On improving failure mode and effects analysis (FMEA) from different artificial intelligence approaches.

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Abstract - *This study describes the Failure Mode and Effects Analysis (FMEA) from the point of view of different artificial intelligence approaches. After discussing the main drawbacks of the traditional methodology and summarize the main techniques recommended for its improvement in the recent literature, three techniques of Artificial Intelligence are compared: a fuzzy inference system (FIS), a case reasoning based method (CBR) and a vector support machine based method (VSM). From the results of this study we conclude that the best approach to properly classify the causes of risk of a system or service is the fuzzy inference system, method that, in addition, allows to overcome most of the drawbacks associated with the traditional methodology*.

Keywords: Failure Mode and Effects Analysis (FMEA), Fuzzy Inference Systems, Case Based Reasoning, Vector Support Machine

1 Introduction

Failure mode and effects analysis (FMEA) first emerged from the aerospace industry in the 1960s and then spread to the manufacturing scope. FMEA is an efficient tool to identify and remove known and potential failures in a system which allows establishing their causes of appearance and preventing their further occurrence [1]. It has been extensively used in many industrial sectors -aerospace, automotive, nuclear, electronics, etc.- [2].

The paper is organized as follows. In Section 2 the traditional method is explained, pointing out the main criticisms on it and outlining the main methodologies employed to gain more efficiency in the method. In Section 3 the foundations of the three methodologies proposed in this work and their comparative results are described. Finally, the conclusions of the study are exposed.

2 The FMEA method

The FMEA method is based on a systematic brainstorming session aimed to uncover the failures that might occur in a system or process [3]. After that, critical analysis is performed on these failure modes taking into account the valuation (between 1 to 10) of three risk indexes (See Table 1): occurrence (O), detection (D) and severity (S) - associated to the likelihood of occurrence, no detection and severity of each failure respectively- . FMEA searches for prioritising the failure modes of a system in order to assign the available and limited resources to the most serious risk items. Generally, the prioritisation is determined through the risk priority number (RPN), which is obtained multiplying the indexes O, S and D of each failure.

FMEA determines the critical level (or risk score) of these failures and proceeds to put them in order, reviewing each design detail and proposing the relevant modifications. The most critical failures (related to higher RPNs) will head the ranking, and will therefore be considered first during design review or during control actions taken to minimise the likelihood of such failures occurring. Those modes of failure with high rates O or S are also considered critical although their RPN is not high. Finally, RPNs should be recalculated after the corrections to check its efficiency.

2.1 Shortcomings about traditional FMEA

Despite the good results obtained with the traditional FMEA methodology, numerous investigations have shown different problems in its application. Table 2 shows the most relevant and frequently cited according to the last review on the issue [4].

2.2 Techniques used to improve the traditional FMEA

Among the techniques used to overcome the drawbacks described in the previous paragraph those included in the five categories and summarized in Table 3 stand out.

As shown in Table 3, the category of method most frequently applied to FMEA was found to be AI (32 times out of 80; that is 40.0% of all the reviewed papers) and within it, the most popular approach is Fuzzy Rule-based system (29 out of 32, which represent 36,25% of the 80 analyzed papers). This can be caused by the different advantages brought by the fuzzy inference systems [5], [6], [7], [8], [9]:

Table 1. Explanation of the risk indexes (O), (D) and (S).

	Score	Likelihood of occurrence
Remote	1	0
Low	2 3	1/20000 1/10000
Moderate	4 5 6	1/2000 1/1000 1/200
High	7 8	1/100 1/20
Very High	9 10	1/10 1/2
O - Occcurrence Index		

	Score	Likelihood of no detection
Remote	1	0-5
Low	2 3	6-15 16-25
Moderate	4 5 6	26-35 36-45 46-55
High	7 8	56-65 66-75
Very High	9 10	76-85 86-100
D - No-detection Index		

	Score
The customer will not perceive (VL)	1
Small nuisance (L)	2 3
No satisfaction (M)	4 5 6
High level of No satisfaction (H)	7 8
Serious safety consecuences (VH)	9 10
S – Severity Index	

Table 2 .The major shortcomings of FMEA. (Extracted from [4])

