.10	0.10	0.10	0.15	0.15	0.15	0.00	0.00	0.00	0.00	0.00
m2(expert2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.10	0.20	0.25	0.35
m3(expert3)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.00	0.10	0.20	0.30	0.40
m4(expert4)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50
m5(expert5)	0.00	0.00	0.00	0.00	0.05	0.15	0.15	0.20	0.20	0.25	0.00	0.00	0.00	0.00	0.00

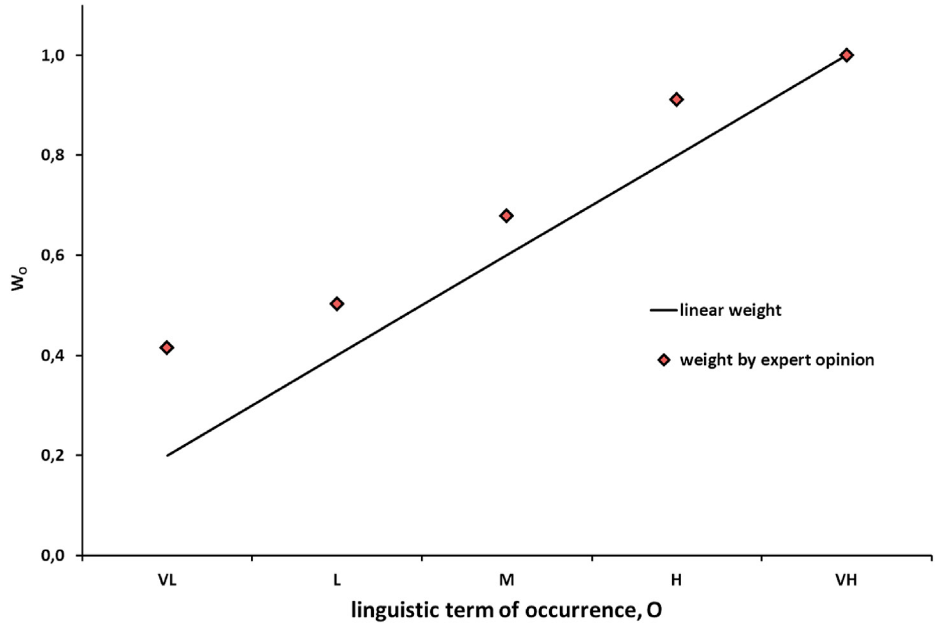

Fig. 2. Weights of language distributions for occurrence, O, obtained by expert judgment.

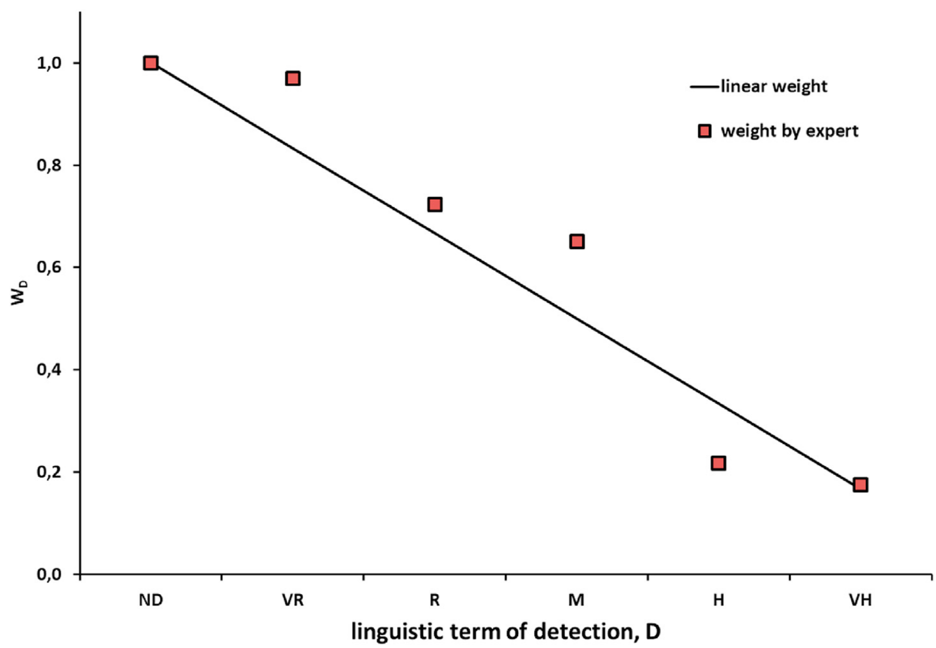

Fig. 3. Weights of language distributions for detection, D, obtained by expert judgment.

if–then-based rules.

