Priorities Assessment for Nuclear Failure Mode Combining Experts´ Similarity Aggregation and Simulation of Choquet Integrals in a CPP Framework

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RESUMO

A análise dos modos e efeitos de falha (FMEA) é uma das principais técnicas utilizadas para análise de risco e engenharia de confiabilidade de produtos em desenvolvimento e processos. Esta abordagem baseia-se no entendimento de uma equipe multidisciplinar a respeito daquilo que está sob análise. Ou seja, trata-se de um procedimento que agrega essas diferentes opiniões acerca dos modos de falha. A priorização destes, considerando-se a abordagem tradicional, vem sendo questionada em inúmeros artigos científicos, que vêm propondo diferentes abordagens para se combinar os três indicadores tradicionais associados a severidade, ocorrência e detecção (SOD). No presente trabalho apresenta-se um procedimento baseado na composição probabilística de preferências para estabelecer essa ordem de prioridade. Os resultados obtidos, numa aplicação real simplificada, demonstram a eficácia da abordagem proposta.

PALAVRAS CHAVE. FMEA, Priorização de Riscos, CPP, Agregação de Especialistas.

AD&GP, ADM, EST&MP

ABSTRACT

Failure mode and effect analysis (FMEA) is one of the main approach for risk analysis and reliability engineering for under-development product or process analysis. This approach is based on the understanding of a multidisciplinary team about what is under analysis. That is, it is an approach that aggregate these different opinions about the failure modes. Its prioritization, considering the traditional approach, have been the concern of many research papers, witch are proposing different ways for combining the three indexes related to severity, occurrence and detectability (SOD). In the present work, one presents a probabilistic composition of preferences approach to establishes a priority order among the failure modes. The obtained results, from a simplified application case, shows the efficacy of the proposed method.

KEYWORDS. FMEA, Risk Prioritization, CPP, Experts´ Aggregation.

AD&GP, ADM, EST&MP

1. Introduction

Risk analysis is a routine activity carried out by reliability engineers and risk analysts in all industries. As part of probabilistic safety analysis (PSA), risk analysis supports decision-makers with respect to maintenance policies and/or early warning of critical vulnerabilities of the system under analysis [Fullwood, 2000]. In PSA, the failure mode and effect analysis (FMEA) process aims to identify and provide semi-quantitative information with respect to the different ways in which the system can fail, and also to constitute the input factors for system modeling [IAEA, 1992].

The FMEA approach provides relevant information to decision-makers regarding risk analysis. Basically, three criteria of failure mode analysis are explored in the FMEA process: the likelihood of occurrence (O), the severity of its effects (S), and the ability to detect a potential cause of failure (D). Specifically, for the detection index, the higher the "D" value, the lower the system response potential will be. These criteria are usually measured in psychometric scales (i.e., 1 to 10, or 1 to 5) [Bowles e Bonnell, 1998; Bowles, 1998]. The traditional method for risk prioritization is to calculate the risk priority number (RPN), which equals the product of "S", "O" and "D". The higher the RPN, the greater the risk of the failure mode will be [SAE, 2009]. The failure mode that is first ranked is usually prioritized for corrective actions to reduce the effects of potential damages. Actions may include safety barriers and emergency plans to mitigate effects, among other measures [Bowles, 1998].

However, the traditional approach to the RPN calculus can cause distortions. One of the problems was first raised by Bowles e Peláez [1995] and refers to the relative importance of the criteria. A second critical point is that equal RPN values can reflect different features of failure modes. Permutations and combinations of S, O and D can return the same RPN. In fact, a "8-1-8" RPN may be associated with a "black swan" event, a very rare failure mode that requires special treatment. On the other hand, a "1-8-8" RPN may be routinely monitored and controlled.

