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A performance evaluation of three inference engines as expert systems for failure mode identification in shafts

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ABSTRACT

This paper aims to present performance evaluation of three different inference engines (rule based reasoning, fuzzy based reasoning and Bayesian based reasoning) for failure mode identification in shafts. This research was done with a focus on the validation cases and results after their use in failure cases from several industries where the three systems were tested under the same conditions.

Each system was implemented using the same user interface and knowledge base, with different frameworks and techniques as follows: rule based inference reasoning (prolog, C#), Mamdani-fuzzy based reasoning (C, MATLAB®) and Bayesian based reasoning with a variable elimination algorithm (C, MATLAB®).

The best performance was obtained using the Bayesian inference engine. The conditional probabilities give flexibility when evidence is not listed, while the fuzzy and classical IF-THEN systems depend on the rules in the inference engine.

The process presented in this paper could be used for validation of any expert system or for comparison with other expert systems (inference engines) when the knowledge base is the same.

1. Introduction

Presently it is common to find different applications of expert systems in several fields of knowledge, especially in medical diagnosis [1] and also there are applications for failure diagnosis in mechanical systems or elements.

Focused on rule based inference process is possible to find in [2] the results of an IF-THEN expert system for car failure diagnosis, [3] presents a classical IF-THEN inference engine applied to the failure mechanism identification in mechanical components, in [4] was used a case based reasoning combined with a rule based inference engine for failure analysis of mechanical elements and [5] shows an intelligent fault diagnosis system for failures in gearbox of rolling mills.

For fuzzy inference engine there are papers focused in failure diagnosis for pump systems [6], based condition diagnosis [7] and application of failure mode and effects analysis (FMEA) and risk analysis in a fishing vessel [8].

The use of Bayesian inference in expert systems is presented in [9], for blast furnace [10] presents the results in failure modes using Bayesian networks, [11] showed an intelligent fault inference in rotating flexible rotors, [12] presented results in corrosion failure identification in refining plants and Weber [13] showed the increase in the use of Bayesian systems in dependability, risk analysis and maintenance areas between 2000 and 2008.

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However, there is a paucity of literature that shows the comparison results focused on the performance of several inference engines applied to failure identification in mechanical systems under the same conditions and validation cases. Previous papers are literature for a set of cases of failure where was applied only one inference method (fuzzy inference, Bayesian, case based reasoning, neural networks, or a combination of them), but frequently in those papers is not presented the performance comparison with other inference engines in order to find or identify what method or strategy could improve the failure identification process.

The most common techniques for comparison between expert systems are indexed and agreement ratios [14].

By means of failure cases in shafts, rule based, fuzzy inference, and Bayesian inference expert systems were tested and compared with the response obtained from an expert human panel. The rule based expert system was developed using a declarative programming language (prolog+logic server), the fuzzy inference engine was developed using the fuzzy inference system included in MATLAB® and the Bayesian inference system was developed using the variable elimination algorithm based on C and MATLAB®.

This validation was performed using the same failure cases as follows: sixteen cases of fracture, ten cases for wear, ten cases for corrosion and ten cases for plastic deformation. The present paper presents the results of each inference engine, using quantitative methodologies based on visual inspection of failed shafts.

At the end of the analysis, the failure mode for each system was shown, as well as its own fault tree analysis diagram (FTA), for corrective actions according to the maintenance procedures.

The human expert panel was composed of four failure analysis engineers, with thirteen, six, five and four years of experience respectively; one of the authors of the present work was part of the expert panel [15].

These experts evaluated the same forty-six cases under which the three inference engines were tested.

2. Expert system structure and knowledge base

The structure of each expert system tested is shown in Fig. 1. The knowledge base was obtained from human expert knowledge; thus the non-expert user entered the evidence based on their observations of the failed shaft, and with the evidence the inference engine tried to find the possible failure mode, showing the result with the FTA. Using the failure mode result and the FTA, the non expert user would be able to improve maintenance procedures or operations, in order to avoid the same failure mode in the future.

The human expert knowledge was provided by the authors of this work. This knowledge was provided through attribute tables to the three inference engines. The attribute tables related failure modes with the most common visual characteristics that can be identified in the failed shafts (e.g. beach marks, distortion, corrosion products and others), according to the experience of the authors and other analysts [16,17].

2.1. Fracture module

The knowledge base for the fracture module includes the following failure modes: brittle fracture in bending (bfb), torsional brittle fracture (tbf), torsional ductile fracture (tdf), bending fatigue fracture (bff), torsional fatigue fracture (tff), torsional fatigue fracture in the splined shaft (tffss), bending corrosion fatigue (bcf), torsional corrosion fatigue (tcf), stress corrosion cracking under bending (sccub) and torsional stress corrosion cracking (tscc).

An example of a table of attributes for fractures is shown in Table 1, where (M) means mandatory and (O) means optional symptom or evidence. The non expert user selects the evidence according to his or her observations of the failed shaft.