Fuzzy *if–then-based* rules of FIS system are determined taking into account relative importance of the input O, S and D and weights of their linguistic terms [11].

In particular, by using weights W_O, W_D, W_S *and* W_{FRPN} and relative importance R_O, R_D, R_S reported in Tab.s (1) through (5), obtained by using expert opinion as reported in section 2.2, FIS system is built as described below.

Weight W_{FRPN} is evaluated by using the following relationship, as suggested in Ref. [11]:

$$W_{FRPN} = R_O\, W_O + R_D\, W_D + R_S\, W_S \tag{19}$$

W_{FRPN} value by using Eq. (19) allows for the identification of linguistic term of FRPN output as explained in the following example for component failure with $R_O = 0.335$, $R_D = 0.255$, $R_S = 0.41$(see Table 5):

Rule → **If** O **is** H with weight $W_O = 0.910$ **and**

D **is** R with weight $W_D = 0.722$ **and**
S **is** M with weight $W_S = 0.621$ **then**
FRPN ***is*** *VH with weight* $W_{FRPN} = 0.821$

Detailing contents of this rule, mathematically it happens that

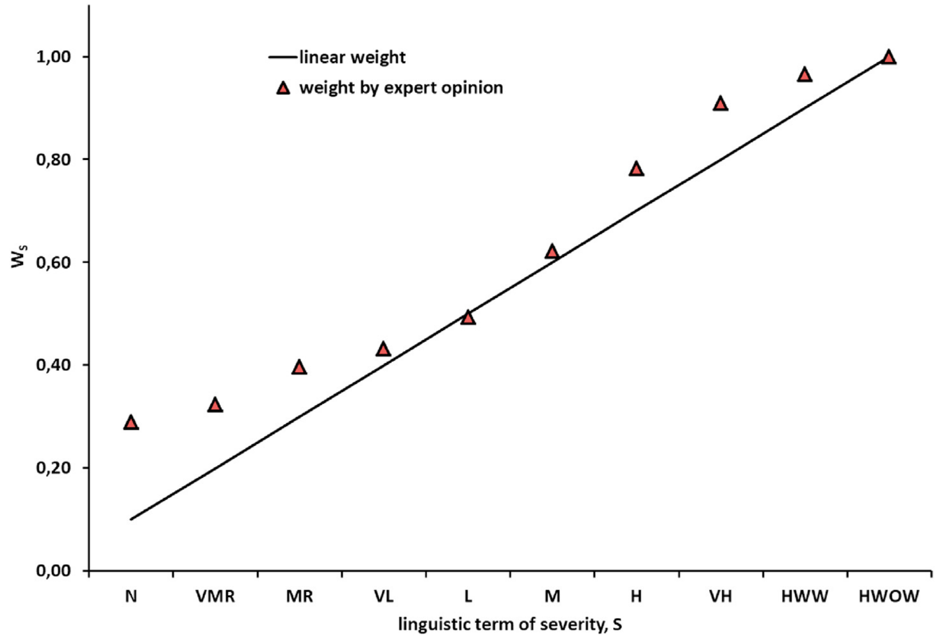

Fig. 4. Weights of language distributions for severity, S, obtained by expert judgment.