A third critical point associated with RPN is that any product greater than ten having a prime number as a criterion factor cannot be formed by the product of three parameters. For example, 22, 33 and 990, all multiples of the prime number 11, are RPN values that cannot be generated by the product of severity, occurrence, and detection indices, considering a (1, 10) criterion scale. For the same reason, the multiples of 13, 17, 19 etc. will be excluded from the RPN spectrum of possible values [Bowles, 2003].

Another problem often mentioned in the literature is that uncertainty sometimes influences experts´ opinions. Exact values may not reflect the experts´ choice about the criterion. According to Morgan [2014] , probability distributions better represent the subjectivity of technical judgment from experts. In fact, decision analysts have long used quantitative expert judgments in the form of probability distributions elicited from relevant experts.

Combined with the above mentioned problems, one must remember that FMEA is an approach based on multidisciplinary team, i.e., it is a tool for group decision making. Considering that, it is important to search for solutions that tackle the prioritization problem and considers a group decision. Based on these assumptions, in the present paper a hybrid Composition of Probabilistic Preferences based approach is proposed. One combines experts´ similarity aggregation with a randomization process of the criteria. The final composition is addressed by the simulation of discrete Choquet integrals.

2. The CPP method

A decision aid consists of trying to provide answers to questions raised by actors involved in a decision process, using a clearly specified model [Bouyssou, 1990]. In order to do so, the analyst often must compare alternatives. In an approach using several criteria, the analyst aims to establish comparisons by the evaluation of alternatives according to more than two criteria. In addition to the existing techniques to support decisions involving multiple criteria, as mentioned in Section 1, the imprecision involved in the present application suggests the use of the CPP method [Sant´Anna e Sant´Anna, 2001]. The probabilistic approach of CPP assumes uncertainties in preference evaluations, which makes the model more attractive for real-world problem solving [Sant´Anna, 2015].

CPP is a multicriteria decision aid (MCDA) method. MCDA methods are intended to search for satisfactory solutions to a problem with multiple alternatives evaluated under different criteria. These criteria may be associated with goals to be maximized or minimized. This in practice hinders the search for an optimal solution that simultaneously achieves these objectives. Thus, the application of MCDA methods results in possible solutions that meet the set of established criteria [Pomerol e Barba-Romero, 2012].

Probabilistic composition, according to Sant´Anna [2015], allows objectively combining, in different ways, classifications according to different criteria. If preference is to be taken into account between criteria, one can treat the probability of choice according to each criterion as a problem of conditional probability. Preferences between criteria are, however, difficult to quantify. In addition, a probabilistic evaluation also provides a variety of ways of combining the criteria without establishing priorities among them. For example, it allows adopting an optimistic view that an option is satisfactory if at least one of the available criteria is also satisfactory, or a pessimistic approach, which requires approval by all the criteria to be good for the option to be approved globally.

2.1. Probability of being the best or worst option

From an operational perspective, the starting point of CPP is to rank options according to each criterion. For a measure of preferences based on the level or degree of presence of some attribute, the relative position of the option can be obtained by numerical values regarding cost, distance, etc. In other circumstances, the attributes cannot be measured quantitatively. In these cases, the primary data are composed of linguistic classifications such as low, moderate, high, etc., inducing a representation similar to fuzzy classifications [Zadeh, 1965]. Regardless of the case, it is possible to establish an order of priority by means of determining the preferences, depending on the type of criterion â the higher the better, the lower the better or the closer to some chosen value the better. For the case of linguistic classifications, a psychometric scale (i.e., Likert scale) can be considered.

After determining the ranking of options based on each criterion, the next step is to calculate the probability that an option is the best according to each criterion individually. According to Sant´Anna [2015], this probabilistic transformation is the key point of CPP. Results from translating each measurement of the basic attribute into an interval of possible satisfaction evaluations that may occur if the alternative is evaluated in successive assessments of the preference based on that attribute. For this purpose, one must consider that the relative position obtained in the preceding step is, for each option, a location parameter of the probability distribution of preference according to the criterion under analysis. Simple normal distributions are considered preferentially, such as being uniform, triangular or normal. However, any other probability model may be employed in a different context.

