Improved Probabilistic Remaining Useful Life Estimation in Structures: Modeling Multi-site Fatigue Cracking in Oil and Gas Service Structures

Abdallah Al Tamimi[1], Mohammad Modarres[1]

[1]University of Maryland, *College Park, Maryland, 20740, USA*

altamimi@umd.edu
modarres@umd.edu

ABSTRACT

The purpose of this research is to develop a multi-site damage probabilistic life prediction model that could be used to assess the integrity of engineering structures susceptible to fatigue in presence of neighboring cracks. Both experiments and simulation were used to produce the data required for the model development. The experiments were performed to investigate the interaction of two adjacent semi-elliptical cracks under cyclic loading. A series of tests at different loads and for different crack aspect ratios were conducted under uniaxial constant amplitude fatigue loads on API-5L grade B steel samples. Crack growth rate of two initial semi-elliptical cracks was investigated both on the sample surface and in the depth direction. Moreover, Crack growth and interaction was investigated using a simulation technique that incorporates the stress intensity factor of a single crack with an existing cracks interaction correction factor models from the literature. Finally, a Bayesian inference modeling technique is adopted to estimate the life prediction model parameters, assess any model bias and uncertainty and validate it.

1. INTRODUCTION

Oil and gas transport and storage systems are a vital cog in the oil and gas industry. Based on the nature of their functions, a combination of straight pipes, pipe-bends, dissimilar welded joints and many other parts are attached, which makes the system susceptible to many different degradation mechanisms leading to its eventual failure. This kind of system usually operates under severe conditions: internal pressure, cyclic load, internal and external environments. As a result, the combination of these different factors can lead to a potential increase in the risk of damage and unexpected fracture.

The continuously raising cost of service structures replacement, maintenance and inspection means that there are now aging systems whose continued operation requires special analysis and improved crack detection techniques. This demands continuous safety and performance improvement so that there can be increased service life of pipeline networks, maintenance, and cost control. Additionally, this necessitates early detection of a growing crack in structures like piping to prevent fracture, predict remaining useful life, schedule maintenance and reduce costly downtimes (Keshtgar & Modarres, 2013).

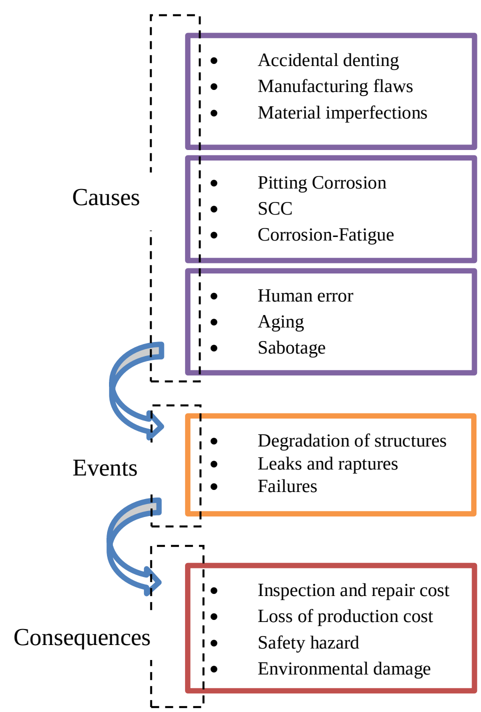

Figure 1. Causes of failures and their relative consequences

One of the critical failure mechanisms in engineering structures is fatigue. According to Bayley (1997), fatigue is a crack growth process that occurs under cyclic loading over the life of most engineering structures. This degradation process occurs at stresses less that the yield strength of the material until either the critical stress intensity factor is reached, leading to fracture, or until the net section yielding takes place. As crack initiation occurs in localized areas of stress concentrations, or due to environmental conditions, accumulations of pits or initial cracks are present in many structures. As these cracks interact and affect each other, the stress intensity factor ahead of the crack tip increases leading to faster crack growth rate and shorter component life. Bayley (1997) defined cracks coalescence, by several small adjacent cracks increasing in size and eventually growing together forming a single larger crack.