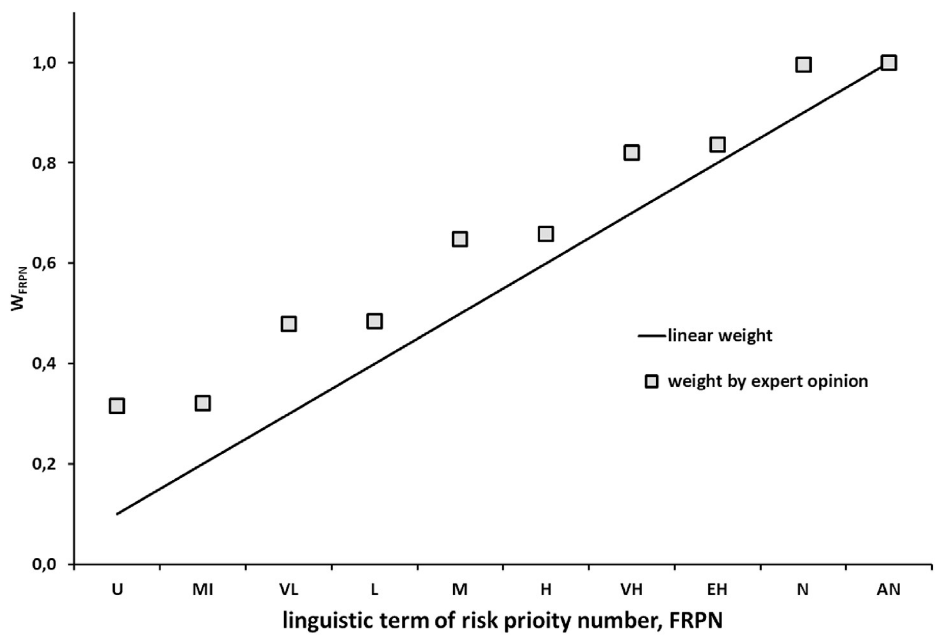

Fig. 5. Weights of language distributions for risk priority number, FRPN, obtained by expert judgment.

by using Eq. (19) $W_{FRPN} = 0.335 \times 0.91 + 0.225 \times 0.722 + 0.41 \times 0.621 = 0.744$. This value is close to risk defined as Very High (VH) (Table 4) with $W_{FRPN} = 0.821$.

A number of 300 rule combinations (5O × 6D × 10S, being 5, 6, 10 number of linguistic terms of *O*, *D*, and *S*, respectively) has been built and used in the analysis.

To evaluate FRPN crisp value, fuzzy inference process flows through these fuzzy *if–then* rules, where *min–max* method for the aggregation of outputs is used [11,25], and then proceeds with the defuzzification procedure by using COG method, as described in Ref. [11].

Note that in the study reported in this paper, HEART approach proposed in Ref. [43] was used to evaluate error probability necessary to define *O* factor for failures related to human factor.

3.2. HA-GRS description

A detailed description about SPES safety and control systems can be found in Ref. [3,5].

The target-ion source system is irradiated by proton for approximately fifteen days. The proton driver is a Cyclotron with variable energy (15–70 MeV) and a maximum current of 0.750 mA upgradeable to 1.5 mA and split on two exit ports.

High vacuum condition (10^{-6} mbar) is provided by a complex

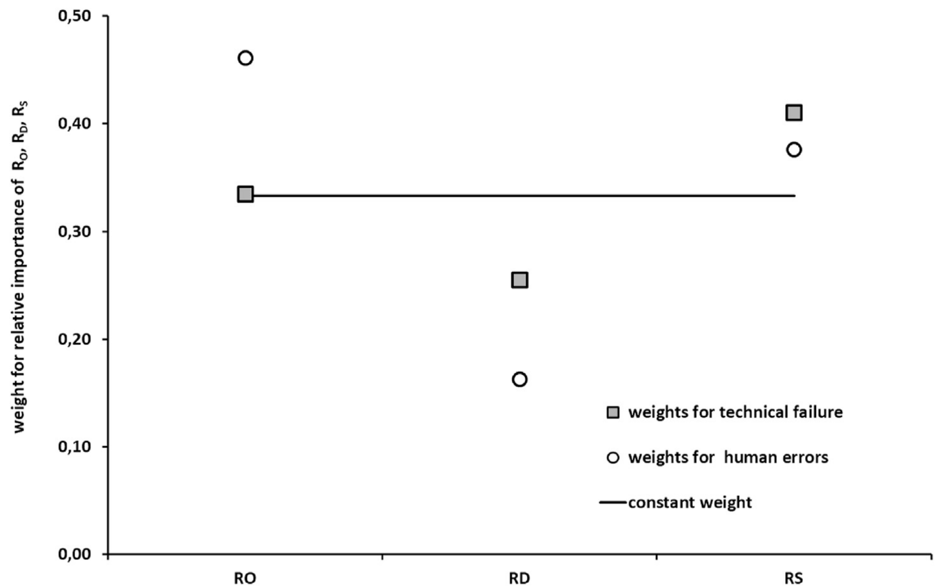

Fig. 6. Values of relative importance R_O, R_D, and R_S, obtained by expert judgment.

system made up of several serially coupled turbo-molecular and roots pumps. The root pumps provide a fore vacuum condition (10^{-2} mbar) for beams channel and discharge of the turbo-molecular pumps. When the beam is switched off no more high vacuum condition is requested and venting operation restore atmospheric pressure into the front-end part of the vacuum line.

It is mandatory that HA-GRS line stays always under ambient pressure, not only during beam operations, but also later time to avoid possible leaks to the working environment.