2.2. Wear, corrosion and plastic deformation module

The knowledge base for the wear module includes the following failure modes: superficial fatigue (sf), abrasive wear (abw), adhesive wear (adw) and fretting (fr). The corrosion module includes pitting corrosion (pc) and uniform corrosion (uc). The plastic deformation module includes the following failure modes: torsional plastic flow (tpf), bending plastic flow (bpf), shell buckling under bending (sbub), shell buckling under torsion (sbut), and damage in keyway or spline (dkws).

The attributes for wear, corrosion and plastic deformation are shown in Table 2. The non expert user selects the evidence according to his or her observations of the failed shaft.

2.3. Inference engine

The rule based inference engine is typically represented as IF-THEN rules (modus ponens); for example IF all the evidence of a failure mode is identified THEN the failure mode is identified.

Fuzzy inference reasoning uses IF-THEN rules, but using fuzzy set theory, it is possible to map the inputs and outputs, using the Mamdani or Sugeno systems. As an example the beach marks could have the following conditions: absence, slight presence or evident.

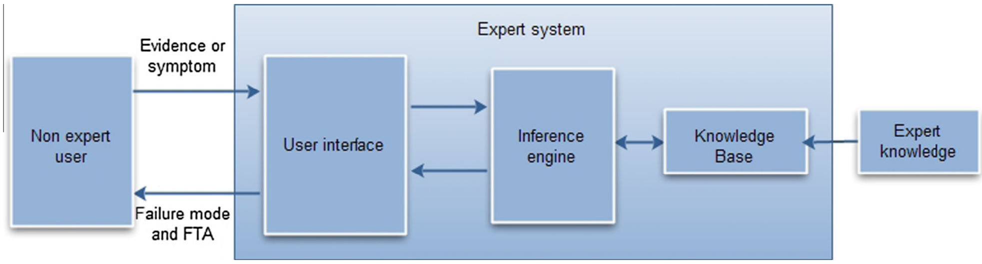

Fig. 1. Basic structure used for each expert system.

Table 1
Attributes for fracture module that the non expert user identifies for the failed shaft.

Attributes	bfb	tbf	tdf	bff	tff	tffss	bcf	tcf	sccub	tscc
Cross fracture	M	–	M	M	–	–	M	–	M	–
Granular appearance	M	M	–	–	–	–	–	–	–	–
Without plastic deformation	O	O	–	O	O	M	–	–	–	–
Diagonal fracture (45°)	–	M	–	–	M	–	–	M	–	M
Fibrous appearance	–	–	M	–	–	–	–	–	–	–
Plastic deformation in rotation way	–	–	M	–	–	–	–	–	–	–
Two zones (smooth and final fracture)	–	–	–	M	M	M	M	M	M	M
Radial cracks with 45° at union	–	–	–	–	–	M	–	–	–	–
Beach marks	–	–	–	O	O	O	O	O	O	O
Radial marks	O	O	–	O	O	O	O	O	O	O
Corrosive environment in operation	–	–	–	–	–	–	M	M	M	M
Corrosion waste	–	–	–	–	–	–	O	O	O	O
Variable load during operation	–	–	–	–	–	–	M	M	–	–
Constant load during operation	–	–	–	–	–	–	–	–	M	M

Brittle fracture in bending (bfb), torsional brittle fracture (tbf), torsional ductile fracture (tdf), bending fatigue fracture (bff), torsional fatigue fracture (tff), torsional fatigue fracture in splined shaft (tffss), bending corrosion fatigue (bcf), torsional corrosion fatigue (tcf), stress corrosion cracking under bending (sccub) and torsional stress corrosion cracking (tscc).

Table 2
Attributes for wear, corrosion and plastic deformation module that the non expert user identifies for the failed shaft.

Attributes	sf	abw	adw	fr	uc	pc	bpf	tpf	sbub	sbut	dkws
Surface modification	M	M	M	M	M	M	–	–	–	–	–
Pitting evidence	M	–	–	–	–	–	–	–	–	–	–
Superficial cracks	O	–	–	–	–	–	–	–	–	–	–
Scratch in surface	–	M	–	–	–	–	–	–	–	–	–
Metal transferring	–	–	M	–	–	–	–	–	–	–	–
Heat or fusion evidence	–	–	O	–	–	–	–	–	–	–	–
Reddish-brown oxide color	–	–	O	M	–	–	–	–	–	–	–
Localized damage	–	–	–	M	–	–	–	–	–	–	–
Corrosion waste	–	–	–	–	M	O	–	–	–	–	–
Homogeneous damage	–	–	–	–	M	–	–	–	–	–	–
Pitting concentrated damage	–	–	–	–	–	M	–	–	–	–	–
Solid shaft	–	–	–	–	–	–	M	M	–	–	–
Bending deformation	–	–	–	–	–	–	M	–	–	–	–
Torsional deformation	–	–	–	–	–	–	–	M	–	–	–
Thin wall hollow shaft	–	–	–	–	–	–	–	–	M	M	–
Elliptical collapse	–	–	–	–	–	–	–	–	M	–	–
Torsional collapse	–	–	–	–	–	–	–	–	–	M	–
Keyway or spline deformation	–	–	–	–	–	–	–	–	–	–	M

Superficial fatigue (sf), abrasive wear (abw), adhesive wear (adw) and fretting (fr), pitting corrosion (pc), uniform corrosion (uc), bending plastic flow (bpf), torsional plastic flow (tpf), shell buckling under bending (sbub), shell buckling under torsion (sbut) and damage in keyway or spline (dkws).

