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Inspection Interval Estimation: A Fuzzy Logic Based RBI Analysis Approach

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Abstract: Risk based inspection analysis (RBIA) on offshore oil and gas (O&G) production systems optimize level of in-service inspection. The potential failure risk of a system, a sub-system or a thickness measurement location (TML) of O&G production systems comprise the consequence of failure (CoF) and probability of failure (PoF). A tailor-made risk matrix supports the estimation of maximum inspection intervals. When the inspection intervals are calculated using a risk matrix, suboptimal classification tends to occur as there are no means to incorporate actual circumstances at the boundary of the input ranges or at the levels of linguistic data and risk categories. This manuscript suggests a fuzzy inference system (FIS) to overcome the aforementioned. Membership functions and the rule base development have been carried out in alignment with a tailor-made risk matrix which has been utilized by a production plant owner operator organization. A rule view and a calculation result have been demonstrated to illustrate the methodology.

Keywords: Risk based inspection analysis, production system, inspection interval, fuzzy inference system.

1 Introduction

The performance of production and/or process plants are sustained by appropriate inspection planning and scheduling [1,2]. However, in this context, it is vital to determine the optimal inspection intervals in terms of a criteria of interest [3,2]. Consequently, risk based inspection analysis (RBIA) has been accepted over the last few years as a method for prioritizing the in-service inspection of a plant as well as for estimating corresponding inspection intervals [4]. These methods have been developed nationally (e.g. American Petroleum Institute (API), a number of private organizations (particularly in the petrochemical industry), etc.) [5] and internationally (e.g. RIMAP – Risk based inspection and maintenance procedures for European industries) [6]. The importance of risk was recognized principally as an important measure in assuring system safety [7]. However, there is a fundamental challenge in the mathematical modeling of RBIA to perform optimum maintenance as a subject [8].

The mathematical modeling enables mitigating subjective judgments based on limited information and also, some of the inherent challenges present in the current RBIA [8, 9]. Alternatively, it mitigates the significant variability and discrepancy present in the current inspection interval estimations. For instance, a report published on a case study evaluation of an onshore process plant revealed that "subjec-

tive judgments based on limited information did lead to some significant differences in inspection periods" [5]. It also revealed that although "generally, the inspection periods reflected the assessed risk", "considerable scatter was apparent in the data and some participants exhibited greater conservatism in their assessments than others" [5]. The same report suggests that "software, expert systems and expert judgment all have merits, greater integration of these elements might be beneficial" [5]. Hence, it is vital to develop expert systems to support expert judgments and alternatively to develop sophisticated software to minimize the variability present in estimating inspection periods (i.e. inspection intervals).

This manuscript proposes a fuzzy logic based expert system for estimating in-service inspection intervals [10]. The estimation of in-service inspection intervals is based on PoF, CoF and currently established values of inspection intervals with respect to different risk levels.

2 Industrial Challenge

Currently, recommended practices, standards (e.g. DNV-RP-G101), operator company procedures, etc., provide decision matrices for estimating inspection intervals (i.e. time to inspect) [11]. However, when the classifications are carried out, there is no formal mechanism to incorporate data and information at the boundaries of the risk categories (i.e. alternatively at the boundaries of the ranges and levels of linguistic data). This is mainly due to the fact that there are no means to incorporate real data (qualitative or quantitative) in a consistent manner in estimating the maximum allowable time intervals. For instance, along a boundary, the spontaneous jumps of risk classification together with recommended inspection intervals (e.g. VH to H: the recommended inspection interval changes from 6 months to 48 months) hinder realistic values depending on the estimated PoF and CoF, leading to suboptimal inspection interval estimations (see Fig. 1). Fig.1 illustrates such a risk matrix along with relevant maximum inspection intervals that have been utilized for piping RBISIA (i.e. in an operator organization which owns a production and process plant).

Due to the lack of a consistent approach, the inspection interval recommendations made are mostly confined to the PoF intervals, CoF intervals, and corresponding inspection interval values in an *ad hoc* manner dependent on the person who is involved in the analysis. Hence, it is vital to have a consistent approach to incorporate PoF, CoF and inspection intervals.

3 Methodology

In order to cater for rapid changes (in inspection interval) at the boundaries of each risk level (see Fig.1), fuzzy membership functions have been introduced for each PoF, CoF and inspection interval. The introduction of fuzzy membership functions enables the inspection interval estimation to be made more realistic. Furthermore, a fuzzy inference system (FIS) enables the mitigation of discrepancies that may occur during the risk assessment process as a result of simultaneous considera-

tion of different PoF and CoF ranges of values for estimating maximum inspection intervals.