HA-GRS can be divided in three main subsystems:

- vacuum pipeline system, that connects turbo-molecular and root pumps with the storage system;
- storage system, where three storage tanks are used to store safely gases coming from vacuum system
- discharge system used to discharge exhaust gases in atmosphere through a chimney, if radiological safety requirements are reached.

Fig. 7 shows early design of HA-GRS system studied in this paper.

The gas flows through an oil condenser (C1 in Fig. 7), used to remove oil impurity produced by rotary vane pumps, C1 is connected in series with expansion vessel, VA, characterized by double wall tanks.

VA pressure cannot fall below a threshold value (about 500 mbar) to cover the specific vacuum pumps operational conditions. Below this limit, the rotary pumps are damaged due to lubricating oil losses. A higher pressure set point is also ensured, with a value lower than atmospheric pressure.

If VA pressure exceeds 500 mbar, an automated back pressure regulator becomes operational. Its operation is based on pressure measurements of PSI_VA transducer that allows V2_VA valve opening and closing by using a stepper motor device, PSE_VA pressure transducer is provided to control the pressure in the gap of the VA tanks. assuring to monitor if breaking event in VA inner wall occurs.

HEPA (High Efficiency Particulate Air filter) allows to purify gas before storage in vessel S1.

S1 and S2 allow to storage gas by using the following operational conditions: if S1 is filled up to the maximum pressure of 800 mbar, valve V1_S1 is closed and valve V1_S2 is opened to fill S2 storage vessel, S3 is used as safety tank, if overfilling of S1 and S2 occurs.

To improve safety, storage vessels, S1, S2 and S3 are characterized by steel double wall tanks in which the pressure is lower than atmospheric pressure.

The filling process is streamlined by using a Programmable Logic Controller (PLC) that closes and opens valves based on measurements of pressure gauges PSI_S1, PSI_S2 and PSI_S3, positioned in vessels S1, S2 and S3, respectively.

Pressure gauges PSE_S1, PSE_S2 and PSE_S3 measure the pressure between the inner and outer walls of the storage vessels to control if break inner wall condition occurs.

Storage vessels can be isolated by manual valves located at inlet and outlet of each storage vessel (VM1_S1, VM2_S1, VM1_S2, VM2_S2, VM1_S3, VM2_S3 in Fig. 7) to carry out maintenance procedures.

Table 12
Fuzzy FMECA scale for occurrence, *O*, of component failure and human error [11].

Linguistic scale	Component failure, probability per operating day	Human error occurrence probability	Risk fuzzy membership function, f(a; b;c) or f(a; b;c; d)
Very Low (VL)	<1/20,000	Less than every 5 years	(0; 0; 1; 3)
Low (L)	1/20,000 ÷ 1/2,000	Every 2 ÷ 5 years, once a year	(1; 3; 5)
Moderate (M)	1/2,000 ÷ 1/200	Several times a year, once a month, several times a month	(3; 5; 7)
High (H)	1/200 ÷ 1/20	Once a week, several times a week	(5; 7; 9)
Very High (VH)	1/20 ÷ 1/2	Once a day, several times a day	(7; 9; 10; 10)

Table 13
Fuzzy FMECA scale for detection, *D* [11].

Likelihood of failure detection	failure detection probability	Risk fuzzy membership function f(a; b;c) or f(a; b;c; d)
Very High (VH). Design control almost certainly detects the failure.	0.00 ÷ 0.15	(0; 0; 2; 3.5)
High (H). High chance that the design control almost certainly detects the failure.	0.15 ÷ 0.35	(2; 3; 4; 5.5)
Moderate (M). Failure remains undetected until the system performance is affected.	0.35 ÷ 0.65	(3.5; 5; 6; 7.5)
Remote (R). Failure remains undetected until an inspection is carried out.	0.65 ÷ 0.85	(5.5; 7; 8; 9)
Very Remote (VR). Design control cannot detect potential cause.	0.85 ÷ 0.90	(7.5; 9; 10)
Non detection (ND). There is no design verification.	0.90 ÷ 1.00	(9; 10; 10)

Table 14
Fuzzy FMECA scale for severity, *S* [11].

