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A Quantitative Method for RI-ISI Assessment

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1 ABSTRACT

Assessing risk impact of a RI-ISI inspection program requires three components: modelling the probability of pipe failures, assessing the consequences of pipe failures and modelling the effect of inspections in detection of degradation before failure. This paper presents a method for modelling each of these parts and combining the results for a full quantitative assessment of any RI-ISI program.

The estimation of piping failure probabilities is based on a combination of probabilistic fracture mechanics (PFM) calculations to simulate crack growth and a discrete-time Markov process for modelling the inspection activities. In the second phase, the analyses are based on Markov processes. First, the PFM simulation results for crack growth are used to construct transition matrices, where the states of the Markov process correspond to crack penetration depths in the component wall, and the transition probabilities from a lower state to higher states (deeper cracks) model the crack growth. Inspections are taken into account with another transition matrix, where the probability of detection (POD) is a function of the crack size. The effects of inspections are included in the model as transitions from a degraded state to a flawless state. An application example is provided.

2 INTRODUCTION

The use of RI-ISI methodologies in planning piping inspections in nuclear power plants (NPPs) is becoming more and more common. The aim of RI-ISI methodologies is to make the inspections more efficient by using risk information to choose the most important locations to be included in the inspections. This allows the operators to reduce risks associated with piping failures while making the same amount, or even reducing, the number of inspections.

Altering the in-service inspection program of a NPP presents a problem, however. How to measure and quantify the effect these changes have on the risk? Nuclear regulatory authorities can require evidence that the risk does not increase, or that it increases only within pre-defined limits. There are several challenges in evaluating pipe failure probabilities and also in analyzing the effectiveness of inspections. Generally pipe failure probabilities can be assessed by two methods: statistical data and probabilistic fracture mechanics. Pipe failure databases have been collected internationally, but the data is usually collected from plants under a certain inspection program, making comparison of different inspection programs difficult. Also expert judgement is needed when confirming the results from pipe failure probability assessments.

In this paper a method for quantifying the risk effect of piping inspections is presented. Fleming has developed a method to evaluate the effects of inspections on piping rupture probabilities using continuous time Markov models (for example Fleming 2004). The approach taken in this paper is a combination of probabilistic fracture mechanics (PFM) and discrete time Markov models, and has been developed over several years at VTT, see for example Cronvall et al. (2007 & 2009).

3 QUANTITATIVE ASSESSMENT OF RI-ISI

3.1 Overview

The purpose of RI-ISI assessment is to allow the comparison of different inspection strategies in terms of their impact on plant risk. The risk associated with the piping system of a NPP can be defined as:

$$R = P*C, \qquad (1)$$

where R is risk, P is the probability of failure and C is consequence of the failure. This system level risk can be broken down to piping segment level:

$$R = \sum_{i=1}^{n} P_i C_i \ , \qquad (2)$$

when the piping systems are divided into n segments for analysis purposes. A piping segment is a continuous length of piping where the characteristics are similar for environmental variables, material and consequences. The main interest in this paper is the assessment of P. C is assessed from the plant probabilistic safety assessment (PSA) study.

To assess the probability of failure P, two distinct parts of ISI are modelled: the phenomenon of crack growth and the activity of inspecting the pipes. Both affect the probability of piping failure.

The overall method can be summarized in seven steps:

1. Definition of Markov model for the segment: piping wall thickness is divided into discrete states for the Markov model. Crack growth through the piping wall corresponds to these states.
2. Crack growth simulations based on PFM.
3. Calculation of state transition probabilities from the PFM simulations and constructing a *degradation matrix* from these values.
4. Modelling the inspection quality by defining probability of detection (POD) based on crack size (and corresponding Markov state) and construction of an *inspection matrix*.
5. Calculation of the failure probability with the Markov model using the matrices defined in steps 3. and 4., taking into account inspection frequency.
6. Assessment of pipe rupture consequences from PSA.
7. Comparison of results for different inspection strategies. Measures of interest include: yearly rupture probability, yearly core damage probability and average values for both over plant lifetime.