Fuzzy inference can work with non exact information while information or evidence in rule based reasoning must be defined exactly and correctly (absent, evident).

Bayesian inference uses Bayesian rules to update the probability when additional evidence is identified for a failure mode using conditional probability tables. For example, bending fatigue fracture has a 75% probability when two zones (smooth and final fracture) are identified as evidence, but if there are additional beach marks on the surface this probability increases to 85%.

2.4. Development of the principle of operation of expert systems

As an example, in Fig. 2, a failed pony rod with a 45° fracture is shown; the fracture surface is shown in Fig. 3.

In Fig. 4, the first part of the fracture module for the shaft used in all the inference engines is shown. The non expert user must select the options according to the failed piece, using the data for the failed pony rod in Figs. 2 and 3.

The first task is to identify which of the following figures or pictures describe the fracture that one is analyzing and the fracture orientation (The non expert user selected "fracture with 45°").

The second task is to identify the pattern of plastic deformation in the fracture that one is analyzing (The non expert user selected "without deformation").

In Fig. 5, third task is to identify the kind of surface in the fracture zone (the non expert user selected "Granular appearance"); the fourth task is to identify marks on the surface (the non expert user selected "Radial marks without beach marks").

In Fig. 6, the fifth task is to identify if the piece was in a corrosive environment (the non expert user selected "I don't know"). The sixth task is to identify corrosion in the fracture zone (the non expert user selected "No"), and finally the last task is to identify the load before the failure (the non expert user selected "Variable load"). Human experts identified torsional brittle fracture as failure mode, the result using the Bayesian inference was torsional brittle fracture (99%) and fuzzy inference result was a torsional brittle fracture.

The rule based inference engine had no response, due to the fact, the rule for corrosive environment was not defined in the inference engine as "I don't know". For the rule based engine, that question has only two values (corrosive environment, non corrosive environment).

Each failure mode had a fault tree analysis diagram, as a tool for identifying the root cause of the failure mode identified. With this FTA, the maintenance and operation department can improve their practices and procedures. An example of a fault tree analysis for brittle torsion fracture is shown in Fig. 7.

3. Validation

Ratios and indexes of agreement are frequently used as validation methods in expert systems. Higher values of ratios and indexes show a better inference engine performance.

3.1. Ratios of agreement

Agreement ratios are based on a 2×2 matrix for each failure mode, as shown in Table 3. Variables a, b, c and d show the relationship between the total number of coincidences between the human experts and the expert system in the test. Variable D represents the presence of evidence or a symptom, and $(\neg D)$ represents an absence of evidence in a failure case.

Variable a indicates the times in the test when the human expert identified a failure mode and the expert system did too, b is the number of times when the human expert identified an absence of a failure mode and the expert system identified a presence, c is when the human expert identified a presence of a failure mode and the expert system in the test showed an absence and d shows when the human expert identified an absence of a failure mode and the expert system gave the same answer.

Using variables a, b, c and d and their relationships, it is possible to find the following ratios of agreement: Index of agreement (for ratios), sensibility, specificity, and receiver operating characteristic (ROC).

3.1.1. Agreement index based on ratios

Represented by *Iar*, it is calculated as shown in Eq. (1).

$$Iar = \frac{a+d}{a+b+c+d} \tag{1}$$

3.1.2. Sensibility

Represented by S, it is calculated as shown in Eq. (2).

$$S = \frac{a}{a+c} \tag{2}$$

3.1.3. Specificity

Represented by E in this paper, it is calculated as shown in Eq. (3).

$$E = \frac{d}{b+d} \tag{3}$$

3.1.4. Receiver operating characteristic

Represented by ROC in this paper, it is calculated as shown in Eq. (4).

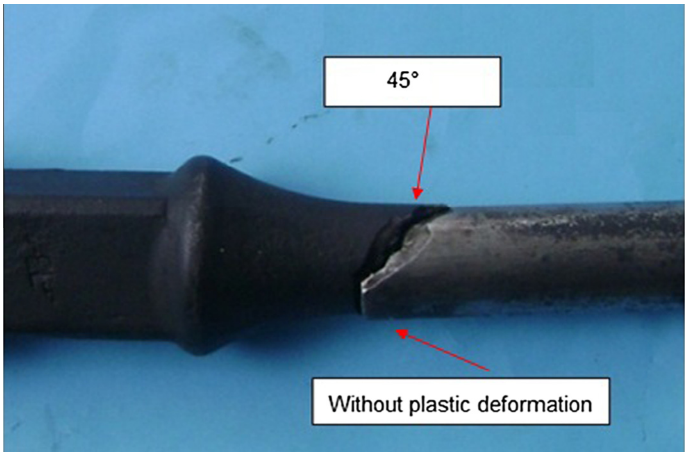

Fig. 2. Failed pony rod 1–1/8″.