The probability of an option being the best according to each criterion is computed by the integral of the joint density function of the option under analysis, considering an interval for which this option is the best among all options. To compute this probability, the data range of each criterion should be considered as limits of the integral for computation, considering the interest in enabling the switching of ranks among all options. Equation 1 presents this computation.

$$M_{ik} = \int_{L_{ik}}^{U_{ik}} \Big[\prod_{j=1}^{n} \int_{L_{jk}}^{X_{ik}} f_{X_{jk}}(x')dx' \Big] f_{X_{ik}}(x)dx \quad (1)$$

In Equation 1, L_{ik} and U_{ik} are, respectively, the lower and upper bounds of the domains of a random variable X_{ik} that represents the preference form option *k* according to criterion *i*, while *n* is the number of options being analyzed and *f* is the probability density function. The product sequence inside the brackets is the product of the probabilities that the variables are lower than X_{ik}, $P\big(X_{.k} < X_{ik}\big)$, for all the other options involved in the analysis. This product has implicit the hypothesis of independence of the disturbances of the evaluations of different options. Note that X_{ik} is compared to the distributions of the other positions, X_{jk}. After making this comparison for each possible value of X_i, since it is a random variable, the next step is to calculate the expected value of this product sequence according to the distribution of X_i. This calculation must be performed for each option in each criterion. Therefore, M_{ik} is the probability that option *k* is the best one according to criterion *i*.

If the aim is to calculate the probability that the option is the worst, given the level criterion *i* for option *k*, equation 2 is used.

$$m_{ik} = \int_{L_{ik}}^{U_{ik}} \Big[\prod_{j=1}^{n} \int_{X_{ik}}^{U_{jk}} f_{X_{jk}}(x')dx' \Big] f_{X_{ik}}(x)dx \quad (2)$$

Note that in this case the value of variable X_{ik} is the lower limit of the integrals in the product sequence in brackets.

Both the results from equations 1 and 2 are considered in the composition of preferences Sant´Anna [2015].

2.2. The CPP applied to FMEA

More recently, FMEA was adapted to the probabilistic calculation by Sant´Anna [2012]. The nonlinear feature of CPP is pertinent to FMEA. The probabilistic approach values the increments of higher evaluations. This corrects possible distortions of final ranks, which are observed with the direct product of the evaluations, to obtain the priority risk number (PRN) [Bowles, 2003]. For example, in the original FMEA model, increasing the evaluation by a given criterion from 1 to 2, keeping the others constant and considering a five-point scale, doubles the PRN of one failure mode in relation to the other. Meanwhile, the increase from 4 to 5, keeping the same conditions, represents a 25% difference between their PRNs. With CPP, however, increments from 4 to 5 are probabilistically higher than lower increments (i.e., 1 to 2, 2 to 3 and 3 to 4).

The use of CPP in FMEA has been widely discussed in the literature, with emphasis on research in the nuclear industry [Garcia et al., 2013, 2015; Sant´Anna et al., 2015], homeland security [Sant´Anna, 2013], power transmission [Sant´Anna e Junior, 2011] and retailing [Sant´Anna et al., 2014].

Most CPP applications in FMEA involve the perception of multiple experts for the "SOD" evaluation. However, expert estimates seldom agree. The likely values and amplitude of variables are usually divergent. This is due to experience, predictability, commitment to research, bias, among other aspects inherent to human judgment, which interfere with the evaluations. In this context, the aggregation of the different estimates is relevant to risk analysis, by simplifying the calculation procedures.