The steps 1-5 are described in more detail in the following subsections. Steps 6-7 are omitted in order to focus more on the analysis of the piping failure probabilities.

3.2 Defining the Markov model

Markov process is used for probabilistic modelling of the crack growth and also the inspections that are conducted to detect the cracks. The basic Markov equation:

$$\overline{p}(t) = \overline{p}(t-1) \times M \quad , \qquad (3)$$

where $p(t)$ is a probability vector with the probabilities for each state as elements at step t and M is a matrix with the transition probabilities, is modified to include different types of transitions. Crack growth transitions occur during every one year step, but transitions corresponding to detection only occur during those years that inspections are conducted in that location. Taking both the degradation and inspections into account, the Markov equation 3 becomes:

$$\overline{p}(t) = \overline{p}(t-1) \times M_d \times \big(S(t) \cdot M_i + \big(1 - S(t)\big) \cdot \mathrm{I}\big), \qquad (4)$$

where M_d is the degradation matrix which contains the transition probabilities for cracks advancing into higher degradation states, M_i is the inspection matrix that contains the transition probabilities for detecting and repairing a piping component with a crack in each state, I is a unity matrix and $S(t)$ is a Boolean variable dependent on the inspections strategy. $S(t)$ has a value of “1” if inspections are conducted during year t, and “0” otherwise.

Figure 1 Illustrates a simple 4-state Markov process for this purpose.

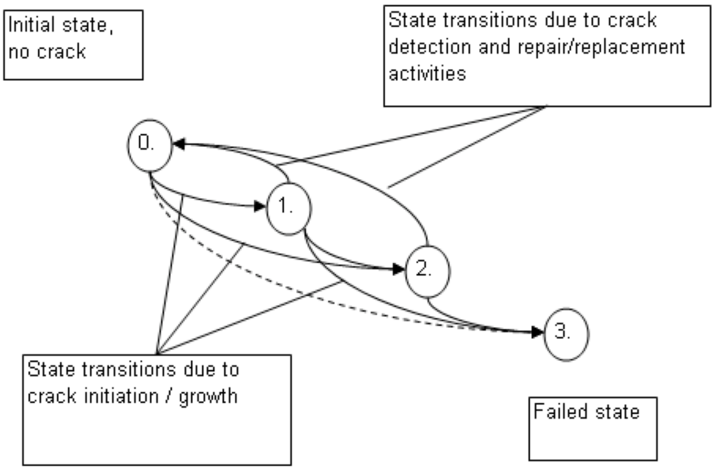

Figure 1. An example of a four state Markov model. Arrows represent state changes due to crack growth or detection and repair/replacement. Initial state 0 is a flawless state and state 3 is a pipe rupture, while states 1 and 2 correspond to a certain degree of crack growth through the piping wall.

To better capture the characteristics of crack growth and the relationship between the probability of crack detection a Markov model with more states is used. The piping wall thickness is divided into discrete parts, each corresponding to a state of the Markov process, and additionally a zero state and failure states are defined. For a pipe segment with L mm thickness a general N-state Markov model might be defined as:

State	
0	Initial state. Crack size below detection limit
1	Crack depth 0-X_1 mm
2	Crack depth between X_1- X_2 mm
…	
N-2	Crack depth X_{N-3}- L mm
N-1	Failed state. Absorbing state of the Markov process.

Transitions between the states correspond to the probabilities that a crack grows to the next state (or even several next states) in the one year interval.

3.3 PFM simulations

In this method PFM calculations are used as the basis for the failure for the failure probability assessment carried out with Markov process application. The failure mechanism considered in this study is high-cycle thermal fatigue. PFM calculations were performed with VTTBESIT code. VTTBESIT code has originally been developed by the Fraunhofer-Institut für Werkstoffmechanik (IWM), Germany and by VTT. With the VTTBESIT it is possible to quickly compute mode I stress intensity factor values along the crack front as well as crack growth (Vepsä 2004). VTTBESIT is originally intended for deterministic fracture mechanics based crack growth analyses, but it has been modified in earlier VTT studies to allow to perform probabilistic calculations. The probabilistic treatment of some of the crack growth analysis input data parameters is described first in the following. Other crack growth analysis input data parameters than those selected here as probabilistically distributed are considered to have single deterministic values.