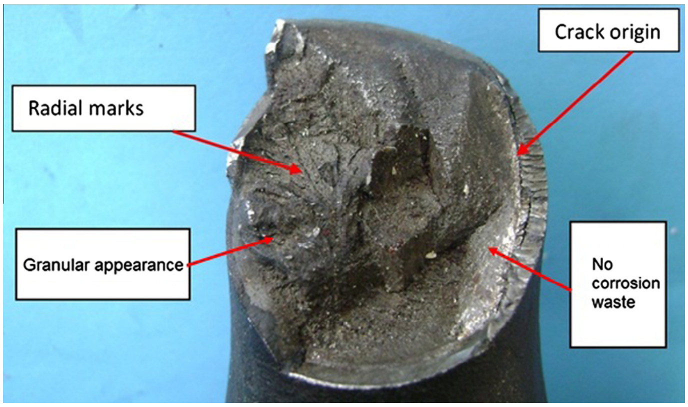

Fig. 3. Fracture surface.

$$\mathrm{ROC} = \frac{\mathrm{Sensibility} + \mathrm{Especificity}}{2} \tag{4}$$

3.2. Index of agreement

There are three different tools: the index of agreement, κ (unweighted kappa index), and κ_w (weighted kappa index) [14]. Using contingency tables, it is possible to calculate the index of agreement (Iap) as follows in Eq. (5):

$$Iap = \frac{\sum_{i=1,j=1,i=j}^{k} n_{ij}}{N} = \sum_{i=1,j=1,i=j}^{k} p_{ij} \tag{5}$$

In Eq. (5), N is the total number of cases, n_{ij} is the total number of cases at cell ij in the contingency table, and p_{ij} is the principal diagonal in the contingency table.

The unweighted kappa (κ) is calculated as shown in Eq. (6):

$$\kappa = \frac{p_o - p_c}{1 - p_c} \tag{6}$$

In Eq. (6), p_o is the proportion of observed agreement and p_c is the proportion of agreement due to causality as the sum of the margin proportions of the principal diagonal of the contingency table. p_c is calculated as the sum of the relative frequencies of row i and column j, as shown in Eq. (7).

$$p_c = \sum_{i=1,j=1,i=j}^{k} p_i p_j \tag{7}$$

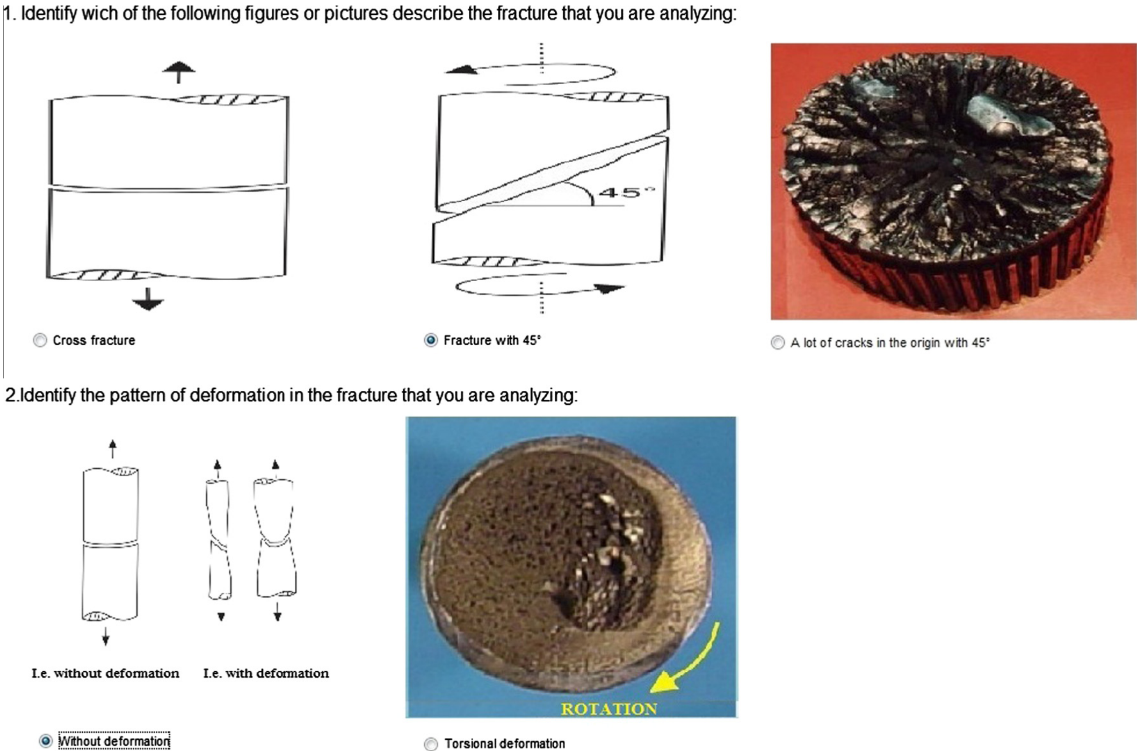

Fig. 4. Task one and two for the fracture module.