CPP applications in FMEA have used statistical measures of position (i.e., mode, mean, median) for aggregation of expert estimates. While meeting the needs of the method, such measures do not always reflect consensus among experts. Thus, several procedures for aggregation of expert estimates have been proposed, with special emphasis on the classic Cooke model [Cooke et al., 1988] and the Mendel-Sheridan model [Mendel e Sheridan, 1989]. Both employ expert estimates in the form of quantile values of a probability distribution to be defined in the process. The Cooke model combines the estimated quantiles with weights obtained in a previous stage of "calibration" of expert evaluations. In the Mendel-Sheridan method, the probabilities associated with each quantile are adjusted by a Bayesian model, also reflecting the results of the calibration phase. However, the performance of the specialists in this previous phase can depreciate their most important evaluations about the real problem, which causes criticism about the usefulness of the calibration, as described by Bolger e Rowe [2015].

3. Methodological Procedure

As stated in the introduction, one must considers an approach to combine the opinion of many experts, in a probabilistic way, to then prioritize the failure modes, also probabilistically. The aggregation of the different opinion will be done based on an adaptation of the similarity aggregation method (SAM) proposed by Hsu e Chen [1996]. Instead of considering fuzzy number, or membership functions, one will approach it by probability density functions. The idea of similarity can be seen in figure 1.

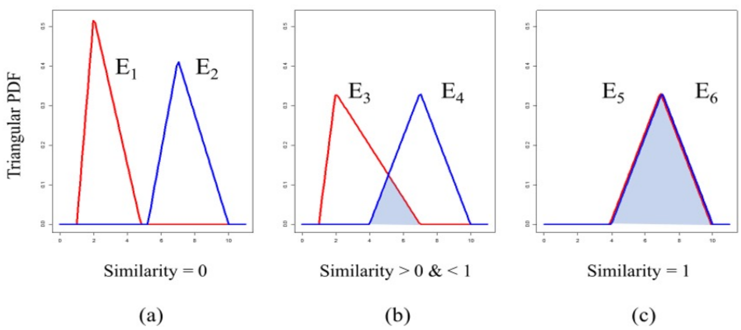

Figure 1: Similarity estimates through triangular distribution

For details concerning the calculations of similarity, please access Gavião et al. [2018].

After aggregating the different opinion, one can proceed to the CPP maximum and minimum probability calculation, by equations 1 and 2. Combining these probabilities value, it is necessary to compose a global scores for the alternative performances. The highest global score indicates the most satisfactory solution for decision making. In Sant´Anna [2015] , three forms of preference composition are presented: weighted sum, axes and Choquet integrals. Regarding the last, the theory of capacities developed by Choquet [1953] was successfully adapted to MCDA problems, with a wide variety of applications [Grabisch e Labreuche, 2010; Grabisch e Roubens, 2000; Merad et al., 2013]. From the MCDA point of view, a "capacity" can be interpreted as a weight assigned to the subsets of problem criteria. A Choquet integral determine the final score for each alternative, which indicates a preference order for the decision-maker [Grabisch et al., 2006].

Despite being the most complex type of composition in the CPP, the Choquet approach is particularly useful for FMEA problems. This composition includes more information for decision-making. The MCDA models generally use algorithms based on the performance of the alternatives in each criterion alone [Pomerol e Barba-Romero, 2012]. In practice, however, decision-making may involve evaluations resulting from interactions of the criteria. So, in FMEA it is possible to consider additional evaluations of criteria sets: "S&O", "S&D", "O&D" and "S&O&D". The term "CPP-Choquet" is used here to refer to the use of CPP in the composition by capacities and Choquet integrals to order alternatives in MCDA problems.

After the initial "randomization" of the database and the computation of M_{ik} and m_{ik}, the capacities of criteria subsets and the composition of Choquet integrals for the alternatives are calculated. In this way, it is already possible to order the alternatives, according to the values returned from the Choquet integrals.

