Probabilistic life prediction and prognostics-based maintenance optimization for gas pipelines

Yuhao Wang, Yongming Liu

Arizona State University, Tempe, AZ
ywang542@asu.edu
yongming.liu@asu.edu

ABSTRACT

Accurate life prediction of infrastructure such as gas pipelines is important in maintaining the system functionality. A good maintenance plan can reduce the failure probability and ensure the infrastructure is always in working condition. A method using a Paris' law equation to predict the creep crack growth (CCG) in plastic pipes is proposed. The model adopted an asymptotic solution for the stress intensity factor (SIF). The model was calibrated and validated via the experimental data from GTI. A maintenance framework using the prognostics results was proposed to optimize the maintenance planning. The pipes were divided into condition stages according to the crack length. The maintenance decision was calculated for each condition via the genetic algorithm. Bayesian updating can be used to update the parameters in the creep crack prediction model and thus achieve dynamic maintenance planning. The proposed method can fuse the information from diagnostics and prognostics for accurate risk assessment and maintenance planning.

1. PROBLEM STATEMENT

The research of the creep crack growth in polymeric materials dates back to 1960s. The behavior of CCG in polymeric materials are different from that in metallic materials. There are craze forming at the crack tip that bridges the edges of the crack. Models based on viscoelastic fracture mechanics [1], linear elastic fracture mechanics (LEFM) with a time dependent Young's modulus [2], and cohesive zone model [3] were developed for describing the crack growth rate. These studies indicated that the stress intensity factor (SIF) is the key for the calculation of the crack growth rate.

Due to the stochastic nature of the crack propagation, a deterministic model would not always be accurate in describing the process. Hence, a model based on probability would be more adequate for such problems. Based on the probability model, a maintenance framework can be developed to optimize the overall reliability of the system. Two statistical models called proportional-hazards model (PHM) [4] and proportional intensity model (PIM) [5] has become a useful tool in remaining useful life (RUL) predictions. A hidden Markov model (HMM) can calculates the transition probability from known experimental data [6]. Some also tried to apply artificial intelligence to RUL [7]. Bayesian updating has been extensively used for damage diagnosis and prognosis of metallic and composite materials [8][9]. The information fusion between diagnostics and prognostics can achieve a more accurate risk assessment and maintenance planning.

2. EXPECTED CONTRIBUTIONS

The proposed study will develop a power law equation for the description of the creep crack growth. The equation will be calibrated and validated by experimental data and used for prediction of the remaining useful life of a pipe. A novel condition-based maintenance planning framework will be formulated. And Bayesian updating will be used to update the model parameters with on-field observation to achieve a dynamic maintenance framework.

3. RESEARCH PLAN

3.1 Work Performed

The accurate detection and prediction of the damage in plastic pipeline system is of critical importance for the accurate risk assessment. The proposed study uses a power law equation to describe the crack growth behavior under constant loading:

$$\frac{da}{dt} = C \cdot K^m \tag{1}$$

Where the left-hand side is the crack growth rate, K is the SIF, C and m are material constant. The crack is assumed to be a semi-circular surface crack at the inner wall of the pipe and is along the longitudinal direction of the pipe, The solution for the SIF is expressed as [10]:

$$K = \sigma \sqrt{\frac{\pi}{Q} a F} \tag{2}$$

where a is the crack length, σ is the hoop stress, Q is the shape factor, and F is the boundary correction factor. Q and F can be calculated from geometry.
An asymptotic solution for SIF that considers the stress concentration factor is used as defined in Liu [11]:

$$K = \sigma \sqrt{\frac{\pi}{Q}(a + d\{1 - \exp[-\frac{a}{d}(K_t^2 - 1)]\})F} \qquad (3)$$

Where K_t is the stress concentration factor, d is related to the geometry of the damage. Integrating Eq.1 from the initial crack length a_i to critical crack length a_c, the failure time can be expressed as:

$$T_f = C^{-1}\int_{a_i}^{a_c} K^{-m} da = C^{-1}(\sqrt{\frac{\pi}{Q}})^{-m}\sigma^{-m}\int_{a_i}^{a_c} F\sqrt{a + d\{1 - \exp[-\frac{a}{d}(K_t^2 - 1)]\}}da \qquad (4)$$

The model will be calibrated and validated against experimental data. The data was collected from tests on Aldyl-A pipe with different types of damage. The experimental data were plotted in Figure 1 in double log scale. Since the subject of this study is the creep behavior, the ductile data will not be used.