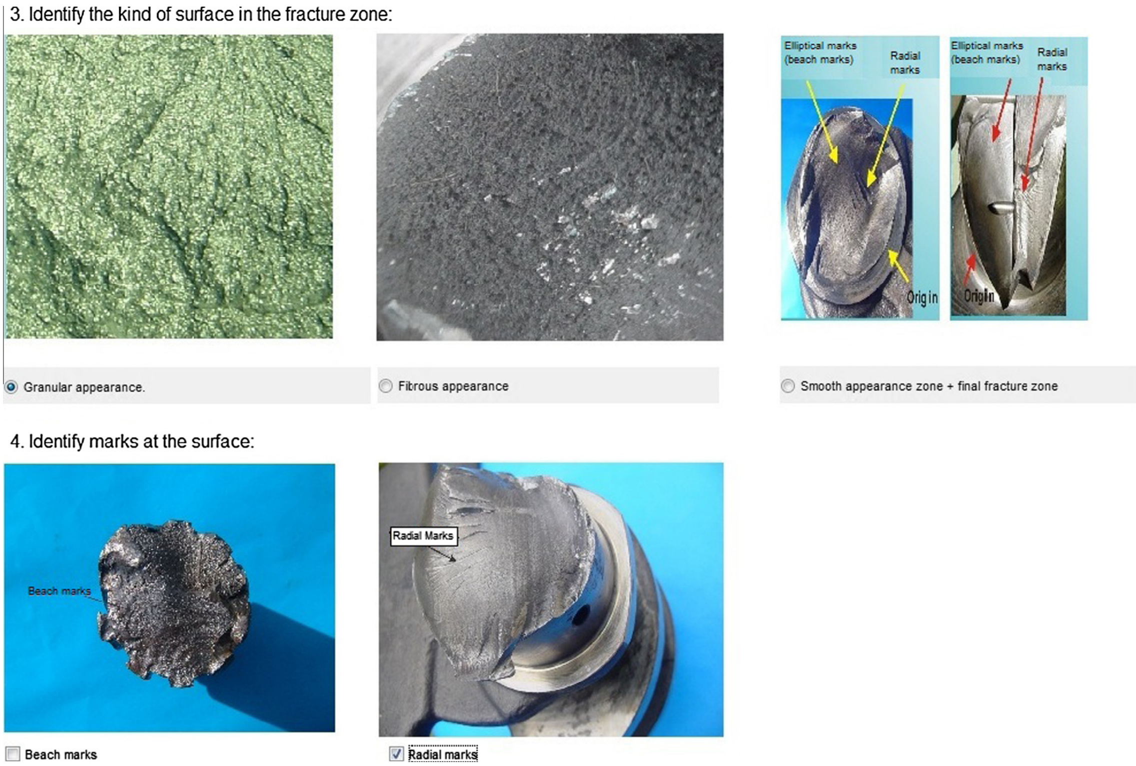

Fig. 5. Fracture surface and mark tasks, tasks three and four.

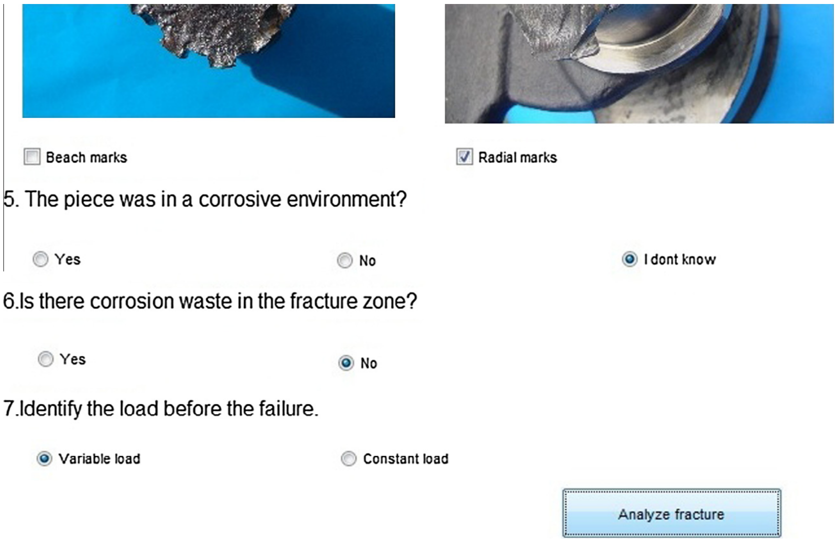

Fig. 6. Corrosion, final tasks, and final failure mode result.