The capacities of criteria sets are derived from the probabilities of the sets of alternatives. For a set N of n criteria, the capacities μ for $2\ddot{E}n$ subsets of criteria must be calculated. The capacities belong to the interval $[0,1]$ and must satisfy the conditions that: (a) $\mu(\{Ø\})$ = 0, and (b) $\mu(\{N\}) = 1$ and, for any subsets E and F ⊂ N, if E ⊂ F, then $\mu(E) \leq \mu(F)$. Three steps are necessary in this process. First, for each S, subset of N with s criteria, $S = (\{C1, \cdots, Cs\})$, the joint probabilities of maximizing the preferences are computed in at least one subset criterion, using Equation 3, where, for each i, Pai denotes the evaluation of alternative a by criterion Ci. This calculation produces a score from the CPP progressive-optimistic (PO) point of view, for independent evaluations [Sant´Anna, 2015].

$$P\left(\left\{C_1, \cdots, C_s\right\}\right) = 1 - \prod_{i=1}^{s} \left[1 - P_{ai}\right] \tag{3}$$

Then, the maximum values of the probabilities of each subset, among the results of applying equation 3, for the alternatives according to equations 4 are selected.

$$P = max\left(\left\{C_1, \cdots, C_s\right\}\right) = \max_a \left\{1 - \prod_{i=1}^{s} \left[1 - P_{ai}\right]\right\} \tag{4}$$

These maximum values are, finally, standardized, making them proportions of the highest value, indicated by U, according to equation 5. The results are associated with $\mu(S)$ capabilities of the subsets of the criteria used in subsequent calculations.

$$\mu\left(\left\{C_1, \cdots, C_s\right\}\right) = \frac{P(\{C_1, \cdots, C_s\})}{P(U)} \tag{5}$$

The probabilistic evaluation of the alternatives are composed by Choquet integrals. The highest result between the final scores defines the preference for decision making. The final score, CH, can be obtained from equation 6.

$$CH_{\mu}(A) = \sum_{j=1}^{n} p_{\tau(j)}(A)\mu(\{\tau(j), \cdots, \tau(n)\}) \tag{6}$$

Equation 6 refers to the Choquet integral for the alternative "A", by the j-th criterion, with respect to the capacity μ in S, considering also that τ is a permutation of S satisfying $p_{\tau(j)}(A) > p_{\tau(j-1)}(A)$ and attributing $p_{\tau(0)}(A) = 0$. More details about the application of Choquet intgrals for probabilistic composition can be found in Sant´Anna [2015].

4. Application to a Simplified

The method proposed here was applied to an auxiliary feedwater system (AFWS), according to Figure 2. The AFWS of a typical PWR plant contains two subsystems: the first has a turbine-driven pump (TDP), which has capacity to deliver 100% of the water needs of the steam generators (SG); the second one has two motor-driven pumps (MDP), each of which can satisfy 50% of the steam generators´ water needs. The AFWS functions are: a) to supply the SGs when the main feedwater system is lost; b) to keep the water level in the SGs able to remove the residual heat generated when the reactor power is less than 10% of nominal power. Some simplifying assumptions were considered: a) the feedwater comes from the auxiliary feedwater tank only; b) valve groups are represented by a single valve "V"; and c) components from redundant groups are considered as a single component.