In general, several of the input data parameters relevant in fracture mechanics analyses have markedly scattered characteristics, which can be observed e.g. from laboratory test results. These include (Besuner 1987):

1. initial crack dimensions: depth and length
2. formation frequency of initial cracks

3. certain material properties: e.g. fracture toughness, tensile strength, and
4. service conditions: e.g. frequencies of load cycles.

It is often sufficient from the viewpoint of the quality of probabilistic analysis results to consider only two or three of the most relevant scattered input parameters as distributed (Besuner 1987).

In this study probabilistic distributions were assessed for the following two input data parameters:

1. depth of initial cracks and
2. length of initial cracks

Flaw data from nine Swedish BWR units was used to determine the crack initiation frequency (Brickstad 1999). According to this data the initiation frequency of cracks is 4.08E-04 initial cracks per year per weld. Main part of this data was used in this study. The uncertainties in the estimation of initial crack dimensions caused by the quality, amount, origin and type of the crack data include:

- *Quality*. There is uncertainty concerning the degradation process that caused the initiation and growth of a crack, i.e. the diagnosis concerning the degradation mechanism that actually caused the cracking may not be correct, or the cracking may have been caused by a combination of two or more degradation mechanisms.

- *Amount*. The amount of available degradation data concerning piping components are in most/all cases so scarce, that the accuracy of statistical estimates based on them is often poor/insufficient.

- *Origin*. Due to differences in loading histories, component replacements, etc., the degradation characteristics of even twin NPP units differ from each other, and obviously more so when compared to units in other plants, and thus if no degradation data concerning the piping system in question is available, it is to varying extent uncertain to use those from other plants of the same type.

- *Type*. As the available piping degradation data contain only information concerning detected cracks/leaks, the unknown sizes of initial cracks have to be somehow estimated recursively, which is in several ways an uncertain procedure.

Exponential probabilistic density functions for estimated initial crack depth and length distributions were fitted to the above mentioned degradation data (Cronvall et al. 2006).

The analysis procedure of the probabilistic version of VTTBESIT is as follows:

- Reading of the deterministic input data is performed.

- Random sampling of certain input data parameters from the specified distributions is performed. For SCC these are probabilistic distributions for initial crack depth and length.

- Crack growth analysis is performed: the amount of crack growth in each time step is calculated with the respective crack growth equation. The ending criterion of the analysis is that crack depth reaches the outer pipe surface.

- For each analysed circumferential piping weld 500 separate simulations were performed, and for each of these values of the above mentioned distributed input data parameters/variables are sampled from the respective assessed probabilistic distributions.

- The degradation state to which the crack has grown is calculated for each year of the considered time of operation and for each simulation.

For stress corrosion cracking the analyses were performed for quasi-stationary operational conditions. The considered operational lifetime of the plant was taken as 60 years. Figure 2, below, shows as an example crack growth simulations for a pipe weld from a boiling water NPP with wall thickness of 25 mm. The simulations are conditional on the existence of an initial crack.