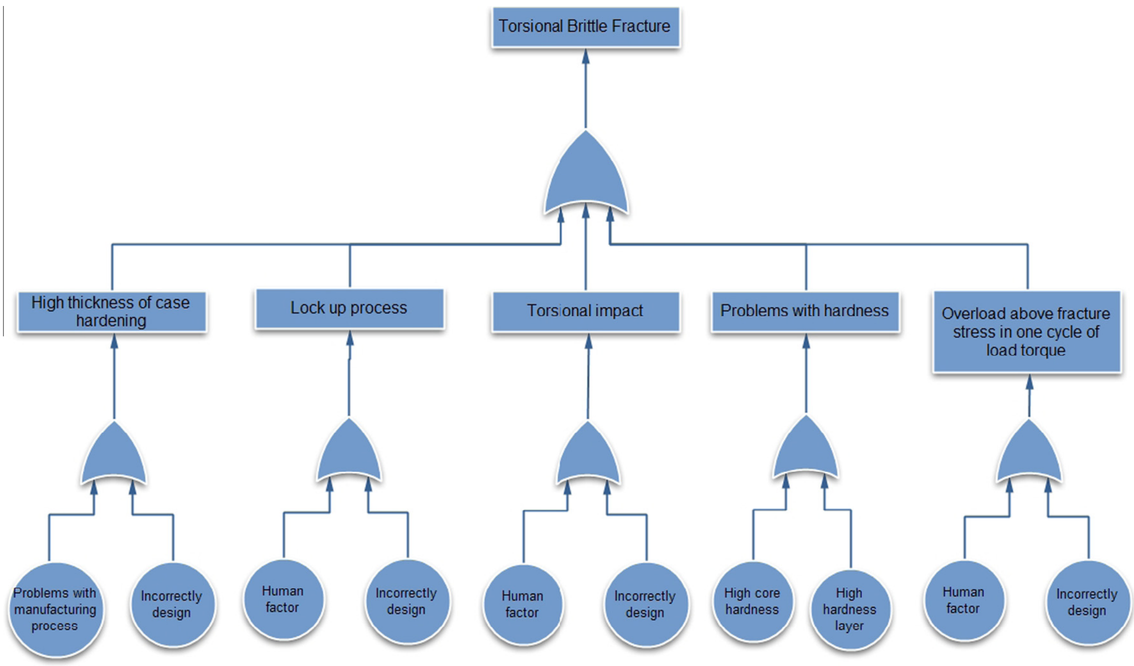

Fig. 7. Example of fault tree analysis for torsional brittle fracture in shaft.

Table 3
Contingency table for agreement ratio [14].

		Human expert response		
		D	$\neg D$	
Expert system for test	D	a	b	$a+b$
	$\neg D$	c	d	$c+d$
		$a+c$	$b+d$	$a+b+c+d$

The weighted Kappa κ_w index is calculated as follows using Eq. (8).

$$\kappa_w = 1 - \frac{\sum_{i=1,j=1}^{k} v_{ij} p_{oij}}{\sum_{i=1,j=1}^{k} v_{ij} p_{cij}} \tag{8}$$

In Eq. (8), p_{oij} is the agreed proportion observed for cell ij, p_{cij} is the agreement due to causality for cell ij, and v_{ij} is the weighted one (punished) in cell ij.

3.3. Failure cases

To validate the result for each expert system, forty-six failure cases in shafts were used, as follows:

- Sixteen cases for fracture.
- Ten cases for wear.
- Ten cases for corrosion.
- Ten cases for plastic deformation.

The cases were analyzed by a panel of four human experts in failure analysis and were then compared with the diagnosis response of each inference system for failure mode identification. Table 4 shown the industry of origin in failure cases.

4. Experimental results

The results of the analysis of the fracture cases are shown in Table 5, wear cases in Table 6, corrosion cases in Table 7, and plastic deformation in Table 8. Each table shows the human expert response and the response for each inference engine tested (rule based, fuzzy inference and Bayesian). On the basis of these results, it is possible to find the contingency table for each failure mode.

Table 4
Industry source of failure cases.

Industry	(%)
Oil & gas	47.8
Industrial machinery	21.7
Automotive	10.9
Aeronautics	10.9
Mining	6.5
Food & beverage	2.2
Total	100

Table 5
Results for fracture cases.