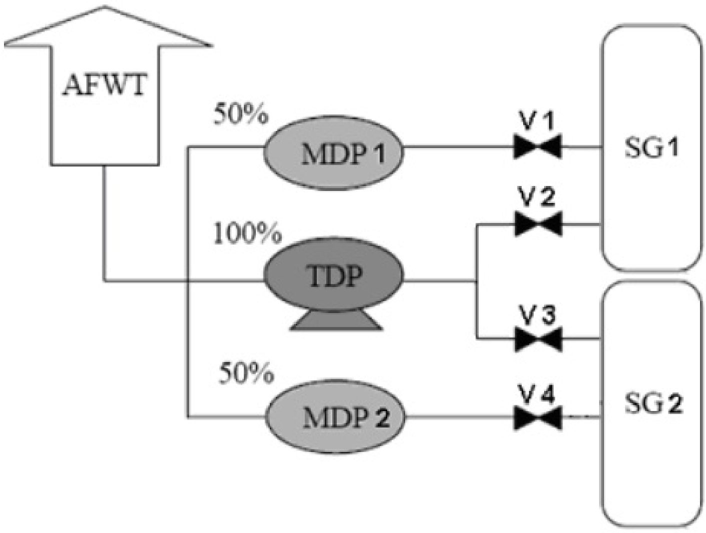

Figure 2: Simplified AFWS diagram

Based on the methodological discussion, the process of ranking the group of failure modes is organized in four steps, as described in figure 3.

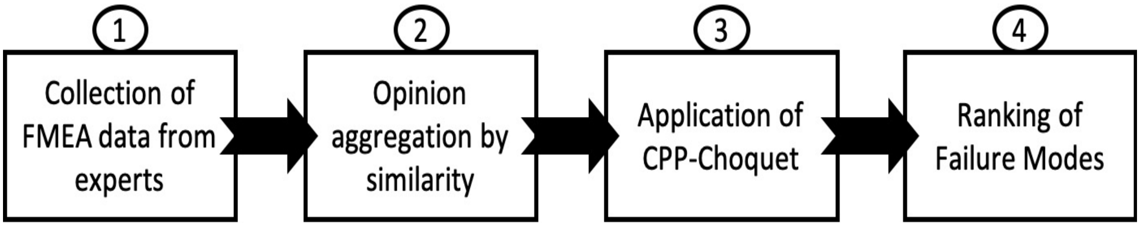

Figure 3: Methodological process

The FMEA data were obtained from Lapa e Guimarães [2004]. Five experts from the Brazilian Nuclear Commission analyzed the simplified AFWS based on eight groups of failure modes, as indicated in tables 1 to 8. In these tables, the "Importance" column denotes the experts´ relevance, based on their length of experience (in years). This information is necessary to compute the expert weights, as described in Gavião et al. [2018]. Columns "O", "S" and "D" present the expert estimates of FMEA criteria on a ten-point scale. Their estimates indicate the parameters "Min", "Mode" and "Max", to model probability distributions of each failure mode.

Table 1: Failure to open a group of valves

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(2, 0, 7)	(3.5, 1.5, 8.5)	(5, 3, 10)
2	0.2	(1.5, 0, 6)	(3.2, 1.7, 6)	(4.8, 2.8, 10)
3	0.2	(1.8, 0, 6.8)	(3.7, 1.6, 8.8)	(5.3, 3.2, 10)
4	0.2	(1.9, 0, 7,2)	(3.6, 1.4, 8.7)	(5.3, 3.2, 10)
5	0.1	(1.8, 0, 6.9)	(3.5, 1.5, 8.1)	(5, 2.9, 10)

Table 2: Failure to close a group of valves

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(2, 9, 2)	(3.5, 10, 3.5)	(5, 10, 5)
2	0.2	(1.5, 8.5, 1.5)	(3.2, 10, 3.2)	(4.8, 10, 4.8)
3	0.2	(1.8, 8.7, 1.8)	(3.7, 10, 3.7)	(5.3, 10, 5.3)
4	0.2	(1.9, 3.4, 1.9)	(3.6, 10, 3.6)	(5.3, 10, 5.3)
5	0.1	(1.8, 8.8, 1.8)	(3.5, 10, 3.5)	(5, 10, 5)

Table 3: Failure operating the motor pump

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(2, 4, 0)	(3.5, 6, 1.5)	(5, 8, 3)
2	0.2	(1.5, 3.5, 0)	(3.2, 5.5, 1.7)	(4.8, 7.8, 2.8)
3	0.2	(1.8, 3.7, 0)	(3.7, 5.7, 1.6)	(5.3, 8.4, 2.5)
4	0.2	(1.9, 3.8, 0)	(3.6, 5.8, 1.4)	(5.3, 8.2, 3.2)
5	0.1	(1.8, 3.6, 0)	(3.5, 5.8, 1.5)	(5, 8.2, 2.9)