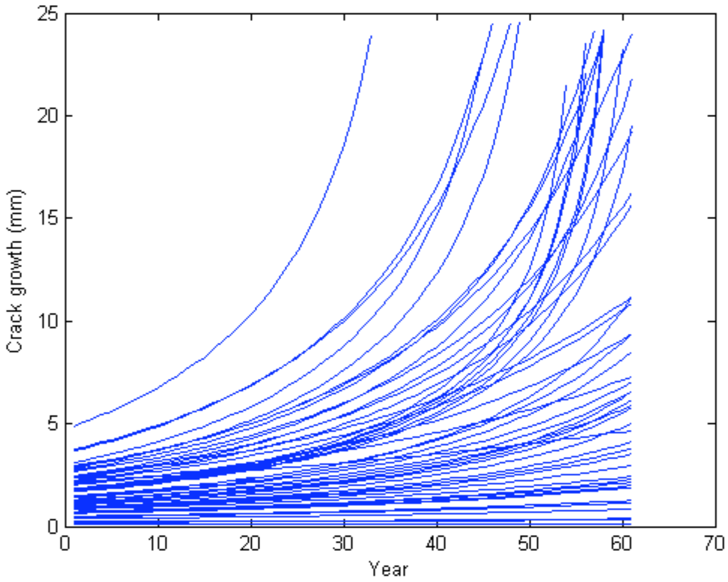

Figure 2. Example of crack growth simulations with the VTTBESIT program. First 100 of the 500 crack growth simulations used in this study.

3.4 Constructing the state transition matrices for degradation

PFM simulations are used to construct the degradation matrices M_d for each piping segment. Elements of M_d are $p_{i,j}$, where $p_{i,j}$ is the probability of transition from state i to j during each year. With a constant M_d (in respect to time), the PFM simulations can be treated in time independent fashion.

Transition probabilities from one state to the others are calculated by dividing the number of transitions to target state by the number of years spent in the source state:

$$p(i \rightarrow j) = \frac{N_{i \rightarrow j}}{N_i} \tag{5}$$

when calculating the transition probability from state i to j, where $N_{i \rightarrow j}$ is the number of transitions from state i to j, and N_i is the number of years spent in state i. Since the system is assumed to be time homogenous, a single matrix is used for the whole of considered 60 years of operational plant life time. This means that all the years from 1 to 60 in the simulation are equal in weight. It follows that the whole simulation data of 500 60-year runs can be used as a single 30000 plant operating year data source.

Time dependency is omitted in this model, but it is possible to include it in the model by dividing the plant lifetime in discrete segments. A new degradation matrix is calculated for each segment. The crack growth calculations would need to be based on a projection of the piping characteristics for the plants full 60-year (or longer) lifetime.

3.5 Modelling probability of detection

Inspections are modelled with the inspection matrix M_i in the Markov process. Elements of the inspection matrix M_i are the transition probabilities corresponding to detection and repair/replacement of cracks. It is assumed in this method that all found cracks are repaired; a limitation due to the lack of ‘memory’ in the Markov process.

As the states in the Markov process correspond to discretized crack growth progress through the piping wall, it is possible to approximate any relationship between crack size and the probability of detection. Constructing the Mi inspection matrix requires the definition POD (probability of detection) function which links each crack size with a probability value:

$$POD = f(a), \tag{6}$$

where *a* is the crack size. To discretize the POD function, *a* is assumed to be the lower limit of the Markov state that POD value is used for. For example if the Markov state is defined as the range 3-5 mm of depth in the piping wall, the POD for that state would be *f(3 mm)*.

4 EXAMPLE APPLICATION

As an example the developed method was applied for RI-ISI analysis a piping case from a Nordic boiling water reactor. The aim of the application was to demonstrate the calculation of failure probabilities of the piping segment when subjected to inspection at different intervals. The analysis was performed according to the method description, above.

4.1 PFM simulations of the application case

A set of 500 PFM simulations were performed, with each calculation representing 60 years of plant operation. Characteristics of the analyzed case for PFM calculations are in Table 2, below. These characteristics were used to complete the PFM simulations for the application case.

Loading		Material data	
Outer diameter D [mm]	323.85	Yield stress [MPa]	125
Thickness t [mm]	25	Ultimate tensile stress [MPa]	383
Degradation mechanism	SCC	SCC growth law;	
Pressure [MPa]	7.0	da/dt = C*(K_I^n), parameters	C = 1.419E-04
Temperature [°C]	286		n = 3
Applied membrane stress [MPa]	19.2	Young's modulus [GPa]	176
Applied primary global bending load / stress [MPa]	18.6	Poisson's ratio	0.3
Residual stress [MPa]	±50		
Years of operation [a]	60		

Table 1. Application case characteristics for PFM calculations.