Effects	Risk fuzzy membership function f(a; b;c) or f(a; b;c; d)
No effect (N).	(0; 0; 1; 2)
Very Minor (VMR). Very minor effect on system. No injury to people.	(1; 2; 3)
Minor (MR). Minor effect on system. Very minor or no injury to people.	(2; 3; 4)
Very Low (VL). Very low effect on system. Minor or no injury to people.	(3; 4; 5)
Low (L). Low effect and system requires repair. Low danger for people.	(4; 5; 6)
Moderate (M). System is degraded. Moderate danger to people	(5; 6; 7)
High (H). System is severely affected but functions. Major injury to people.	(6; 7; 8)
Very High (VH). System losses primary function. Failure can involve hazardous outcomes. Major injury to people.	(7; 8; 9)
Hazardous with warning (HWW). Failure involves hazardous outcomes. Very dangerous condition or death of people.	(8; 9; 10)
Hazardous without warning (HWOW). Failure is hazardous and occurs without warning. Extremely dangerous, cause death of people.	(9; 10; 10)

Table 15
FMECA scale for FRPN.

Linguistic Value of the FRPN	Risk fuzzy membership function f(a; b;c) or f(a; b;c; d)
Almost unnecessary to take measures (U).	(0; 0; 25; 75)
Minor priority to take measures (MI).	(25; 75; 125)
Very Low priority to take measures(VL).	(75; 125; 175)
Low priority to take measures (L).	(125; 200.300)
Moderate priority to take measures (M).	(200; 300; 400)
High priority to take measures (H).	(300; 400; 500)
Very high Very High priority to take measures (VH).	(400; 550; 700)
Extremely High priority to take measures (EH).	(500; 650; 800)
Necessary to take < hyperlink refid = "https://context.reverso.net/traduzione/inglese-italiano/take + measures"> measures (N).	(700; 800; 900)
Absolute Necessary to take measures (AN).	(800; 900; 1000; 1000)

Electro-pneumatic valves V2_S1, V2_S2 e V2_S3, at the exit of storage vessels, allow to isolate HA-GRS from the chimney during the experimental tests, and perform gas discharge operations when radiological safety conditions are achieved.

Discharge process is performed by using extraction piston pump X-DRY of Fig. 7, following the opening of valves V2_S1, V2_S2 e V2_S3 and valve V_ROT, located downstream of X-DRY.

Before gas releasing from the chimney, a gas sample is analysed to determine if radiological safety requirements are ensured. The operator gives the authorization to exhaust gas release on the basis of measurement results.

3.3. Results and discussion

Collection of component failure rate data is one of the main tasks needed to perform FMECA analysis.

A large part of information (operational conditions, materials, construction features, element functions of components, etc.) comes by companies which are manufacturers of devices used in "vacuum technology".

Some reliability data result from a review of literature reported in Ref. [53–57].

The analysis involved compilation of more than one hundred FMECA forms by using Risk Analysis Database (RAD) software [58].

This activity has allowed to create a failure modes taxonomy which can be useful in further safety analysis performed, for example, by using fault tree analysis (FTA) or in risk assessments of other accelerator systems.

Two main operating steps were taken into account to compile FMECA worksheets:

- storage operation during experimental test;
- exhaust gases discharge operation.

Maintenance procedures were also examined to identify possible HA-GRS malfunctions due to human factor. For example, in the isolation procedure of parts of system for carrying out replacement of components, failure to open (or to close) of manual valves, caused by carelessness or oversight, can negatively affect performance of both safety and control systems.

Traditional RPN application and FRPN obtained by fuzzy procedure reported in Ref. [11] are also evaluated for comparison and