3.1 Risk Matrix

During the detailed risk analysis process, the static mechanical pressure systems are subject to an investigation of PoF and CoF according to the categorization presented in Fig.1. This is a 5x5 matrix, indicating levels of both PoF and CoF whilst providing five risk levels (i.e. VL, L, M, H and VH). These risk levels represent a combination of PoF and CoF based on the relevant numerical value ranges. The numerical value ranges for PoF and CoF have been retrieved from the documentation pertaining to the case study plant operator's organizations (see Fig. 1). In addition, the corresponding maximum inspection interval (in months) has been indicated within the parenthesis under each risk level.

	Cate-gory	PoF (per year)	Time to release (years)	Risk level [maximum inspection interval (MII) in months]								
PoF	VH	> 1E-2	< 3	VL (144)	L (120)	M (72)	VH (6)	VH (6)	VH (6)	VH (6)	VH (6)	VH (6)
	H	(1E-2 – 1E-3)	(3 - 7)	VL (144)	L (120)	M (72)	H (48)	H (48)	H (48)	VH (6)	VH (6)	VH (6)
	M	(1E-3 – 1E-4)	(7 - 15)	VL (144)	VL (144)	L (120)	M (72)	M (72)	H (48)	H (48)	H (48)	H (48)
	L	(1E-4 – 1E-5)	(15 - 30)	VL (144)	VL (144)	L (120)	L (120)	M (72)	M (72)	M (72)	M (72)	M (72)
	VL	< 1E-5	> 30	VL (144)	VL (144)	VL (144)	L (120)	L (120)	L (120)	M (72)	M (72)	M (72)
*Potential loss of life		Safety CoF (*PLL due to a release)		< 1E-5	(1E-4 – 1E-5)		(1E-3 – 1E-4)			(1E-2 -1E-3)		> 1E-2
**000' Norwegian Krone		Economical CoF (**KNOK)		< 50	(50 – 500)		(500 – 5000)			(5000 – 50000)		> 50000
		CoF Category		VL	L		M			H		VH
		CoF										

Fig. 1. RBI matrix (maximum inspection interval in months).

3.2 Probability of Failure Assessment

In essence, the piping equipment is organized into corrosion groups which can contain several degradation mechanisms. Two models have mainly been used for evaluating the probability of failure (PoF) of piping equipment due to degradation: I. a susceptibility model for stainless steels; and II. a rate model for carbon steels.

Susceptibility models are used when the PoF is related to operating conditions. In this context, for a given set of conditions that are constant over time, the PoF also remains constant over time. This indicates that it is not easy to monitor the development of damage mechanisms by using inspection. Hence, actions are related to the monitoring of key process parameters, which are used as a trigger for inspection. DNV-RP-G101, Appendix A [11] provides guidance about typical materials and environmental conditions where this model is expected to be applicable and suggest values for PoF for typical conditions. For the susceptibility models there are two governing conditions required for degradation: I. wet environment; and II. temperature. The results from the monitoring of these conditions are the most important in setting the probability.

Rate models have increasing probability over the time, which makes it difficult to express as one probability value. Even though 'time to release' is itself not a probability expression, it explains the speed at which the probability increases, and therefore represents a useful profile of the probability. Hence, the development of degradation is measured by inspection. Then, the PoF is documented as an estimated 'time to release', based on the wall thickness and degradation rate on the area found to have the shortest time to release. In corrosion loops, both stagnant and varying flow conditions indicate very different estimated time to release (leak). Hence, the time to inspection is split among them in order to obtain the optimal time to inspection and this is reflected in the RBI analysis.

This manuscript provides a knowledge based engineering approach with the help of a fuzzy logic based inference system for estimating the inspection interval using a tailor-made risk matrix.

3.3 Fuzzy Logic Based Inference System

A 'pure fuzzy logic system' consists of a fuzzy rule base, which comprises a collection of fuzzy IF–THEN rules. These rules are utilized by the fuzzy inference engine to determine a mapping from fuzzy sets in the input universe of discourse $U \subset R^n$ to fuzzy sets in the output universe of discourse $V \subset R$ based on fuzzy logic principles. The fuzzy IF–THEN rules follow the form below:

$$R^{(1)} : \text{IF } x_1 \text{ is } F_1^1 \text{ and } \ldots x_n \text{ is } F_n^1 \text{ THEN y is } G^1 \qquad (1)$$