The aggregate parameters Min, Mode and Max were used to model triangular distributions. This type of distribution was chosen because it is better to associate its parameters with the

Table 4: Failure in stating the motor pump

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(2, 7, 0)	(3.5, 8.5, 1.5)	(5, 10, 3)
2	0.2	(1.5, 6, 0)	(3.2, 8, 1.7)	(4.8, 10, 2.8)
3	0.2	(1.8, 6.8, 0)	(3.7, 8.8, 1.6)	(5.3, 10, 2.5)
4	0.2	(1.9, 7.2, 0)	(3.6, 8.7, 1.4)	(5.3, 10, 3.2)
5	0.1	(1.8, 6.9, 0)	(3.5, 8.1, 1.5)	(5, 10, 2.9)

Table 5: Common-cause failure of the motor pumps

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(0, 7, 0)	(1.5, 8.5, 1.5)	(3, 10, 3)
2	0.2	(0, 6, 0)	(1.7, 8, 1.7)	(2.8, 10, 2.8)
3	0.2	(0, 6.8, 0)	(1.6, 8.8, 1.6)	(2.5, 10, 2.5)
4	0.2	(0, 7.2, 0)	(1.4, 8.7, 1.4)	(3.2, 10, 3.2)
5	0.1	(0, 6.9, 0)	(1.5, 8.1, 1.5)	(2.9, 10, 2.9)

Table 6: Failure in operating the turbo pump

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(7, 2, 2)	(8.5, 3.5, 3.5)	(10, 5, 5)
2	0.2	(6, 1.5, 1.5)	(8, 3.2, 3.2)	(10, 4.8, 4.8)
3	0.2	(6.8, 1.8, 1.8)	(8.8, 3.7, 3.7)	(10, 5.3, 5.3)
4	0.2	(7.2, 1.9, 1.9)	(8.7, 3.6, 3.6)	(10, 5.3, 5.3)
5	0.1	(6.9, 1.8, 1.8)	(8.1, 3.5, 3.5)	(10, 5, 5)

Table 7: Failure in starting the turbo pump

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(4, 4, 2)	(6, 6, 3.5)	(8, 8, 5)
2	0.2	(3.5, 3.5, 1.5)	(5.5, 5.5, 3.2)	(7.8, 7.8, 4.8)
3	0.2	(3.7, 3.7, 1.8)	(5.7 5.7, 3.7)	(8.4, 8.4, 5.3)
4	0.2	(3.8, 3.8, 1.9)	(5.8, 5.8, 3.6)	(8.2, 8.2, 5.3)
5	0.1	(3.6, 3.6, 1.8)	(5.8, 5.8, 3.5)	(8.2, 8.2, 5)

Table 8: Common-cause failure of the trains

Experts	Importance	min(O, S, D)	mode(O, S, D)	max(O, S, D)
1	0.3	(0, 9, 0)	(1.5, 10, 1.5)	(3, 10, 3)
2	0.2	(0, 8.5, 0)	(1.7, 10, 1.7)	(2.8, 10, 2.8)
3	0.2	(0, 8.7, 0)	(1.6, 10, 1.6)	(2.5, 10, 2.5)
4	0.2	(0, 9.4, 0)	(1.4, 10, 1.4)	(3.2, 10, 3.2)
5	0.1	(0, 8.8, 0)	(1.5, 10, 1.5)	(2.9, 10, 2.9)

experts´ perceptions regarding the O, S and D criteria. However, to establish aggregations by similarity, only the mode parameter was considered, keeping the others according to the limits of the evaluation scale. Thus, the parameters min = 0 and max = 10 were considered. This procedure favors the probabilistic modeling of CPP, since it enlarges the intersection of the triangular distributions, avoiding extreme values of M_{ik} and m_{ik}. Based on these parameters, aggregate triangular distributions are obtained, whose modes for each criterion are set out in Table 9. An algorithm to aggregate values by similarity is available in the R-package CPP, by the function Agg.Sim [Gavião et al., 2018].