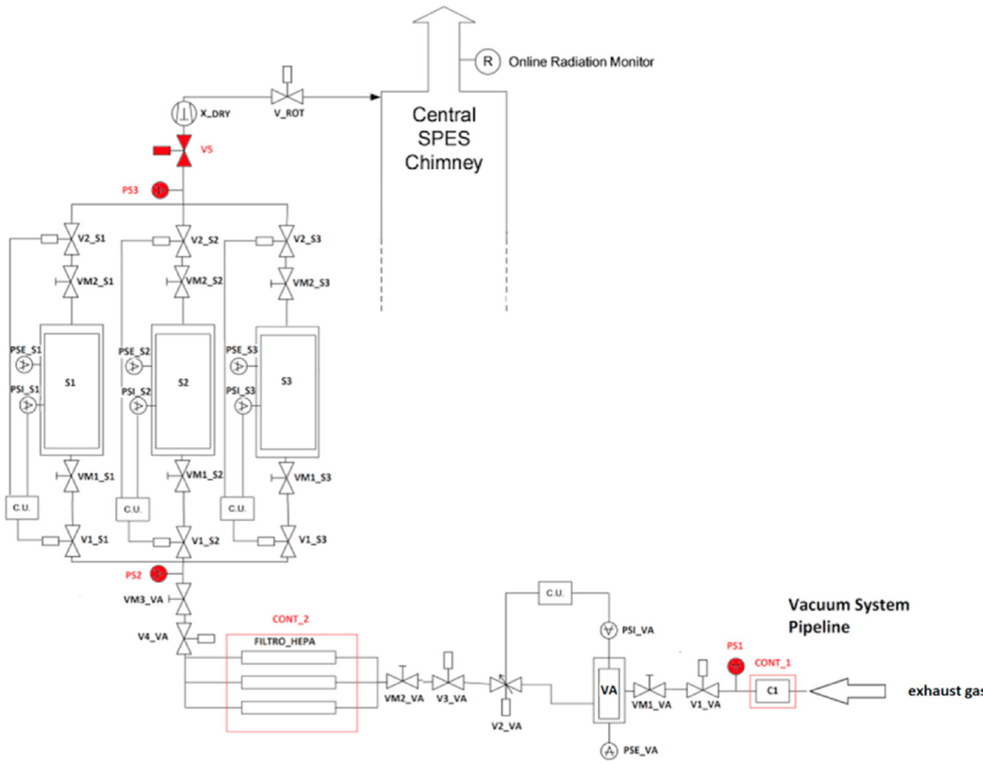

Fig. 7. HA-GRS layout. Design changes, suggested on the basis of fuzzy FMECA results, are reported in red.

verification of the proposed methodology. Data of FRPN higher than 250 are reported in Tables 16 and 17 for storage operational conditions, and Table 18 for discharge operation. Note that in these tables results obtained by using the proposed method are indicated with FRPN*.

As expected, comparison among results highlights that traditional RPN scoring is different from one obtained by FRPN and FRPN*.

For example, during storage operations, failure modes of PSI_VA (measurements errors, less than) and HEPA (rupture, gas leakage) show same RPN value (RPN = 120 in Table 16). However, HEPA failure leads to releases in environment of radioactive gas with very high severity, i.e. S = 8. This issue is highlighted by FRPN and FRPN* that result in FRPN = 393.1 and FRPN* = 379.5, respectively (about 3 times compared to RPN value).

In like manner, failure modes of C1 (oil external leakage) and HEPA (gas external leakage) show same RPN value of 160 in Table 16. These failures are classified with same severity S = 8 but a bit of difference among parameters O and D. Alternatively, FRPN and FRPN* provide high scorings, pointing out prioritization of C1 failure characterized by highest risk factor O.

FRPN and FRPN* rank as a critical failure event the measurement error (ΔP overestimation) of pressure gauge PSI_VA (FRPN = 513.1 and FRPN* = 500.1 in Table 16), the consequences of which can result both in stopping storage operation and damages of the vacuum system (oil leakage from the root pumps).

On the whole of failure modes of Table (16), FRPN* values are lower than FRPN ones. However, it should be underlined that FRPN* retains same ranking order of failure modes obtained by FRPN, but the risk prioritization is based on a more noticeable scale (e.g. in Table 16, FRPN* = 459.8 and FRPN* = 430.8 related to two different failures with same RPN = 160 compared to FRPN = 461.0 and FRPN = 458.9 that define a close ranking of these failures).

Critical failures are obtained for a set of valves located in vacuum pipeline system and inlet of storage system (Table 17).

In particular, failure mode with gas external leakage in V1_VA and V1_S1 valves is characterized by very remote detection and very dangerous conditions for people and operator. For this failure, defined by a triplet of risk factors (O; D;S)=(5; 8;8), FRPN* provides a scoring higher than FRPN one (FRPN* = 583.6 compared to FRPN = 555.1). This result can be attribute to new FIS system that seems to highlight circumstance under which two out of three evaluation criteria are characterized by very high value, i.e. D = 8 and S = 8.

For failure modes of V1_VA valve with triplet of risk factors (O; D;S)=(6; 3;6) and (4; 5;6), we note that FRPN* gives a scoring for (6; 3;6) that is higher than one obtained for (4; 5;6) (i.e. FRPN* = 306.3 compared to FRPN* = 295.5). This result shows that

Table 16
FMECA results of component failures that are critical for the safety of storage operations.