4.2 Markov model for the application case

The analyzed case was transferred into the Markov model by defining the Markov states for each case and then calculating the degradation matrix and the inspection matrix. The degradation matrix was based on the PFM simulations in section 4.2. The defined states for each case are in Table 2, below.

	Markov state									
State number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Crack depth [mm]	**I**	0-1	1-2	2-3	3-5	5-7	7-10	10-20	20-25	**F**
POD	N/A	0,00	0,55	0,65	0,70	0,76	0,80	0,84	0,89	N/A

Table 2. Markov state upper limits [mm] for each state. I is the initial (flawless) state and F is the failed state. POD is the probability of detection based on the crack size.

The POD (probability of detection) values in Table 2 were calculated with the equation (Jelinek et al. 2005) which links crack size to probability of detection:

$$P = \Phi(0.1218 + 0.372 * \ln(a)), \qquad (7)$$

where *a* is the crack depth and is an the inverse normal distribution. The inspection matrix M_i elements (values in Table 2) are calculated from eq. (7) by using each Markov states *lower* limit for *a*. In this way the probability of detection for each Markov state is conservatively based on the lowest crack size possible in that state. The result is a 10x10 Matrix where the transition probabilities are greater than zero only for transitions to initial state from damaged state (crack is detected) or for no transitions (crack is not detected).

4.3 Results

Yearly failure probabilities were calculated for each of the three cases under three different inspection intervals: 3, 6 and 12 years. For reference purposes the yearly piping failure probability with no inspections was also included.

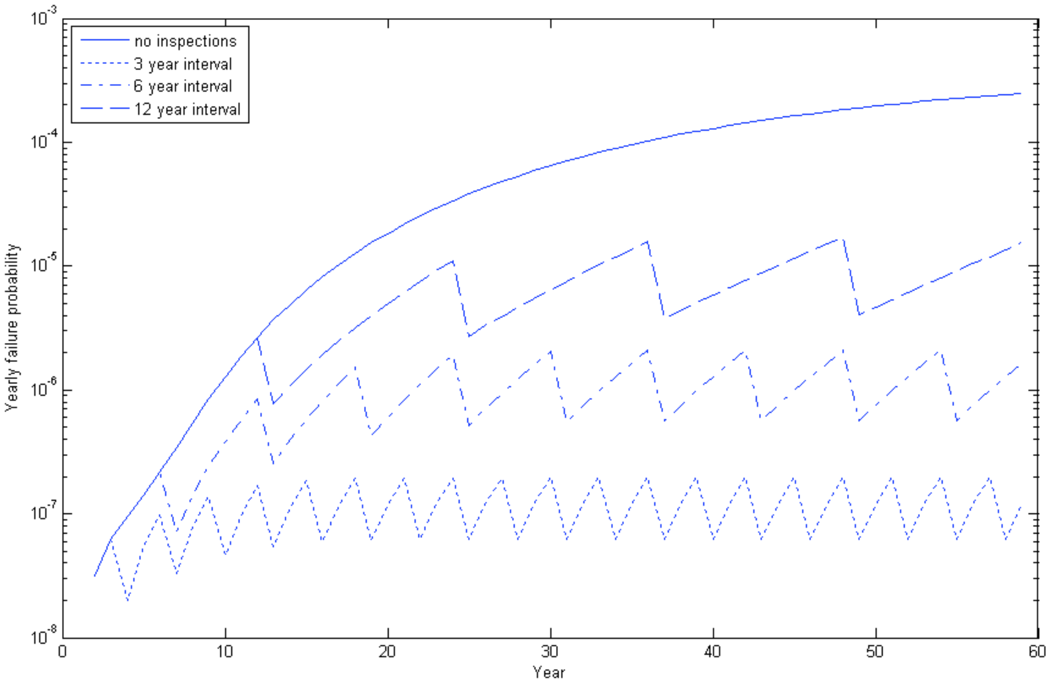

Figure 3. Yearly failure probabilities for cases BWR1 (top left), BWR2 (top right) and PWR3 (bottom) with inspections at 3, 6 and 12 year intervals.

