Estimation of Maximum In-Service Inspection Intervals Based on Risk: A Fuzzy Logic Based Approach

R.M. CHANDIMA RATNAYAKE*
Department of Mechanical and Structural Engineering and Materials Science, Faculty of Science and Technology, University of Stavanger, NORWAY

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Abstract: Risk based inspection analysis (RBIA) on offshore topsides static mechanical pressure systems aid the optimum performance of in-service inspection. Risk based in-service inspection analysis (RBISIA) essentially considers failures by loss of containment of the pressure envelope and supports decision making in inspection planning. This is based on the potential failure risk of a system, a sub-system or a thickness measurement location (TML) comprising the consequence of failure (CoF) and probability of failure (PoF). The RBISIA process is designed to aid the development of optimized inspection and recommendations for monitoring and testing plans for production systems. In this context, a tailor-made risk matrix supports the estimation of maximum inspection intervals (MIIs). When the MIIs 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 fuzzy logic based approach via a fuzzy inference system (FIS) to overcome the aforementioned. Membership functions (MFs) and the rule base development have been carried out in alignment with a tailor-made risk matrix which has been utilized by a plant operator organization. A rule view and a calculation result have been demonstrated to illustrate the methodology.

Keywords: Risk based inspection, in-service inspection, maximum inspection interval, risk matrix, inspection planning, thickness measurement location, fuzzy inference system

1. Introduction

It is possible to improve the performance of a production and/or process plant 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 “subjective 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 maximum in-service inspection intervals [10]. The estimation of maximum in-service inspection intervals is based on PoF, CoF and currently established values of MIIs with respect to different risk levels.

2. Industrial Challenge

Currently, based on the recommended practices, standards (e.g., DNV-RP-G101), operator company procedures, etc., the risk evaluation matrices (together with predefined MIIs) have been developed for estimating MIIs (i.e., time to inspect) at hot points of Oil and Gas (O&G) operating assets depending on the present status of the PoF and CoF [11]. Based on the particular O&G asset owner’s risk philosophy, the maximum time durations for making inspections have been predefined in relation to different risk levels.

Figure 1 illustrates such a risk matrix that has been utilized by the industrial organization which has been selected to study in this manuscript. The maximum inspection intervals that have been indicated in the parenthesis are utilized for piping RBISIA by the O&G operator organization which owns production and process plants.

<table>
<thead>
<tr>
<th>PoF</th>
<th>V (144)</th>
<th>VL (144)</th>
<th>L (120)</th>
<th>M (72)</th>
<th>VH (6)</th>
<th>VH (6)</th>
<th>VH (6)</th>
<th>VH (6)</th>
<th>VH (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H (144)</td>
<td>L (120)</td>
<td>M (72)</td>
<td>H (48)</td>
<td>H (48)</td>
<td>VH (6)</td>
<td>VH (6)</td>
<td>VH (6)</td>
<td>VH (6)</td>
<td>VH (6)</td>
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<tr>
<td>L (144)</td>
<td>L (120)</td>
<td>M (72)</td>
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<tr>
<td>VL (144)</td>
<td>VL (144)</td>
<td>L (120)</td>
<td>L (120)</td>
<td>L (120)</td>
<td>M (72)</td>
<td>M (72)</td>
<td>M (72)</td>
<td>M (72)</td>
<td>M (72)</td>
</tr>
</tbody>
</table>

Figure 1: RBI Matrix (MII in Months).

In this context, when the MIIs are estimated based on the risk (i.e., in relation to corresponding CoF and PoF) of a potential failure (or failures), the common practice is to use discrete scales. However, these discrete input ranges cause uncertainty, given that an input values at the boundary of the range, e.g., from very high (VH) to high (H), H to medium (M), M to low (L), L to very low (VL), etc. 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 MII changes from 6 months to 48 months) hinder realistic values depending on the estimated PoF and CoF, leading to
suboptimal inspection interval estimations. This has been further exacerbated due to the fact that 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).