Numerous researchers have studied cracks interaction and coalescence including: Harrington (1995), Leek and Howard (1994, 1996), Soboyejo and Knott (1990), Kishimoto, Soboyejo, Smith, and Knott (1989), Twaddle and Hancock (1988) and O'Donoghure, Nishioka and Atluris (1984). Different assessment methods of neighboring cracks interaction and coalescence were investigated in order to identify a method that is reliable, safe and reasonably conservative and use it in order to further understand the phenomenon from a reliability/integrity stand point. Neglecting neighboring cracks interaction effect on the SIF could lead to over conservative life prediction model and assessment of structure integrity. Leek and Howard (1994) compared SIF models that does not account for cracks interactions and assume cracks re-characterization only with models that does. It was found that the safety margins achieved by re-characterization models induce overly conservative results of up to 37%.

Experimental work was performed in this research in order to investigate neighboring cracks growth rate. Different neighboring cracks geometries were investigated in order to understand the neighboring cracks dimensions effects on crack growth. Moreover, the experiments were performed under various loading conditions also in order to illuminate the role different operating conditions on the cracks growth rate. The experimental work was executed based on an improved existing technique discussed by Leek and Howard (1996) through the use of real time microscopy and digital image processing techniques of monitoring crack growth. For a more comprehensive discussion of the experimental work performed in this research, please refer to (Al Tamimi & Modarres, 2014).

Moreover, simulation efforts were also performed in order to justify the cracks interaction and coalescence behavior and explain the physics of failure aspect of the problem. The simulation provided values of the SIF at the cracks fronts and showed how it changes after each increment of growth. The simulation performed was developed by integrating Newman and Raju (1979, 1981) SIF solutions for a single semi-elliptical crack along with a cracks interaction correction factors proposed by Leek and Howard (1994).

The purpose of this study is to investigate the effect of fatigue, in presence of neighboring cracks, and integrate that into a more realistic life prediction model that could be used to predict the life of engineering structures. The need for a method of accounting for applicable and realistic cracks interaction, validated with acceptable modeling error, is the main objective of the study. This paper illustrates the modeling technique used to develop the PoF crack growth rate models. Yet, insights about the data gathering techniques and the models uncertainty quantification are also addressed mildly.

2. METHODOLOGY

The probabilistic life prediction model refers to fatigue in presence of neighboring cracks and will be developed by a procedure developed and illustrated in this paper. Two main steps are required to achieve the final modeling product. The first step is the data generation and the second step is the modeling development. In this work, the data was generated both experimentally and using simulation. Data treatment and analysis comes next in preparation for the reliability modeling. Finally, estimating the model bias and uncertainty, and validating the proposed models are considered as major steps in this model developed.

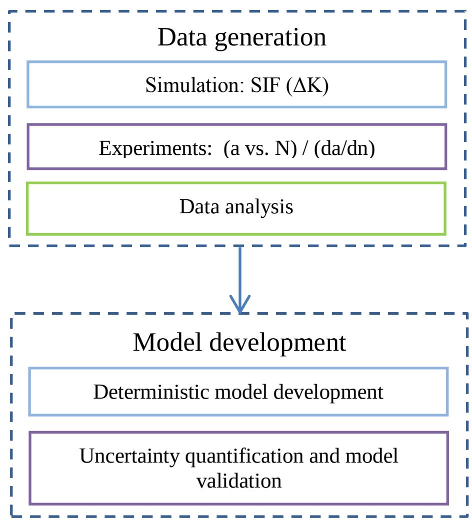

Figure 2. Modeling development steps

3. DATA GENERATION

The first step includes performing experiments in dry conditions in order to collect data about the material fatigue behavior and failure. However, the simulation focuses on understanding the SIF distribution around the cracks and how it changes around the crack as it propagates in presence of neighboring cracks.

3.1 Experimental work

The main purpose of performing the fatigue testing was to study the fatigue properties of the material, further understand the impact of different stress levels and different crack aspect ratios on neighboring cracks, coalescence and propagation, and finally use the results for the life prediction model development.