where F_i^j and G^j are fuzzy sets, $x = (x_1, x_2, \ldots, x_n)^T \in U$ and $y \in V$ are input and output linguistic variables which belong to the input and output universes, respectively, and $j=1, 2, \ldots, m$. Practical experience reveals that these fuzzy IF–THEN rules provide a convenient framework to incorporate human expert knowledge. In Eq. (1), each fuzzy IF–THEN rule defines fuzzy set $F_1^j, F_2^j \ldots F_n^j \Rightarrow G^j$ for $i = 1, 2, \ldots, n$, in the product space $U \times V$. Expert opinions and data/information retrieved from different sources are taken into the mathematical model using the aforementioned rules. The main focus is to enhance the discerning power in the risk analysis process, whilst minimizing the uncertainties that may occur in dealing with the linguistic variables of the risk levels (i.e. H, VH, VL, etc.) at the boundaries of quantitative ranges. Essentially, membership functions (MFs) are developed with experienced personnel who are familiar with the risk analysis process [12]. Then, along with a rule base, MFs provide the possibility of recycling experts' knowledge in a consistent manner.

In 1975, Mamdani built one of the first fuzzy systems which used a set of fuzzy rules supplied by experienced human operators to control a steam engine and boiler combination [13]. To date, Mamdani's approach has been successfully applied to a variety of industrial processes and consumer products [14]. Fig. 2 illustrates the work process of the proposed fuzzy inference system.

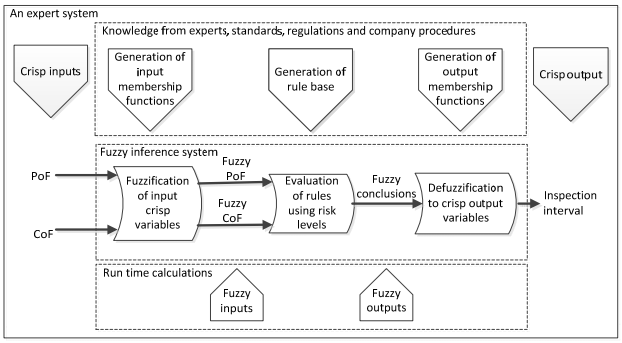


Fig. 2. An expert system for estimating maximum inspection intervals.

The PoF, time to release (TTR), safety consequence of failure, which is estimated by potential loss of life (PPL) (i.e. CoF_{PPL}) and economic consequence of failure (i.e. CoF_{Econ}) have been selected as the input variables. The inspection interval has been selected as the output. These variables consist of quantitative, qualitative and judgmental (i.e. linguistic) data. For each of the aforementioned variables, there is an associated membership function, which is established with the help of data, information and expert opinion [13]. The fuzzification process aids fuzzifiying the inputs by determining the value of the membership functions corresponding to the different inputs. Furthermore, instead of restricting the user to a single, crisp, input value, this process allows an interval of values to be given, with values near the center of the interval being assumed to be 'more certain' than those near the edges, and the width of the interval indicating the amount of uncertainty present in the different input variables. The aforementioned has been achieved by associating appropriate membership functions (MF) for the input variables. Using an appropriate MF, the user has 'more confidence' that the input parameter lies relatively closer to the center of the interval than at the edges. In this study the author has incorporated triangular membership functions [15].

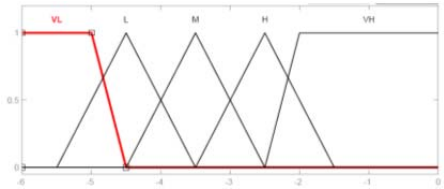
The fuzzy inference system (FIS) parameters were selected as follows: 'And' method with 'minimum', 'Or' method with 'maximum', 'Implication' with 'minimum', 'Aggregation' with 'maximum' and 'Defuzzification' with 'centroid' algorithm. Fuzzy rule bases were developed using the table-look-up approach (see Fig. 1). The toolbox simulator of the MATLAB (R2011a) tool was utilized to implement a fuzzy criticality ranking system [16].

4 Fuzzy Logic Based Modeling

4.1 Membership Functions for PoF

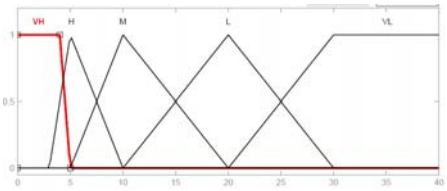
In essence, the PoF per year has been related to degradation mechanisms in the susceptibility model. At the same time, the TTR has been utilized in the rate models to express the speed at which the probability increases (note: the probability related to rate models is a variable with time). The PoF is also subjected to an analysis for both external and internal failure mechanisms. The membership functions

(MFs) for inputs PoF and TTR have been developed based on data, information and expert opinions (see Fig. 3 and Fig. 4).