Due to the lack of a consistent approach, the MII 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. The ad hoc assignments create high variability. Hence, it is vital to have a consistent approach to incorporate PoF, CoF and MIIs.

3. Methodology

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

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 Figure 1.

<table>
<thead>
<tr>
<th>PoF</th>
<th>Category</th>
<th>PoF (per year)</th>
<th>TIR (years)</th>
<th>Risk level (MII in months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VH</td>
<td>&gt; 1E-2</td>
<td>&lt; 3</td>
<td>VL (144)</td>
<td>L (120)</td>
</tr>
<tr>
<td>H</td>
<td>(1E-2 – 1E-3)</td>
<td>(3 - 7)</td>
<td>VL (144)</td>
<td>L (120)</td>
</tr>
<tr>
<td>M</td>
<td>(1E-3 – 1E-4)</td>
<td>7 - 15</td>
<td>VL (144)</td>
<td>V (144)</td>
</tr>
<tr>
<td>L</td>
<td>(1E-4 – 1E-5)</td>
<td>(15 - 30)</td>
<td>VL (144)</td>
<td>V (144)</td>
</tr>
<tr>
<td>VL</td>
<td>&lt; 1E-5</td>
<td>&gt; 30</td>
<td>VL (144)</td>
<td>V (144)</td>
</tr>
</tbody>
</table>

*Potential loss of life
**000' Norwegian Krone

**Economical CoF (**KNOK) < 50 (50 – 500) (500 – 5000) (5000 – 50000) > 50000

CoF Category | CoF | CoF | CoF | CoF |
<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>VL</td>
<td>L</td>
<td>M</td>
<td>H</td>
<td>VH</td>
</tr>
</tbody>
</table>

Figure 2: RBI Matrix (Maximum Inspection Interval in Months).

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 Figure 2). In addition, the corresponding MII (in months) has been indicated within the parenthesis under each risk level.

3.2 PoF and CoF 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 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 [11]. 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. Overall probability is estimated by taking the product of the probability of having a certain environment and temperature. Hence, 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.

The CoF’s have been estimated in relation to the defined consequence classes for safety (i.e., in relation to potential loss of life due to a release) and potential economical losses (i.e., in relation to the loss of production and damage of operating assets). These ranges are mostly assets’ owners specific. In this manuscript, generic values for CoF ranges have been selected using two assets’ owners and one engineering contractor specific internal documents.

This manuscript provides knowledge based engineering approach with the help of a fuzzy logic based inference system for estimating the MII 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 as follows:
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R^0: IF \( x_1 \) is \( F_1^j \) and \( \ldots \) \( x_n \) is \( F_n^j \) THEN \( y \) is \( G^j \) \hspace{1cm} (1)

where \( F_1^j \) 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 \( F_1^j \), \( F_2^j \), ..., \( F_n^j \Rightarrow G^j \) for \( i = 1, 2, \ldots, n \), in the product space \( U \times V \) \cite{12}.

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. Then, along with a rule base, MFs provide the possibility of recycling experts’ knowledge in a consistent manner.

In order to use FIS in engineering systems, it is necessary to add a fuzzifier to the input and a defuzzifier to the output of the FIS. The fuzzifier maps crisp points in \( U \) to fuzzy sets in \( U \), and the defuzzifier maps fuzzy sets in \( V \) to crisp points in \( V \). The fuzzy rule base and fuzzy inference engine are the same as those in the pure fuzzy logic system. The ‘fuzzy logic system’ has also been referred to as the ‘fuzzy logic controller’ due to its usage as a controller \cite{12}. 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 \cite{13}. To date, Mamdani’s approach has been successfully applied to a variety of industrial processes and consumer products \cite{14}. Figure 3 illustrates the work process of the proposed FIS.

The PoF, time to release (TTR), safety consequence of failure, which is estimated by potential loss of life (PPL) (i.e., CoFPPL) and economic consequence of failure (i.e., CoFEcon) have been selected as the input variables. The MII 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 \cite{13}. The fuzzification process aids fuzzifying 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 \cite{15}. 
Figure 3: An Expert System for Estimating MII

The FIS’s 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 Figure 2). The toolbox simulator of the MATLAB (R2013a) tool was utilized to implement a FIS [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 Figure 4(a) and Figure 4(b)].