Specimens were manufactured from an actual pipeline that was previously used in the oil and gas industry. Specimens are dog bone shaped following the ASTM E466-07, Standard Practice for Conducting Force Controlled Constant Amplitude Axial Fatigue Tests of Metallic Materials. Two initial cracks of multiple aspect ratios were machined on the sample using the electric discharge machining technique. The two cracks are semi-elliptical and co-planar simulating corrosion pits based on findings of an earlier work done by Nuhi, Abu Seer, Al Tamimi and Modarres (2011). The notches have a thickness of 0.1 mm, to assure a co-planar growth of the cracks which leads to an idealized interaction between the two cracks.

In the experimental work, the neighboring cracks were assumed to keep a semi-elliptical shape after each increment of crack growth. This assumption was made based on Nuhi et al. (2011) findings about the nature of corrosion pits shapes and geometrical development.

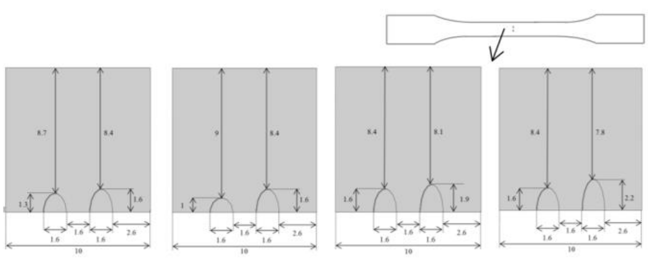

Figure 3. An illustration of the test dog bone sample and some of the notches designs used in the experimental work

Experiments were carried out at room temperature in air. An MTS fatigue-testing machine with capacity of 100 kN in tension and compression and frequency range up to 30 Hz was used. Figure 4 shows the testing setup. An optical microscope was also used to monitor the crack coalescence on the surface. The microscope is equipped with a camera to capture and save images of the specimen surface as the crack grows. Experiments are performed at constant amplitude, stress controlled cyclic loading. Frequencies of 0.2 and 2 Hz were chosen for the loading cyclic.

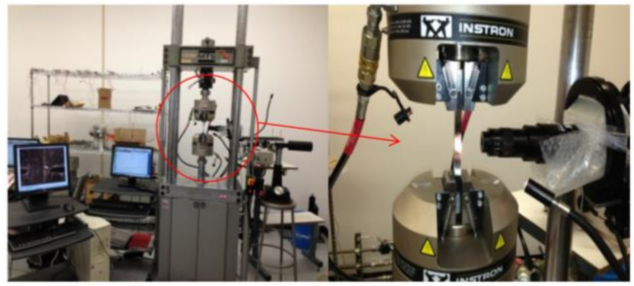

Figure 4. Experimental setup: MTS machine layout and a closer illustration of the microscope positioning

In order to gather the data required to build the probabilistic life prediction model, failed samples have to be studied and information has to be elicited. There are two main sources of information in the experimental setup used: Surface crack measurements at different number of cycles and the crack depth measurements. Linking the crack depth measurements with the recorded number of cycles at different surface crack lengths provided the scatter required for the probabilistic life prediction model.

Figure 5 shows the surface crack length and depth for one of the experiments. When enough experiments are performed and a scatter is developed, conclusions could be drawn on the applied stress and aspect ratio effect on cracks coalescence and growth.

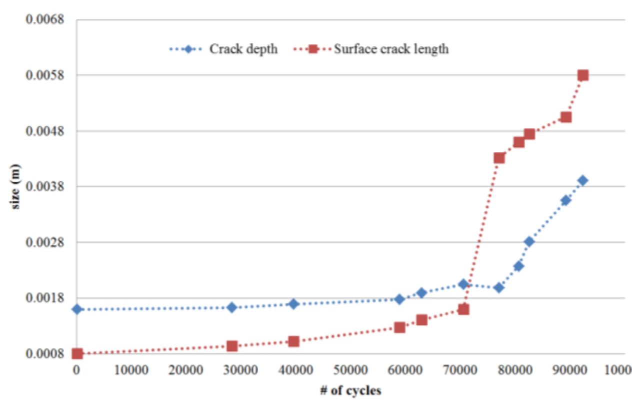

Figure 5. Example of the data elicited from the experimental work, Stress=290 MPa, Frequency=2 Hz

The experimental data scatter development is a fundamental step in the model development. An example of the data scatter developed is illustrated Figure 6 and Figure 7:

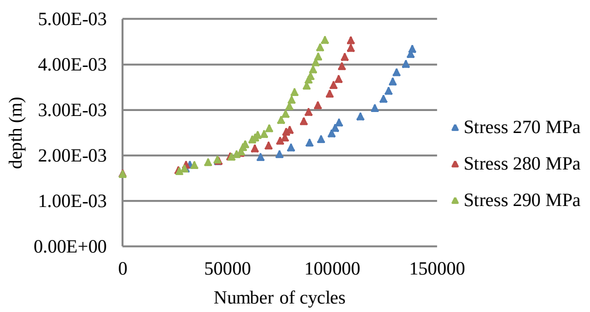

Figure 6. Effect of different stress levels on crack growth

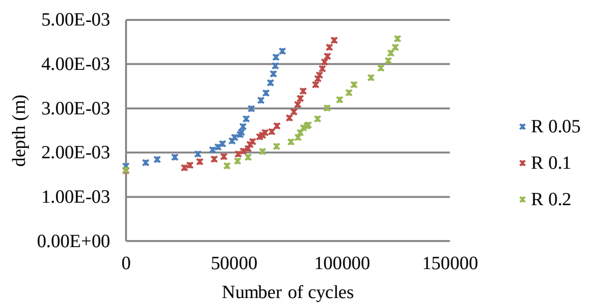

Figure 7. Effect of different loading ratios on crack growth

For more information and details about the experimental work performed in this research, please refer to (Al Tamimi & Modarres, 2014).

3.2 Simulation work

The simulation efforts were performed in order to justify the cracks interaction and coalescence and explain the physics of failure aspect. The simulation focuses on the SIF around the cracks and how it changes around the crack as it propagates in presence of neighboring cracks.

A MATLAB simulation code was developed by integrating Newman and Raju (1979, 1981) SIF solutions for a single semi-elliptical crack along with a cracks interaction correction factor empirical model by Leek and Howard (1994). The code can provide information about the SIF around a crack in presence of neighboring cracks.

The code covers a wide range of aspect ratios (a/c) and separation distance ratios (s/c). It requires certain inputs in order to find the SIF. Initial sample or plate geometry, initial cracks geometry and the development of these crack geometries are all necessary to calculate the SIF along the fatigue process.

The program can perform SIF calculation for two coplanar and identical semi-elliptical cracks geometries. However, it could be extended to cover more than two cracks. The SIF around the crack tips and front are recalculated after each increment of growth until the two cracks touch. When the cracks are predicted to touch, a single enveloping crack is immediately assumed with no further interaction factor calculations. Figure 8 illustrates both cracks front and tips.

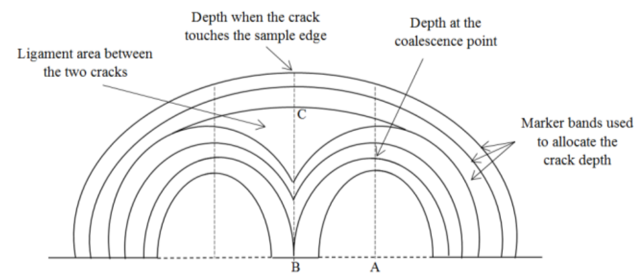

Figure 8. Cracks interaction illustration

A sample of the SIF simulation data performed for two identical cracks and its development throughout the cracks interaction and coalescence process is illustrated in Figure 9:

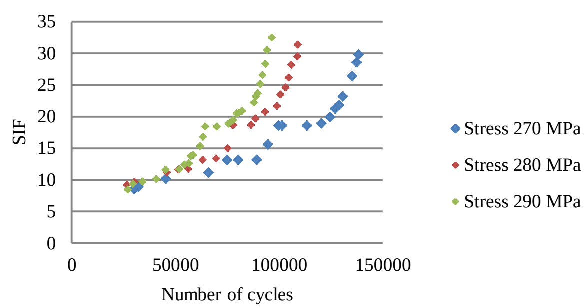

Figure 9. Crack front SIF simulation data at different stress levels

The SIF simulation data along with the experimental crack growth rate measurements will be used mainly to develop the crack growth rate models.