	Shortcomings	Frecuency of citation	% citation
1	The relative importance among O, S and D is not taken into consideration	45	24,32%
2	Different combinations of O, S and D may produce exactly the same value of RPN, but their hidden risk implications may be totally different	33	17,84%
3	The three risk factors are difficult to be precisely evaluated	21	11,35%
4	The mathematical formula for calculating RPN is questionable and debatable	14	7,57%
5	The conversion of scores is different for the three risk factors	13	7,03%
6	The RPN cannot be used to measure the effectiveness of corrective actions	12	6,49%
7	RPNs are not continuous with many holes	10	5,41%
8	Interdependencies among various failure modes and effects are not taken into account	10	5,41%
9	The mathematical form adopted for calculating the RPN is strongly sensitive to variations in risk factor evaluations	9	4,86%
10	The RPN elements have many duplicate numbers	9	4,86%
11	The RPN considers only three risk factors mainly in terms of safety	9	4,86%

Table 3. Main risk evaluation methods in FMEA. Frequency of use. (Adapted from [4])

Method	n	%
Multi-Criteria Decision Making	18	22,50%
Mathematical Programming	7	08,75%
Artificial Intelligence	32	40,00%
Hybrid	9	11,25%
Others	14	17,50%

- “Ambiguous, qualitative or imprecise information, as well as quantitative data can be used in criticality/risk assessment and they are handled in a consistent manner”.
- “It permits to combine the occurrence, severity and detectability of failure modes in a more flexible and realistic manner”.
- “It allows the failure risk evaluation function to be customized based on the nature of a process or a product”.
- “The fuzzy knowledge-based system can fully incorporate engineers’ knowledge and expertise in the FMEA analysis and substantial cost savings can thus be realized”.

As far as the disadvantages of this method is concerned, the difficulty of adapting the model to real-life circumstances is often argued, basically for design reasons (need to define a large number of rules and the membership functions in the model variables). On the other hand, it is suggested that the new methods on FMEA should obviate the subjective weighting of risk factors involved in the model (weights which are the most frequently used in the analyzed literature).

3 Artificial intelligence approaches for the FMEA improvement

In this section the theoretical foundations of three techniques that attempt to improve some of the above- mentioned drawbacks. Nine risk categories associated to the risk priority numbers given by the traditional methodology have been considered (see Table 4).

The classification error from these methodologies for the cases corresponding to all the integer inputs in the range of 1-10 for the "O", "D" and "S" input variable will be calculated for comparison purposes. The classification error will be measured as the percentage of cases misclassified for the used test set (800 cases) -lack of concordance between the output assigned by the method and the correct output of Table 4-.

Table 4: Risk priority categories corresponding to different intervals of risk priority numbers

RPN (Class interval)	Class Score	Category (RPC)
0-50	25	VL
50-100	75	VL-L
100-150	125	L
150-250	200	L-M
250-350	300	M
350-450	400	M-H
450-600	525	H
600-800	700	H-VH
800-1000	900	VH

3.1 FMEA with Fuzzy Inference Systems

Fuzzy inference systems are based on the theory of fuzzy sets [10], and allow an uncertainty component to be incorporated into models, making them more effective in terms of approximating to reality [11]. Linguistic variables can be used to handle qualitative or quantitative information, so that its content can be labelled taking words from common or natural language as values. This contrasts with numeric variables, which can only take numbers as values [12]. All decision problems require a knowledge base provided by an expert who is able to explain how the system works through a set of linguistic rules involving the system's input and output variables; the system's variables, that is, the form and range of the labels for each variable, must therefore be defined in fuzzy form. Mamdani Fuzzy Inference Systems depend on this to model systems in a process which has five stages: the fuzzification of the input variables, the application of fuzzy operators (AND/OR) to each rule's antecedent, the implication process from each rule's antecedent to consequent, the consequent aggregation process, and the defuzzification process [13].

A fuzzy inference system to develop the FMEA has been designed based on qualitative rules using MATLAB 6.5 – Toolbox 'Fuzzy' (v. 2,0). The system assigns a risk priority class (RPC) to each of the causes of failure in an FMEA, depending on the importance given to the three already mentioned indexes "O", "D" and "S" (which will be the input variables in the decision system –with integer scores between 1 and 10-). The output variable of the decision system is the risk priority category (RPC) assigned to the cause of a failure. Here, a division of the traditional domain of the Risk Priority Number (RPN) from 1 to 1000 into nine class intervals was opted for, so that each of the class intervals has a different RPC (very low: "VL", between very low and low: "VL-L", Low: "L", ... very high: "VH"). Figure 1 shows the potential linguistic labels to be assigned to all these variables.