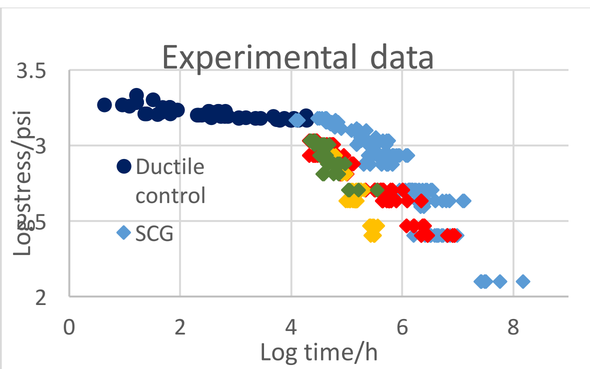

Figure 1. Experimental creep data shifted to 23°C (73.4°F)

The initial crack length was determined using the SEM image shown in Figure 2. The measurement of the micro-crack is about 25 μm. Hence, the initial crack length is assumed to be $a_i = 10^{-3}$ in . And the critical crack length is set to be $a_c = 0.1$ in.

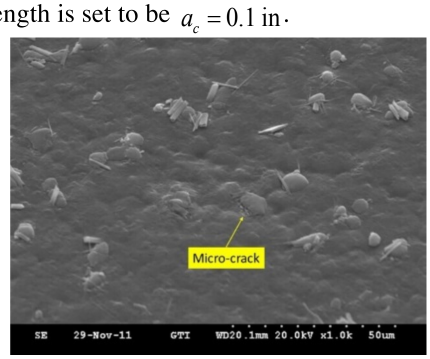

Figure 2. The SEM image showing the initial crack

Using the SCG group data as reference, we could calibrate the material constant C and m. By changing the Kt factor, the equation can be used to predict the life of pipes with damages. The prediction can be compared with the experimental data (Figure 3).

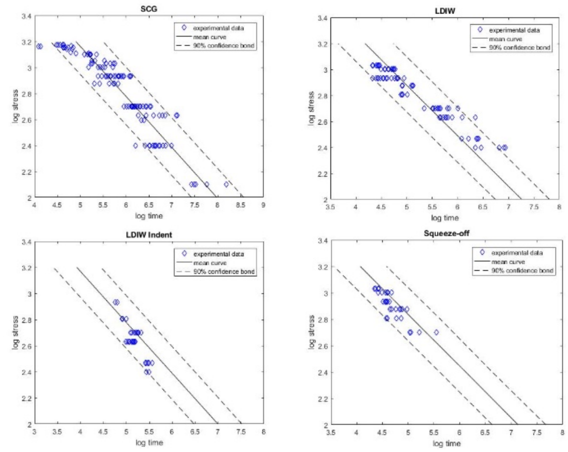

Figure 3. Stress vs. Life curve for all 4 groups

By changing the upper limit of the integral in Eq. 4 to an arbitrary crack length a_t , we can calculate the corresponding time on the left-hand side. This gives an implicit equation for the crack length as a function of time. The crack growth curve can then be plotted.

$$t = C^{-1}(\sqrt{\frac{\pi}{Q}})^{-m}\sigma^{-m}\int_{a_i}^{a_t} F\sqrt{a + d\{1 - \exp[-\frac{a}{d}(K_t^2 - 1)]\}}da \qquad (5)$$

The uncertainty quantification is done by assuming the stress concentration factor K_t and the material constant C are random variables. The failure probability is a function of time and stress level. With repeated MC sampling simulation, the failure probability can be counted as the percentage of simulated crack length that exceeds the critical value. The implicit function of the crack length vs. time is plotted in Figure 4.

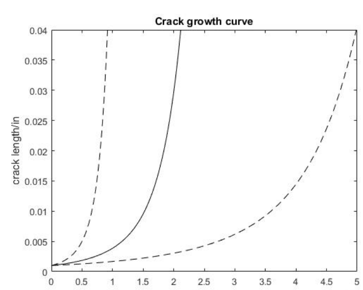

Figure 4. The crack length prediction as a function of time for SCG at 1000 psi

3.2 Remaining Work

In the proposed maintenance framework, assume the pipes are categorized into S conditions and there are M possible maintenance method. The maintenance framework iterates the condition in each time step as:

$$\mathbf{D}_{new} = \sum_m \mathbf{D} \cdot \times \mathbf{X}(m,:) \times \mathbf{M}_m \times \mathbf{P} \tag{6}$$

Where $\mathbf{D}(1\times S)$ and $\mathbf{D}_{\mathrm{new}}(1\times S)$ are the condition vector which contain elements representing the percentage of samples in each stage. The degradation matrix $\mathbf{P}(S\times S)$ represents the natural probability transition matrix. $\mathbf{M}_{\mathrm{m}}(S\times S)$ is the maintenance transition matrix of doing maintenance m. When no maintenance is done, M is an identity matrix. $\mathbf{X}(M\times S)$ is the decision matrix contains the percentage of pipes that will go over maintenance m. The cost of the for each time step is calculated as:

$$\text{Budget} = \sum_m Q \times \mathbf{D} \cdot \times \mathbf{X}(m,:) \times \mathbf{C}(m,:) \tag{7}$$

$\mathbf{C}(M\times S)$ is the cost matrix, meaning the cost for doing a type of maintenance to pipes in each condition. Q is the total quantity of pipes.