Case/expert	Human experts	Rule based	Fuzzy inference	Bayesian inference
1	bfb	No response	bfb	bfb
2	tbf	No response	tbf	tbf
3	tbf	No response	tbf	tbf
4	bff	bfb	No response	bfb
5	bff	bff	No response	bff
6	tbf	tbf	No response	tbf
7	tdf	No response	tdf	tdf
8	bff	No response	bff	bff
9	sccub	sccub	sccub	sccub
10	bff	bff	No response	bff
11	bcf	No response	bff	bcf
12	tdf	sccub	sccub	bfb
13	bfb	No response	No response	bfb
14	bfb	bfb	No response	bfb
15	tbf	No response	tbf	tbf
16	bff	bff	No response	bff

Brittle fracture in bending (bfb), torsional brittle fracture (tbf), torsional ductile fracture (tdf), bending fatigue fracture (bff), torsional fatigue fracture (tff), torsional fatigue fracture in the splined shaft (tffss), bending corrosion fatigue (bcf), torsional corrosion fatigue (tcf), stress corrosion cracking under bending (sccub) and torsional stress corrosion cracking (tscc).

Table 6
Results for wear cases.

Case/expert	Human experts	Rule based	Fuzzy inference	Bayesian inference
1	sf	sf	sf	sf
2	abw	No response	abw	abw
3	adw	adw	adw	adw
4	sf	sf	sf	sf
5	adw	adw	adw	adw
6	fr	fr	fr	fr
7	fr	fr	fr	fr
8	adw	adw	adw	adw
9	fr	No response	fr	fr
10	fr	No response	fr	fr

Superficial fatigue (sf), abrasive wear (abw), adhesive wear (adw), fretting (fr).

Table 7
Results for corrosion cases.

Case/expert	Human experts	Rule based	Fuzzy inference	Bayesian inference
1	uc	uc	uc	uc
2	pc	pc	pc	pc
3	uc	uc	uc	uc
4	pc	pc	pc	pc
5	pc	pc	pc	pc
6	pc	pc	pc	pc
7	pc	pc	pc	pc
8	pc	pc	pc	pc
9	pc	pc	pc	pc
10	pc	pc	pc	pc

Pitting corrosion (pc), uniform corrosion (uc).

Table 8
Results for plastic flow cases.

Case/expert	Human experts	Rule based	Fuzzy inference	Bayesian inference
1	tpf	tpf	tpf	tpf
2	tpf	No response	tpf	tpf
3	tpf	No response	tpf	tpf
4	tpf	tpf	tpf	tpf
5	bpf	bpf	bpf	bpf
6	bpf	bpf	bpf	bpf
7	sbub	sbub	sbub	sbub
8	sbut	sbut	sbut	sbut
9	dkws	dkws	dkws	dkws
10	tpf	No response	tpf	tpf

Torsional plastic flow (tpf), bending plastic flow (bpf), shell buckling under bending (sbub), shell buckling under torsion (sbut) and damage in keyway or spline (dkws).

4.1. Results for indicators

Table 9 shows the indicators and ratios for all the modules as a response of the rule based inference engine.

Table 10 shows the indicators and ratios for all the modules as a response of the fuzzy inference engine.

Table 11 shows the indicators and ratios for all the modules as a response of the Bayesian inference engine.

Fig. 8 shows a comparison of the indicators based on indexes of agreement as Iap, κ and κ_w for the three inference engines.

According to Fig. 8, the index of agreement (Iap) showed that Bayesian inference exhibited better performance (96.9%), in comparison to fuzzy inference (87.5%) and the rule based inference engine (69.4%). Using the unweighted κ index and the weighted κ_w index, the rule based inference engine exhibited the worst performance, with 64% for κ and 59% for κ_w. The fuzzy inference engine obtained 85.7% for κ and 83.5% for κ_w. Finally, the Bayesian inference engine gave a result of 96% for κ and 95.9% for κ_w.

Fig. 9 shows a comparison of the indicators based on ratios of agreement as S, E, and ROC obtained for the rule based, fuzzy inference, and Bayesian inference engines.

Table 9
Indicators and ratios for the rule based inference engine.

	Iap	κ	κ_w	*Iar*	*S*	*E*	ROC
Fracture	0.375	0.301	0.154	0.875	0.364	0.976	0.670
Wear	0.700	0.620	0.647	0.925	0.750	0.913	0.831
Corrosion	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Plastic flow	0.700	0.639	0.558	0.940	0.880	1.000	0.940
Average	0.694	0.640	0.590	0.935	0.748	0.972	0.860
σ	0.255	0.286	0.347	0.051	0.276	0.041	0.145

Iap (Index of agreement), κ (Unweighted kappa index), κ_w (Weighted Kappa index), *Iar* (Index of agreement ratio), *S* (Sensibility), *E* (Specificity), ROC (Receiver operating characteristic), σ (Standard deviation).

Table 10
Indicators and ratios for fuzzy inference engine.

	Iap	κ	κ_w	*Iar*	*S*	*E*	ROC
Fracture	0.500	0.426	0.340	0.885	0.464	0.974	0.719
Wear	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Corrosion	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Plastic flow	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Average	0.875	0.857	0.835	0.971	0.866	0.993	0.930
σ	0.250	0.287	0.330	0.057	0.268	0.013	0.141

Iap (Index of agreement), κ (Unweighted kappa index), κ_w (Weighted Kappa index), *Iar* (Index of agreement ratio), *S* (Sensibility), *E* (Specificity), ROC (Receiver operating characteristic), σ (Standard deviation).