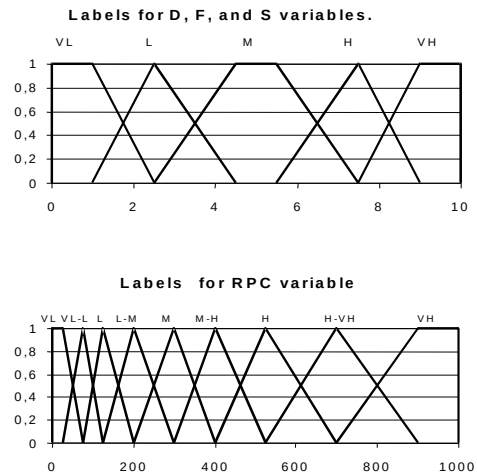

Figure 1. Labels for input and output variables

As each of the three input variables can be given one of five categories or classes, we have as many as 125 rules at our disposal to assign the RPCs to each of the causes of failure analysed in the FMEA. The rules, given by the expert about the RPC evaluation, are shown in Figure 2.

The rule structure in the system is of the type: "if ((O=M) & (D=VL) & (S=H)), then (RPC=H)"; this would mean that if "occurrence" is moderate, "no-detection" is very low, and "severity" is high for a cause of failure, then the risk priority category should be high.

The results obtained for different configurations of parameters in the designed fuzzy inference system (FIS) are shown in Table 5. Three of the five configurations tested, produce 0% classification errors, highlighting the goodness of the FIS method to carry out the evaluation of risk categories in the FMEA.

D (No-Detection)	O (Occurrency) VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH	VL	L	M	H	VH	RPC
VL	VL	VL	VL	VL-L	VL-L	L	L	L	L-M	L-M	M	M	M	M-H	M-H	H	H	H	H-VH	H-VH						
L	VL	VL-L	VL-L	L	L	L	L-M	L-M	M	M	M	M-H	M-H	H	H	H	H-VH	H-VH	VH	VH						
M	VL	VL-L	L	L	L	L	L-M	M	M	M	M	M-H	H	H	H	H	H-VH	VH	VH	VH			VH			
H	VL-L	L	L	L-M	L-M	L-M	M	M	M-H	M-H	M-H	H	H	H-VH	H-VH	H-VH	VH	VH	VH	VH						
VH	VL-L	L	L	L-M	M	L-M	M	M	M-H	H	M-H	H	H	H-VH	VH	H-VH	VH	VH	VH	VH						
S (Severity)			VL					L					M					H					VH			

Figure 2. Rule Base of the decision system proposed
VL: Very Low, L: Low, M: Medium, H: High, VH: Very High

Table 3: Classification errors for different configuration parameters of the FIS

AND Method	Implication Method	Aggregation Method	Errors (%) for different defuzzification methods: Centroid	Bisector	MOM*	LOM*	SOM*
MIN	MIN	MAX	33%	8.9%	0%	0%	0%

** MOM: middle of maximum, LOM: largest of maximum, SOM: smallest of maximum.*

3.2 FMEA with Case Based Reasoning - C4.5.

C4.5, a learning system based on examples that produce decision trees or sets of decision rules [14], is the second of the systems proposed in this study to assign criticality to error causes in FMEA.

For the case in question, three attributes corresponding to occurrence, non-detection, and severity indexes were used in each training example. All were defined as continuous attributes in the 1-10 domain and each example's class corresponds to the Risk Priority Category (RPC) given to each failure cause (maintaining the structure of nine possible categories: "VL"(1), "VL-L"(2), ... , "VH"(9)). The training examples were 20% of all possible discrete cases of the input variables ("O", "D", and "S") with the corresponding output RPC. Thus, 200 cases were selected from the base total of 1000 discrete traditional possible cases.

Once the decision tree had been formed from the training examples with C4.5, the 1000 possible discrete inputs for the 'O', 'D' and 'S' indexes were processed to determine the criticality assigned by the algorithm to each of them and compare results with the system initially proposed. The obtained results showed a 14,5% classification error, only superior in efficiency to the FIS when this latter method uses the center of gravity as a method of defuzzyfication.

A comparison with the results from the other systems shows that the C4.5 system proposed gives rather poor classification compatibility compared to the initial system (note that certain fuzzy system parameter combinations gave zero classification error).