4. MODELING DEVELOPMENT

In this work, two models will be developed. Both models will be based on the relationship between crack growth rate and the SIF. However, different PoF base models will be used.

The first model will be constructed based on the Walker crack growth equation and the second will be based on a modified form of the Paris law equation. The two models address the same problem; however, the most suitable model with least error and uncertainties will be chosen to represent the data developed in this research. A similar modeling development strategy was used to develop both models. Table 1 summarizes and compares the two models:

Table 1. Comparison between the two crack growth models developed

Model	Walker equation model	Modified Paris law equation model
Form	$\frac{da}{dN} = \frac{C\Delta K^n}{(1-R)^{n(1-\lambda)}}$	$\frac{da}{dN} = C\Delta K^n \left(\frac{R}{R_0}\right)^m$
Variables	ΔK, LR	
Uncertain parameters	C, n, λ	C, n, m
Deterministic parameters	/	R_0
Data sources	Experimental data (da/dn values)	
	Simulation data (ΔK values)	

The main sources of data scatter in this work are fatigue experiments and simulation. Producing usable results that can appropriately capture not only the effect of time, applied stress levels, but also the effect of cracks aspect ratios is one of the main objectives of this work. The models main variables are the SIF and loading ratio, however, other variables like the applied stress are still considered in this work. Although the stress term is not apparent in the PoF model, yet it is embedded in the SIF term. The same applies for other variables like the neighboring cracks dimensions. Experimental data has been split into two different sets:

1. Deterministic model development data set
2. Uncertainty quantification and model validation data set

The use of each set, which are independent from each other, is represented in Figure 10. Each model development stage requires an independent data set which will minimize the bias in the model development.

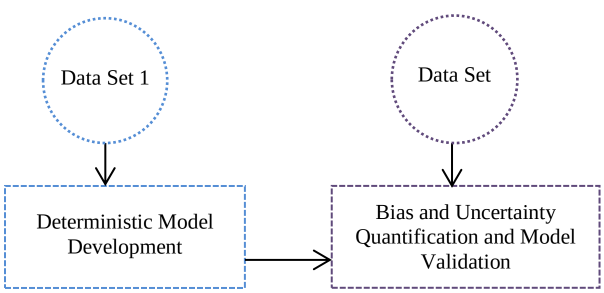

Figure 10. Model development stages

4.1 Deterministic model development

As deliberated earlier, the modeling efforts discussed developing two PoF crack growth models. The first proposed model is based on the Walker equation having the illustrated mathematical representation in Equation 1:

$$\frac{da}{dn} = f(\Delta K, R|\mathrm{C, n}, \lambda) \quad (1)$$

On the other hand, the second PoF crack growth rate model is slightly different as it is based on the Paris law equation. However, a correction factor term was added to the equation to account for the effect of loading ratio on the crack growth rate. The mathematical form of this model is illustrated in Equation (2):

$$\frac{da}{dN} = f(\Delta K, R|\mathrm{C, n, m, R_0}) \quad (2)$$

The same deterministic model development methodology is followed when developing both forms of the crack growth rate model. However, and for illustration purposes, the procedure will be explained and illustrated based on the Walker equation PoF crack growth model.

In order to shape the final form of the deterministic model, a proper evaluation of the model uncertain parameters is required. The proposed model parameters C, n and λ have been estimated from generic data available in literature, experiments and simulations developed in this research.

As there are an infinite number of possible fatigue experiments and simulations to perform to fully understand the nature of interactions between neighboring cracks, Obtaining data for such failure mechanism has proven to be difficult, time consuming and very expensive. Yet, a great analytical tool that enables the integration of new evidence with the existing prior knowledge and produces an updated knowledge of the uncertain model parameters is Bayes' theorem. As such, the Bayesian estimation method was applied in this research to estimate the uncertain parameters C, n and λ.