Component	Failure mode	Main effects	O	D	S	RPN	FRPN [11]	FRPN*
PSI_VA	Measurement error (more than)	Oil leakage from fore vacuum pumps (ΔP overestimation)	5	7	7	245	513.1	500.1
	Measurement error (less than)	Anomalous storage interruption due to ΔP underestimation	5	4	6	120	386.6	351.0
C1	External leakage	Oil leakage	5	4	8	160	461.0	459.8
HEPA	External leakage	Gas leakage	4	5	8	160	458.9	430.8
	Rupture	Gas leakage	3	5	8	120	393.1	379.5

Table 17
FMECA results of valve failures that are critical for the safety of storage operations.

Component	Failure mode	Main effects	O	D	S	RPN	FRPN [11]	FRPN*
V1_VA	External leakage	Pressure increases into the storage vessel (S_1 or S_2) and probable gas leakage	5	8	8	320	555.1	583.6
	Spurious closing	Storage interruption	6	3	6	108	327.8	306.3
	Opening failure on demand	Storage interruption	4	5	6	120	352.2	295.5
VM1_VA	Valve is closed, human error in valve maintenance		5	5	7	175	434.8	444.6
V2_VA	External leakage	Pressure increases into the storage vessel (S_1 or S_2) and probable gas leakage	5	4	8	160	461.0	459.8
	Spurious closing	Storage interruption	6	3	6	108	327.8	306.3
	Opening failure on demand	Storage interruption	4	5	6	120	352.2	295.5
V1_S1	External leakage	Pressure increases into the storage vessel S_1 and probable gas leakage	5	8	8	320	555.1	583.6
	Spurious closing	Storage interruption	6	4	6	144	438.4	403.0
	Opening failure on demand	Storage interruption	4	4	6	96	321.3	292.6
VM1_S1; VM1_S2; VM1_S3	Valve is closed, human error in valve maintenance	pressure increases in storage line	4	5	7	140	378.7	410.7

Table 18
FMECA results of component failures that are critical for the safety of discharge operations.

Component	Failure mode	Main effects	O	D	S	RPN	FRPN [11]	FRPN*
V_ROT	External leakage	Gas leakage	5	5	8	200	470,4	483.9
	Spurious closing	Gas discharge interruption	6	5	4	120	305,5	278.5
X-DRY	Breaking	Gas leakage	5	2	9	90	410,7	426.4

the proposed approach is coherent with the expert opinion that consider the impact of parameter O in FRPN* calculation more important than parameter D. Note that opposite result is obtained by using FRPN.

Moreover, human roles are critical for failure modes of valves VM1_S1, VM1_S2, VM1_S3 that result to be closed due to human error in maintenance procedure. Tre triplet of risk factors (O; D;S)=(4; 5;7) leads to FRPN* higher than the one obtained by FRPN (see Table 17, FRPN* = 410.7 compared to FRPN = 378.7). In this case, the result is influenced by two main factors:

- weights of linguistic terms for risk factor, O, used to define the new FIS system, are higher than those reported in Ref. [11], especially for linguistic attributions VL and L (see Fig. 2) that define risk factor, O, lower than 5 (Table 12);
- relative importance distribution of risk factors O, D, and S, reported in Table 5 emphasizes the importance of O in case of human errors.

During discharge operations, critical events are related to external leakage of valve V_ROT and extraction pump X_DRY (Table 18).

For valve V_ROT with failure causing gas external leakage characterized by S = 8, traditional RPN provides a low value of 200 compared to results obtained by FRPN and FRPN* that give FRPN = 470.4 and FRPN* = 483.9. Note that FRPN* enhances the visibility of this critical event.

Finally, for X_DRY failure mode concerning breaking with gas external leakage, it should be noted that traditional RPN has a low value of 90, despite this fault is characterized by very dangerous conditions with S = 9 (i.e. failure involves hazardous outcomes or death of people can occur). FRPN and FRPN* highlight the criticality of this event by giving FRPN = 410.7 and FRPN* = 426.4. This outcome is better highlighted by FRPN* that provides a value higher than FRPN one.

On the basis of the above results, design improvements, to increase safety conditions and reduce consequences, are suggested as follows:

- add external containment in oil condenser C1 and in filter HEPA, to mitigate consequences of oil or gas leakages;
- use a pressure gauges, upstream of VA and upstream of storage systems (see PS1 and PS2 in Fig. 7) to improve redundancy of pressure measurements in vacuum pipeline and at the inlet of the storage vessels;
- add a pressure gauge immediately downstream of storage vessels (PS3 in Fig. 7) to monitor possible leakage in discharged pipeline during experimental tests;
- use valve lockouts to keep machine and equipment parts secure during maintenance/repairs;
- use colored labels that enable to operators to understand properly (no misunderstanding) if valves are open or close correctly, on the basis of the required condition in the performed maintenance procedure;
- add an electrically-actuated valve (see valve VS in Fig. 7) before the extraction pump X_DRY to isolate storage system from discharge line against occurrence of valve failures downstream storage system.