The probability transition matrix is a function of time. It can be calculated using the predicted crack growth curve. The reliability constraint is defined as the threshold value for the last element in the condition vector. By optimizing the cost of maintenance under the reliability constraint, the decision matrix can be solved.

The dynamic maintenance is achieved through the continuous updating of the model parameter via Bayesian updating. The Bayes' theorem states that the posterior probability is proportional to the product of the prior and the likelihood:

$$p(\theta) \propto \mu(\theta)\mu(x'\,|\,\theta) \tag{8}$$

The continuous updating of the model parameters can decrease the uncertainty in the model, hence increase the prediction accuracy of the crack growth behavior. This could help the maintenance planning to reduce the unnecessary costs or avoid unwanted failure.

4. CONCLUSION

The study used a power law equation to describe the creep crack behavior in polymeric materials. With some proper assumptions, the model was calibrated and validated using the experimental data. Within the margin of error, the prediction of the stress life curve agrees well with the experimental data. By introducing the concept of uncertainty, the stochastic process of crack growth can be evaluated using probability. MC method was used to simulate the random process. Hence, the implicit function of the crack length against time can be calculated and used for the transition matrix in the proposed maintenance framework. In the later study, the effect of the updating will be discussed. The fusion of prognosis with diagnosis is achieved by the real-time Bayesian updating of the model parameters with diagnostic results. The effect of the Bayesian updating will be studied. And the maintenance framework with consideration of the consequence cost is under development.

Acknowledgement

The reported work is sponsored by the DOT-PHMSA core research program through GTI. (Contract Number: DTPH5615T00007; DOT program manager: James Merritt; GTI program manager: Ernest Lever). The authors thank the technical discussions and suggestions from Dr. Ernest Lever from GTI.

REFERENCES

[1] R. Schapery, "A theory of crack initiation and growth in viscoelastic media," *Int. J. Fract.*, pp. 141–159, 1975.

[2] J. Williams and G. Marshall, "Environmental crack and craze growth phenomena in polymers," in *Proceedings of the royal society of London*, 1975.

[3] E. J. Kramer and E. W. Hart, "Theory of slow, steady state crack growth in polymer glasses," *Polymer (Guildf).*, vol. 25, no. 11, pp. 1667–1678, 1984.

[4] D. Banjevic and A. K. S. Jardine, "Calculation of reliability function and remaining useful life for a Markov failure time process," *IMA J. Manag. Math.*, vol. 17, no. 2, pp. 115–130, 2006.

[5] P. J. Vlok, M. Wnek, and M. Zygmunt, "Utilising statistical residual life estimates of bearings to quantify the influence of preventive maintenance actions," *Mech. Syst. Signal Process.*, vol. 18, no. 4, pp. 833–847, 2004.

[6] C. Kwan, X. Zhang, R. Xu, and L. Haynes, "A Novel Approach to Fault Diagnostics and Prognostics," in *IEEE International Conference on Robotics and Automation*, 2003.

[7] R. C. M. Yam, P. W. Tse, L. Li, and P. Tu, "Intelligent predictive decision support system for condition-based maintenance," *Int. J. Adv. Manuf. Technol.*, vol. 17, no. 5, pp. 383–391, 2001.

[8] T. Peng, J. He, Y. Liu, A. Saxena, J. Celaya, and K. Goebel, "Integrated fatigue damage diagnosis and prognosis under uncertainties," *Natl. Aeronaut. Sp. Adm. MOFFETT F. CA AMES Res. Cent.*, 2012.

[9] T. Peng *et al.*, "Probabilistic fatigue damage prognosis of lap joint using Bayesian updating," *J. Intell. Mater. Syst. Struct.*, vol. 26, no. 8, pp. 965–979, 2015.

[10] J. Newman J. C. and I. S. Raju, "Stress-Intensity Factors for Internal Surface Cracks in Cylindrical Pressure Vessels," *J. Press. Vessel Technol.*, vol. 102, no. 4, pp. 342–346, 1980.

[11] Y. Liu and S. Mahadevan, "Fatigue limit prediction of notched components using short crack growth theory and an asymptotic interpolation method," *Eng. Fract. Mech.*, vol. 76, no. 15, pp. 2317–2331, 2009.