Table 9: Common-cause failure of the trains

Failure Mode	mode(O, S, D)
FM 1	(3.512671999, 1.539010614, 8.455280309)
FM 2	(3.512671999, 10.00000000, 3.512671999)
FM 3	(3.512671999, 5.772513179, 1.539010614)
FM 4	(3.512671999, 8.455280309, 1.539010614)
FM 5	(1.539010614, 8.455280309, 1.539010614)
FM 6	(8.455280309, 3.512671999, 3.512671999)
FM 7	(5.772513179, 5.772513179, 3.512671999)
FM 8	(1.539010614, 10.00000000, 1.539010614)

Considering these parameters for the triangular distributions in each criterion, the probability of each failure mode being higher than the others is depicted in Table 10. Algorithms to compute M_{ik} are available in the R-package CPP [Gavião et al., 2018].

Table 10: Maximizing preference (M_{ik})

Failure Mode	PMax(O, S, D)
FM 1	(0.093813389, 0.027041071, 0.364101)
FM 2	(0.093813389, 0.269157994, 0.106412)
FM 3	(0.093813389, 0.056562882, 0.079166)
FM 4	(0.093813389, 0.142898902, 0.079166)
FM 5	(0.070121088, 0.142898902, 0.079166)
FM 6	(0.332371311, 0.035728194, 0.106412)
FM 7	(0.152132576, 0.056562882, 0.106412)
FM 8	(0.070121088, 0.269157994, 0.079166)

Considering the probability presented in Table 10 the Choquet integrals, as in equation 6, are applied and the results are presented in table 11.

Table 11: CPP-Choquet results and failure mode ranking

Failure Mode	CPP-Choquet	Rank
FM 1	0.328560143	1
FM 2	0.210511031	3
FM 3	0.090240652	8
FM 4	0.123175029	6
FM 5	0.119534442	7
FM 6	0.285007819	2
FM 7	0.141558019	5
FM 8	0.201240313	4

As an essay to understand the prioritization obtained, one considered the Shapley index

[Shapley, 1953]. The concept of Shapley index helped us to approach the importance of the criteria SOD associated to the experts´ opinion. Considering the formulation presented in Sant´Anna [2015], the value of Shapley index were 0.346, 0.236 and 0.418 for O, S and D respectively. This means that higher importance concerned to detectability are associated to the conditions monitoring of nuclear power plants. Lower capacity for failure detection is considered more important than the other criteria. This raised the score of FM1, while the negative interaction perceived between the other two criteria reduced the scores of failure modes with higher evaluations by these criteria, like FM2, FM6 and FM7.

5. Final Considerations

The importance of FMEA is well known as a procedure to aid in the identification, prioritization and mitigation of failures or risks in processes and products. It is also recognized that the traditional approach to this, the RPN, has limitations that may compromise the whole process. Considering these findings, different approaches have been proposed to improve the efficiency of the traditional FMEA approach. In the present paper, a differentiated approach that combines experts´ opinion similarity aggregation and discrete Choquet integrals, in a fully probabilistic framework is employed. The choice of CPP for modeling a FMEA problem was based on the literature on risk analysis. The main advantage of the CPP for this kind of applications is concerned to its nonlinearity, which makes it especially useful for solving FMEA problems, by assigning values at the extremes of the "SOD" criteria scales. This reduces possible distortions identified when applying the product directly from the evaluations to the RPN. To illustrate the proposed method, a simplified real case associated with an auxiliary feed water system of two loop nuclear power plant is discussed. The results showed the applicability and the accuracy of the methodological proposal to cases like those presented here.

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