A Bayesian inference will be used to develop the deterministic model as it is a powerful mathematical tool that could estimate/update the model parameters with minimum amount of data. The Bayesian inference is a method used to update a given state of knowledge based on new given evidence. A summary of this process is illustrated in Figure 11:

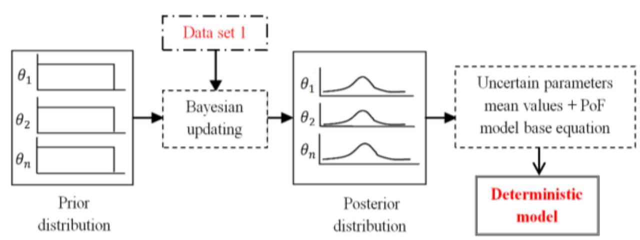

Figure 11. Deterministic model development (Azarkhail & Modarres, 2012)

In the Bayesian inference, a subjective prior probability distribution (pdf) of each of the model uncertain parameters f_o(C, n, λ) was defined based on a comprehensive literature search. For example, different researchers like Neves

Beltrao, Castrodeza, & Bastian (2010), Shi, Chen and Zhang (1999), Fernandes (2002) and Hamam, Pommier and Bumbieler (2007) have investigated crack growth in carbon steel materials and provided quantifications of the Paris law equation coefficients. Such quantifications was be used as priors in the Bayesian inference performed to update the knowledge of the model uncertain parameters. When there was no prior information available in the literature about a certain uncertain parameter, a non-informative uniform distribution was assumed.

Subsequently, this prior was combined with the evidence data in the form of a likelihood function. The likelihood equation of the crack growth rate was assumed to follow a normal distribution and is illustrated in Equation 3:

$$L(\mathrm{C},\mathrm{n},\lambda,\sigma|Data) = \prod_{i=1}^{j}\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{\frac{da}{dN_i}-\left(\frac{C\Delta K_i^{\,n}}{(1-R_i)^{n(1-\lambda)}}\right)}{2\sigma^2}} \quad (3)$$

The result is an updated state of knowledge identified as the posterior distribution, f(C, n, λ,σ |Data). This process is shown mathematically in Equation (4):

$$f(\mathrm{C},\mathrm{n},\lambda,\sigma|Data) = \frac{L(\mathrm{C},\mathrm{n},\lambda|Data)f_0(\mathrm{C},\mathrm{n},\lambda)}{\int_\theta L(\mathrm{C},\mathrm{n},\lambda|Data)f_0(\mathrm{C},\mathrm{n},\lambda)} \quad (4)$$

To accomplish this task, WinBUGS software program was employed to run the Bayesian analysis. In line with Spiegelhalter, Thomas, Best and Lunn (2003) the WinBUGS program is a windows-based environment for MCMC simulation. A wide variety of modeling applications could benefit from using such software. This program has been previously reported to be used in uncertainty management according to Azarhkail and Modarres (2007) as well as accelerated life testing data analysis and has proved to be a reliable tool for such calculations. In this research the WinBUGS platform was used for Bayesian updating and related numerical simulations. After running the developed WinBUGS code, a posterior knowledge of the uncertain parameters C, n and λ is obtained.

4.2 Uncertainty quantification and model validation

As the proposed model uncertain parameters C, n and λ were initially estimated using the information available in the literature. However, these estimations require further validation before it can be deployed for additional analysis. Hence, Bayesian approach was utilized to investigate the validity of this prior estimation and then was applied to the updating procedure.

In this step, a more comprehensive model bias and uncertainty analysis is performed. A method developed by Azarkhail and Modarres (2007) and Ontiveros, Cartillier and Modarres (2010) and modified and used later by Keshtgar (2014) to quantify the model uncertainties will be used. However, a different set of evidence data is used for this purpose. The bias and uncertainty quantification is based on comparing the model predictions with the experimental results as illustrated in Figure 12:

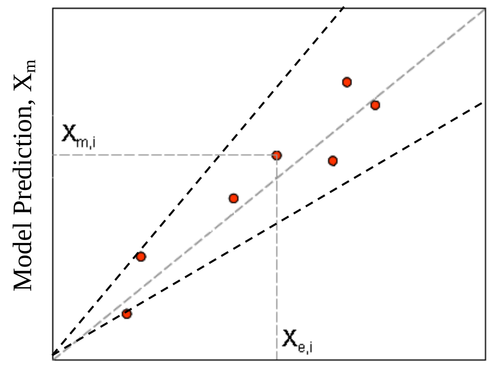

Figure 12. Deterministic model predictions compared to experimental results (Azarkhail, Ontiveros, & Modarres, 2009)

If the model predictions perfectly matched the experimental results, then all the points would lie exactly on the dotted line which is not highly probable. This is because of the uncertainties and possible bias in both the model predictions and the experimental measurements.