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...
Figure 4(c) and Figure 4(d)]. The membership function for MII is illustrated in Figure 4 (e).

5. Analysis And Results

The toolbox simulator of the MATLAB (R2013a) has been utilized to implement the suggested FIS. PoF and CoF_PLL have been utilized to illustrate the calculation of MII [see Figure 4(e)] using the suggested FIS based approach. The table look-up approach has been employed (see Figure 2) to develop a rule base. For instance, 45 rules have been generated to estimate MII in relation to different PoF and CoF_PLL levels. The rule base is illustrated in Table A1. Figure 5 illustrates approximately 29 rule views and the corresponding calculation of MII (i.e., MII = 34.5) for PoF=$1E\cdot3.5$ and CoF_PLL=$1E\cdot2.5$. Figure 6 illustrates three dimensional surface view of MII (i.e., Log (PoF) and Log (CoF_PLL) vs. MII). Similarly, PoF and CoF_Econ vs. MII; TTR and CoF_PLL vs. MII; and TRR and CoF_Econ vs. MII are possible to model for making MII calculations. It is also possible to merge all the combinations into a single workspace using the ‘Simulink’ facility available in
‘Matlab (R2013a)’ [16]. The overall MII is determined based on the assets owners risk philosophy [17].

\[
\begin{align*}
\text{Log(PoF)} &= -3.5 \\
\text{Log(CoF:PLL)} &= -2.5 \\
\text{MII} &= 34.5
\end{align*}
\]

Figure 5: A Calculation of MII

Figure 6: Surface View: Log(PoF) & Log(CoF:PLL) vs. MII

6. Discussion

This paper addresses the issue of assessing the MIIs piping equipment via FIS. Using the MFs and rule base an effort has been put for mechanization of human expertise. The quantitative variables as well as related linguistic significance have been defined as fuzzy sets with appropriate MFs. The MFs have been built with the support of human experts (i.e., experienced users). The work process of MMI estimation has been explained in relation to asset owners’ specific risk matrix which has been utilized for RBI analysis for piping equipment in O&G assets operating in the Norwegian sector of North Sea. The suggested FIS based approach reduces the cost of querying experts and the need for their presence when a risk based decision has been made. It is also evident from the results of the analysis that the suggested FIS based approach provides a fast response for given inputs in MII assessment. The variances (or variability) that may be caused during MII assessments are minimized as all the inspection planners (or analysts) will use the same MFs and rule in a selected industrial organization. Hence, suboptimal MII assessments are minimized. Moreover, the FIS based approach proposed in this manuscript allows dynamic updating via the revision of the rule base and MFs to suit the latest developments in the piping systems. Hence, the performance of the selected FIS based development would get better and better as it develops. It also provides the opportunity for integration of expertise from many fields into one system for making MII assessments. It is possible to make similar developments in relation to top side rotating equipment (i.e., using NORSOK Z008) and subsea pipeline systems (i.e., using DNVRP-F116) for making effective assessments. Essentially, the suggested FIS based approach provides an opportunity to incorporate expert knowledge in a consistent manner. In addition, the suggested approach can be integrated in an existing structured information management system in an engineering contractor company or in a CMMS in an operator company.
7. Conclusion

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.

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 (i.e., rescue of the existing expertise or existed, however not available to date due to knowledge migration from one to the other industrial organization). 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.

References


R.M. Chandima Ratnayake is a Professor of Mechanical Engineering in the University of Stavanger and Integrity Management Technical - Senior Advisor in Wood Group Kenny, Norge AS. He has also served as a Maintenance Specialist in the Applysorco AS, Norway (2012-2014) and Senior Engineer in the AkerSolutions Offshore Partner (2009 – 2011) in Stavanger, Norway.

Table A1: Rule Base for MII Assessment.