3.3 FMEA with Support Vector Machines

Support vector machines (SVMs) [15] were originally designed for binary classification. Let (x1, y1), (x2, y2), … , (xn, yn) be a group of data belonging to Class 1 or Class 2, where xi□RN and the associated labels be yi=1 for Class 1and -1 for Class 2 (i=1, … , n). The formulation of SVMs is as follows:

$$Min \quad \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \qquad \text{(Eq. 1)}$$

subject to the constraints:

$$y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i \quad i = 1,..., n$$

$$\xi_i \geq 0 \quad i = 1,..., n$$

where w is the weight vector; C is the penalty weight; ξ_i are non-negative slack variables; b is a scalar, and xi are mapped into a higher dimensional space by a non-linear mapping function ϕ . Mapping function ϕ needs to satisfy the following equation:

$$k(x_i, x_j) = \phi(x_i)^T \phi(x_j)$$

Where $k(x_i, x_j)$ is called kernel function.

Minimizing $\frac{1}{2} w^T w$ implies that SVMs tries to maximise $\frac{2}{\|w\|}$, which represents the margin of separation between both classes. The data that satisfy the equality in Eq. (1) are called support vectors. Moreover, by adding a set of non-negative Lagrange multipliers α_i and β_i to generate the Lagrangian, the upper- mentioned constrained optimization problem can be worked out with the dual form shown below:

$$Max \quad \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j k(x_i, x_j)$$

subject to the constraints:

$$\sum_{i=1}^{n} \alpha_i y_i = 0$$

$$0 \le \alpha_i \le C \quad i = 1,..., n$$

Having obtained the support vectors (SVs), the decision function for an unseen data (x) is as follows:

$$y = sign \left\{ \sum_{SVs} \alpha_i y_i k(x, x_i) + b \right\}$$

The use of SVMs in FMEA essentially implies a multi-class classification problem. This study uses the one-against-one method to extend the binary SVMs to generate the multi-class scheduler since this method is more suitable for practical use than other methods [16]. It was introduced in [17], and the first use of this strategy on SVMs was in [18] and [19].

One of the steps that precedes the application of the proposed method to the different sets of examples is that of standardising the attributes so that their maximum and minimum values are one and zero respectively. In the same way, in this study, the radial basis function (RBF) and the polynomial function have been used as kernel functions. After several preliminary tests, it has been decided to make use of the RBF Kernel since it is the one that shows a better performance. Furthermore, by employing the grid search technique on the examples, the best performance for the SVMs is obtained when C=8 and σ=0.03. The program that has been used to perform the upper-mentioned study is LIBSVM [20]. The test error obtained with this methodology from the 800 examples is 21,63% lagging behind both the C.4.5 and the FIS methods.

Nevertheless, all the employed methodologies allow overcoming some of the drawbacks mentioned in Table 2. In particular, the best of the three methodologies, FIS, not only gets an excellent classification error but also it permits circumvent the shortcomings 1, 2, 4, 5, 7, and 9 of the above-mentioned table, which corroborates the suitability of the method for the evaluation of risks with the FMEA methodology.

4 Conclusions

This study reviews the traditional FMEA methodology, analyzing their main drawbacks as well as the main categories of tools used in their assessment. These evidences have been observed in the unique and recent review written on the FMEA method in the academic literature.

In view of these drawbacks, a proposal is made to structure expert knowledge to assign risks to the system failure causes in the form of qualitative decision rules whereby a risk priority category (RPC) can be assigned to each cause of failure. The method being proposed here effectively mitigates one of the main criticisms imputed to the traditional model, since the structure of the proposed rule system allows to emphasize one index over the rest (in this case, the severity index “S” associated to a cause of failure). Furthermore, the method being proposed is flexible and easily implemented, making it a useful new tool for most risk classification problems.

In addition, recent techniques of artificial intelligence have been tested to evaluate categories of risk priority of different and potential system or service failure causes. In particular a Fuzzy Inference System (FIS), a Case Based Reasoning system (CBR) developed with the program C4.5 and a Vector Machine Support method of classification (VMS) have been analyzed. The results show that none of the studied methods exceeds in efficiency the behavior of the FIS, which is moreover able to overcome most of the drawbacks targeted in the recent literature regarding the traditional methodology.

5 References

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