In this research, the model prediction and experimental result are considered to be estimations of the crack growth rate (da/dN), given some error as shown in Equations 5 and (6):

$$\frac{da/dN_i}{da/dN_{e,i}} = F_{e,i}\ ;\ F_e \sim LN(b_e, s_e) \quad (5)$$

$$\frac{da/dN_i}{da/dN_{m,i}} = F_{m,i}\ ;\ F_m \sim LN(b_m, s_m) \quad (6)$$

As the modeling addresses crack growth values, then the model outcome is always expected to be a positive value, for that reason, a multiplicative error model is assumed. Moreover, the error is assumed to be distributed log-normally for the same reason.

As the true value of the crack growth rate da/dN_i is unknown, Equations 5 and 6 are combined yielding the following equations:

$$F_{e,i}\left(da/dN_{e,i}\right) = F_{m,i}\left(da/dN_{m,i}\right) \quad (7)$$

$$\frac{da/dN_{e,i}}{da/dN_{m,i}} = \frac{F_{m,i}}{F_{e,i}} = F_{t,i} \quad (8)$$

Assuming independency of F_m , F_e then:

$$F_t \sim LN\left(b_m - b_e, \sqrt{{s_m}^2 + {s_e}^2}\right) \tag{9}$$

The likelihood used in the Bayesian inference is illustrated in Equation 10:

$$L\left(F_{t,i}, b_e, s_e \middle| b_m, s_m\right) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi}\left(F_{t,i}\right)\sqrt{{s_m}^2 + {s_m}^2}} e^{-\frac{\left[ln\left(F_{t,i}\right)-\left(b_m-b_e\right)\right]^2}{2\left({s_m}^2+{s_m}^2\right)}} \tag{10}$$

Finally, the Bayesian inference is performed, where Equation 11 shows the relation between the posterior distribution of the model parameter with the likelihood function and the prior evidence.

$$f\left(b_m, s_m \middle| F_{t,i}, b_e, s_e\right) = \frac{L\left(F_{t,i}, b_e, s_e \middle| b_m, s_m\right) f_0\left(b_m, s_m\right)}{\int\left(L\left(F_{t,i}, b_e, s_e \middle| b_m, s_m\right) f_0\left(b_m, s_m\right)\right)} \tag{11}$$

The data used in this step of the analysis must be data independent of the data used in the model development step.

Quantifying the bias and uncertainty is considered also a validation of the models proposed. Assuming the model-based predicted crack growth rate is da/dn_m, the true crack growth rate prediction can be estimated by multiplying da/dn_m by the estimated F_m:

$$\frac{da}{dN}_{true} = \frac{da}{dN_m} . F_m \tag{9}$$

The model prediction results will be modified using the resulted bias distribution which can be estimated by a lognormal distribution:

$$\frac{da}{dN}_{true} \sim LN\left(ln\left(\frac{da}{dN_m}\right) + b_m\ , s_m\right) \tag{10}$$

5. CONCLUSION

Many different degradation mechanisms act on engineering structures causing all different types of flaws and imperfections which eventually cause failure affecting the integrity of many critical systems. Given that capturing all degradation mechanisms would be a challenging task, this work focuses on fatigue as the main failure mechanism. Fatigue is one of the degradation failure mechanisms that accelerate the failure of engineering structures. However, other critical failure mechanisms like corrosion, stress corrosion cracking and creep are also of great importance and should not be disregarded. Moreover, factors like the type of material and the loading conditions plays a crucial role in the degradation rate of the structure. So in order to have a best estimate of the structure reliability, these factors should be taken into consideration.

This paper provides a summary of the methodology used to develop a PoF life prediction model that addresses fatigue of neighboring cracks. This summary includes highlights of the data gathering techniques. Moreover, it discusses the possible forms of the life prediction model and how to identify its uncertain parameters using Bayesian inference.