Input variable: Log(PoF)

Fig. 3. MF for PoF.

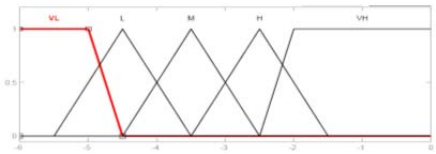


Input variable: TTR

Fig. 4. MF for TTR.

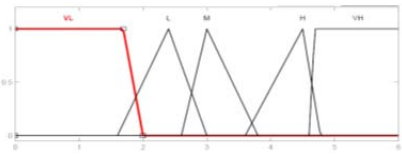
4.2 Membership Functions for CoF

The CoF_{PPL} values are estimated by quantitative risk analysis. The COF_{Econ} values are determined based on the inputs from relevant operation and process personnel (production loss) and from piping/vessels discipline engineers (repair costs). Fundamentally, COF_{Econ} covers costs related to loss of production and costs for repair in the case of a leak. Consequence of loss of functionality is also considered as an economic loss due to reduced or lost production and/or major repair cost, not necessarily given a leak or shutdown of equipment. For instance, typical loss of functionality is mostly related to failure of internals in vessels and coolers. However, in this manuscript the values of CoF_{PPL} and COF_{Econ} have been retrieved from the tailor-made company specific topside inspection manual of the case study operator company. The MFs for inputs CoF_{PPL} and COF_{Econ} have been developed based on data, information and experts' opinions (see Fig. 5 and Fig. 6).



Input variable: Log(CoF_{PLL})

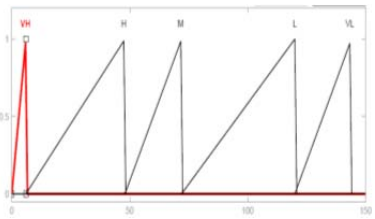
Fig. 5. MF for CoF_{PPL}.



Input variable: Log(CoF_{Econ})

Fig. 6. MF for COF_{Econ}.

The membership function for maximum inspection interval (MII) is illustrated in Fig. 7.



Output variable: MII

Fig.7. MF for MII.

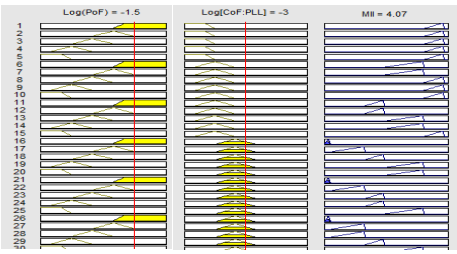


Fig.8. Calculation of MII when PoF=1E-1.5 and CoF_{PLL}=1E-3 (i.e. MII = 4.07).

5 Analysis and Results

PoF and CoF_{PLL} have been utilized to illustrate the calculation of MII (see Fig. 8). Using the table look-up approach (see Fig.2) to estimate MII in relation to different PoF and CoF_{PLL} levels, 45 rules have been generated. Fig. 8 illustrates approximately 29 rule views and the corresponding calculation of MII (i.e. MII = 4.07) for PoF=1E-1.5 and CoF_{PLL}=1E-3.

It is possible to use a similar approach for PoF & CoF_{Econ} vs. MII; TTR & CoF_{PLL} vs. MII; and TRR & CoF_{Econ} vs. MII. All the combinations can be merged into a single workspace using the 'Simulink' facility available in 'Matlab' (MATLAB, 2011).

6 Discussion

The suggested approach enables the quantitative values in a range to be distributed in relation to their significance. For instance, the left-hand side and right-hand side of a quantitative range have more relation to the previous and following qualitative category (i.e. VH, H, M, etc.) respectively. In the suggested approach, the aforementioned relationship is consistently established with the help of MFs. Using a rule base, the different MFs are consistently interrelated incorporating the practical significance of the PoF and CoF in calculating the MII.

7 Conclusion

The suggested method enables gaps present to be mitigated, for instance in-between H to VH (i.e. 48 to 6 months), L to M (i.e. 120 to 72 months), etc. In addition, the suggested method enables the experts' knowledge to be recycled. Such recycling provides the opportunity to reduce variability present in the analysis due to human error, inconsistency of awareness, lack of experience, etc. Alternatively, the use of the suggested approach facilitates the improvement of the quality of the MII calculation process in terms of time and accuracy. However, special attention should be paid to developing the MFs.

Future research should be carried out to investigate the effect of triangular vs. Gaussian MFs on the accuracy of the MII analysis process.

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