4. Conclusion

The challenge of Selective Production of Exotic Species experimental project is to build up a world level facility for the production of exotic beams for nuclear physics experiments. Very high vacuum conditions are required together with a system to storage radioactive exhaust gases safely. For such purposes, high activity gas recovery system (HA-GRS) is designed to reduce radiological risk for operators and people.

In this paper, fuzzy failure mode effect and criticality analysis (FMECA) is used to support a preliminary risk assessment of the HA-GRS system. This tool has been modified by using a new method to evaluate the fuzzy risk priority number (FRPN).

FRPN, developed to overcome some deficiencies in conventional risk priority number (RPN) applications highlighted in literature [18–24], is a powerful method of ranking critical failures. It requires to build fuzzy inference system (FIS), i.e. well-defined rule base consisting of fuzzy *if–then rules* for FRPN calculations [11]. For this purpose, risk factors occurrence (O), detection (D), severity (S), used as inputs, and FRPN, used as output, are classified into fuzzy linguistic distributions and a weight is attributed to each linguistic variable by using linear function [11]. Moreover, relative importance among O, D, and S is assigned.

However, there are several technical problems associated to these tasks, i.e.:

- linear weight for linguistic variables of O, D, and S and RPN not always can be applied;
- equal importance among O, D and S could lead to inaccurate risk ranking of final failure modes;
- aggregate expert opinions on risks associated to failure modes for components/human actions when safety aspects are mainly related to extensive use of one-of-a-kind devices for which experiences in failure modes and reliability data collections are limited;
- aggregate multiple point of views from experts and dampen the effects of variability associated with their estimates.

Another point of attention is that when we make recourse to expert opinion, if measurements are replaced by observations and linguistic descriptions, this type of uncertainty cannot be properly handled by stochastic methods, but must be treated by the possibility theory or other uncertainty theories [59].

Having taken into consideration the above-said, it is proposed to use expert elicitation process to be incorporated in FRPN calculations and so to evaluate a new FRPN index, i.e. FRPN*. This is performed by resorting to evidence theory, both for technical failures and faults related to human factors.

The success of any expert elicitation process is highly dependent upon how carefully the experts are chosen, whether the experts provide unbiased judgments, and, finally, how multiple opinions are reconciled or combined.

The proposed approach allows to take into account importance of interpretations by experts of data related to risk assessments of failure modes of component/human error, but at the same time to consider the uncertainty that exists among alternative points of view provided by experts [60,61].

Results of HA-GRS analysis by using traditional RPN, FRPN reported in Ref. [11] and FRPN* as proposed in this paper are compared.

As expected, comparison among results highlights that RPN ranking is different from one obtained by using FRPN and FRPN*. In particular, RPN scoring doesn't highlight potential problems according to the real criticality of failure modes and doesn't allow to clearly distinguish those items which should be improved.

This task is properly performed by FRPN* and FRPN, but some differences.

FRPN* retains same ranking order of failure modes obtained by FRPN, but the risk prioritization is based on a more noticeable scale, e.g. in Table 16 FRPN* = 459.8 and FRPN* = 430.8 related to two different failures with same RPN = 160 compared to FRPN = 461.0 and FRPN = 458.9 that define a close ranking of these failures.

Moreover, FRPN* provides scorings higher than FRPN if two out of three evaluation criteria are characterized by very high value (e.g. D = 8 and S = 8 for failure mode of valve V1_VA of Table 17), or in case of failures modes related to human errors the a higher probability of happening.

Another difference between FRPN and FRPN* is that, for example, for failure modes with triplet of risk factors (O; D;S)=(6; 3;6) and (4; 5;6), FRPN* gives a prioritization to (6; 3;6) (FRPN* = 306.3 compared to FRPN* = 295.5 of Table 17). Opposite result is obtained by using FRPN. This result shows that the proposed approach is coherent with the expert opinion that consider the impact of parameter O in risk priority number calculations more important than parameter D.

Critical analysis of the results has allowed to provide recommendations able to improve safety requirements for equipment and procedures, reducing the occurrence of accidental conditions. These suggestions will be used in revised design of the HA-GRS system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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