One of the main outcomes of this research is probabilistic life prediction models that address fatigue as a failure mechanism in presence of neighboring cracks. This kind of models could be used in assessing the integrity of certain engineering structure and serve as a guide for maintenance planning. This kind of models could be continuously updated along the spectrum of the structure life by adding more evidence gathered from monitoring its health and operation.

Both experiments and simulation were used to produce the data required for the model development. The experiments were performed to investigate the interaction of two adjacent semi-elliptical cracks of variable dimensions under different cyclic loading conditions. This will allow the model to capture a wide range of applications and make it more realistic. A series of tests at different loads and loading ratios were conducted under uniaxial constant amplitude fatigue loads on API-5L grade B steel samples. Crack growth rate of two initial semi-elliptical cracks was investigated both on the sample surface and in the depth direction.

Furthermore, the simulation was performed to understand the SIF behavior around a crack when it is surrounded by neighboring cracks providing a better understanding of the failure mechanism and justifying its behavior under different loading conditions. Crack growth and interaction was investigated using a simulation technique that incorporates the stress intensity factor of a single crack with an existing cracks interaction correction factor models from the literature.

The Bayesian approach was used to construct the life prediction models using both the experimental and simulation data and estimate their parameters. Uncertainties about the structure of the model and its parameters were also characterized in this work.

ACKNOWLEDGEMENT

The authors would like to thank Abu Dhabi National Oil Company (ADNOC), Abu Dhabi Company for Onshore Oil Operations (ADCO) and the Petroleum Institute (PI).

NOMENCLATURE

C	Paris law empirical constant
n	Paris law empirical constant
LR	Loading ratio
λ	Empirical constant that indicates the influence of the loading ratio on the fatigue crack growth in different materials
m	Uncertain parameter in the Paris law loading ratio correction factor
R_0	Deterministic parameter in the Paris law loading ratio correction factor
N	Number of cycles
θ_i	Uncertain parameter
da/dn_i	Crack growth rate true value
$da/dn_{e,i}$	Crack growth rate value obtained experimentally
$da/dn_{m,i}$	Crack growth rate value obtained from the model developed
$da/dn_{true,I}$	Corrected crack growth rate value
F_e	The multiplicative error of the experimental crack growth value with respect to the true value
F_m	The multiplicative error of the model crack growth prediction with respect to the true value
b_e	The experimental mean multiplicative error
s_e	The Standard deviation of the experimental multiplicative error
b_m	The model mean multiplicative error
s_m	The standard deviation of the model multiplicative error
F_t	The multiplicative error of experiment with respect to model prediction

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BIOGRAPHIES

Abdallah Al Tamimi is a mechanical engineer and a current PhD student in the University of Maryland, College Park, USA. He earned his mechanical engineering degree from the Petroleum Institute, Abu Dhabi, United Arab Emirates. Also, he earned his Master's in Reliability engineering from the University of Maryland, College Park, United States. Over the last four years, he has worked in a variety of professional organizations in both academia and industry. He worked in Abu Dhabi Marine Operating Company (ADMA-OPCO) as a mechanical supervisor in the oil and gas industry. Afterwards, he made his transition to academia by working as a teaching assistant at the Petroleum Institute. He started his PhD studies in reliability engineering in 2011 after he was granted a fellowship by Abu Dhabi National Oil Company (ADNOC).

Mohammad Modarres is the Director of Reliability Engineering and Minta Martin Professor of Engineering in the University of Maryland, College Park, United States. He specializes in probabilistic risk assessment and management, uncertainty analysis, probabilistic physics of failure and probabilistic fracture mechanics modeling. He earned his B.S. degree from Tehran Polytechnic in mechanical engineering, a Master's degree from Massachusetts Institute of Technology in mechanical engineering and a PhD from Massachusetts Institute of Technology in nuclear engineering. He has served as a consultant or board member to several governmental agencies including the Nuclear Regulatory Commission, Department of Energy, National Academy of Sciences, and several national laboratories in areas related to nuclear safety, probabilistic risk assessment, probabilistic fracture mechanics and physics of failure. He has over 300 papers in archival journals and proceedings of conferences. He has published a number of textbooks, edited books and book chapters in various areas of nuclear safety, risk and reliability engineering. He is a University of Maryland Distinguished Scholar-Teacher and a fellow of the American Nuclear Society.