Table 11
Indicators and ratios for the Bayesian inference engine.

	Iap	κ	κ_w	*Iar*	*S*	*E*	*ROC*
Fracture	0.875	0.841	0.837	0.958	0.883	0.974	0.929
Wear	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Corrosion	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Plastic flow	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Average	0.969	0.960	0.959	0.990	0.971	0.994	0.982
σ	0.063	0.080	0.082	0.021	0.058	0.013	0.036

Iap (Index of agreement), κ (Unweighted kappa index), κ_w (Weighted Kappa index), *Iar* (Index of agreement ratio), *S* (Sensibility), *E* (Specificity), ROC (Receiver operating characteristic), σ (Standard deviation).

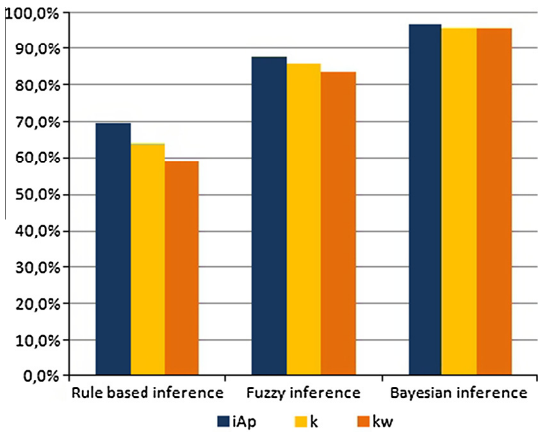

Fig. 8. Index agreement comparison.

The best sensibility (*S*) and specificity (*E*) performance was obtained with the Bayesian inference engine, $S = 97.1\%$ and $E = 99.4\%$. The highest value for the ROC (the relationship between the sensibility and specificity), was for the Bayesian inference engine (98.2%), followed by the fuzzy inference engine (93%) and the rule based engine (86%).

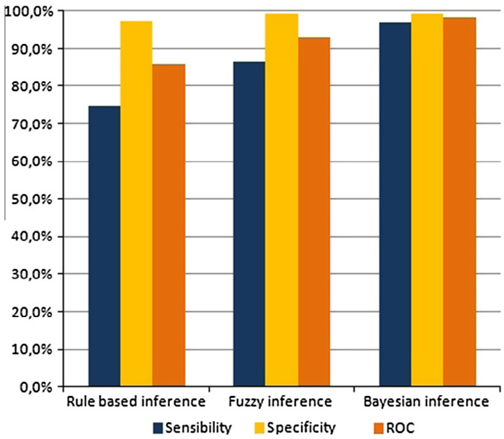

Fig. 9. Ratios of agreement comparison

5. Discussion

The fracture module had the most complex system of relationships between evidence and failure modes. There are several failure modes with similar evidence in their symptoms (e.g. beach marks, radial marks and two zones of fracture). The experimental results showed that more relationships, increase the completeness in the expert system. It will be challenging to identify all the differences between the different failure modes.

Bayesian inference had the best indicators compared with fuzzy inference and rule based reasoning. Bayesian inference is more flexible due to the fact that uses conditional probabilities to evaluate a failure mode between 0% and 100%, while fuzzy inference and rule based systems use IF-THEN rules.

If an evidence (rule) is not listed in a failure mode, Bayesian inference decreases the probability, but it is still possible at the end of the analysis to identify the correct failure mode with a small similarity, in this case the IF-THEN systems (rule based and fuzzy) cannot identify the failure mode unless a new rule is added to the knowledge base. This condition gives an advantage to Bayesian inference in complex failure cases such as fracture identification.

Fuzzy inference engine can accept non exact information that depends on observations of the non expert user (beach mark identification as an example), compares with the rule based system where it is necessary to define all the rules in order to solve the failure mode, fuzzy inference had better indicators.

6. Conclusion

1. In expert systems applied to failure analysis more relationships between an evidence involved in several failure modes (e.g. radial marks), often increase the complexity of the diagnosis, because, the evidence is no longer a variable in the inference process, thus there is less information available in order to identify a failure mode, this condition had a notorious negative effect on the rule based inference where in some cases the engine could not identify any failure mode.
2. Rule based reasoning has been applied with success in previous papers for diagnosis in failure mode identification, according to the ROC in this paper 86%, but failure analysis is a non-deterministic procedure due to the different interpretations and possibilities that a failure analyst could find in a case, thus the use of non-deterministic inference process in failure analysis as fuzzy or Bayesian inference could have better performance in the failure mode identification as the discussion of this work.
3. The process of validation for an expert system presented in this paper could be used as an example for quantitative validation of any expert system applied in failure mode identification, when the result is compared with the human expert response.
4. This paper is designed to be an introduction to developing future expert systems for failure mode identification. According to results presented, it will be better to implement for failure mode identification an expert system based on Bayesian inference.

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