Figure 3 shows a general trend of increased yearly failure probability for the analyzed weld when no inspections are carried out. When the weld is inspected at 3, 6 or 12 year intervals the failure probability is naturally lower. The saw-line edge of the graphs represents the safety increased gained from inspections and repairs. Immediately after the inspections the yearly failure probability is lower since the weld is probably in a better condition.

Several different statistics can be gained from the analysis, since the method stores the probabilities of the Markov process states into time series for the whole 60 year analysis time. From these time series several summary statistics can be calculated. Usually the interesting statistics include the average yearly failure probability and the cumulative failure probability. Summary statistics are presented in Table 3, below.

Statistic	**Inspection interval**	**Probability**
Average yearly failure probability	No inspections	8,80E-05
	12 year	6,13E-06
	6 year	9,37E-07
	3 year	1,13E-07

Average yearly failure probability - last 10 years	No inspections	2,17E-04
	12 year	9,42E-06
	6 year	1,22E-06
	3 year	1,26E-07
Probability of failed state at end of life	No inspections	5,20E-03
	12 year	3,62E-04
	6 year	5,53E-05
	3 year	6,65E-06

Table 3. Summary statistics of the analysis: average yearly failure probability, average yearly failure probability during last 10 years and the cumulative failure probability at end of life.

5 CONCLUSIONS

A fully quantitative RI-ISI methodology was presented in this paper, with focus on the piping failure probability of different kinds of pipes subject to varying inspection strategies. The method was showcased by applying it to one piping weld from a Scandinavian NPP with varying inspection strategies. While the method is designed to take into account the consequences of the pipe break, in this paper only the failure probability calculations were examined.

The method allows the analysis of piping failure probabilities by basing the results on the application of probabilistic fracture mechanics and Markov model. Due to the nature of the Markov calculations, time series for the probabilities of different states are calculated. This allows the method to generate several simulated statistics on the crack growth and possible pipe failures.

The method is currently being benchmarked against other probabilistic RI-ISI methods, with the results expected during summer 2009 in NKS publication series.

REFERENCES

Besuner, P.M, 1987, Probabilistic fracture mechanics. In: Provan, J. W. (ed) Probabilistic Fracture Mechanics and Reliability. Martinus Hijhoff Publishers, Pp. 325-350.

Brickstad, B., 1999, the Use of Risk Based Methods for Establishing ISI-Priorities for Piping Components at Oskarshamn 1 Nuclear Power Station. SAQ/FoU-Report 99/5, SAQ Control AB, p. 83.

Cronvall, O., et al 2006, Continuation of the RI-ISI pilot study of the shut-down cooling system of the Olkiluoto 1/2 NPP unit, VTT Research Report TUO72-056667, p. 60.

Cronvall, O., et al 2007, Development and testing of VTT approach to risk-informed in-service inspection methodology, VTT Research Notes 2382, 43 p.

Cronvall, O., et al 2009, Development of Risk Informed In-Service Inspection Analysis Procedures and Application to Finnish BWR Unit Piping Components, VTT Research Report VTT-R-00650-09, 48 p.

Dillström, P., Zang, W., 2007. ProLBB – A Probabilistic Approach to Leak Before Break Demonstration, SKI, 125 p.

Fleming, K. N. 2004, Markov models for evaluating risk-informed in-service inspection strategies for nuclear power plant piping systems. Reliability Engineering & System Safety, Elsevier Science. p. 19.

Jelinek, T., Tidström, L. & Brickstad, B. Probability of Detection for the Ultrasonic Technique According to the UT-01 Procedure. SKI report 3/2005

Raiko, H., et al, Paineistetun termoshokin analysointiohjelma DIFF. Työraportti LUJA-1/ 94. VTT. p. 27. In Finnish.

Vepsä, A., 2004. Verification of the stress intensity factors calculated with the VTTBESIT software. VTT. 40+2 p.