Finding optimal maintenance policy for pipeline corrosion using data fusion

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Summary

The overarching goal of this work is to estimate remaining useful life (RUL) for a segment of an oil and gas pipeline under internal pitting corrosion as part of the Pipeline System Integrity Management Project (PSIM). We are creating a hybrid physics-based and data-based prognostic model for pipeline corrosion. Once the model is developed, it will be used to estimate the RUL of pipeline segments and subsequently used to propose an optimal maintenance policy, considering both cost and reliability. The available pit depth prediction models in the literature are based on the assumption that operational conditions remain the same during the life of the pipeline. In this paper, we address an actual case where operational conditions change over time. In this way, we fuse together data from infrequent, full pipeline inspection with in-line inspection (ILI) tools with data from frequent, high-accuracy sensors in localized sections of the pipeline. Specifically, we define a similarity index which allows us to fuse inspection data of two different pits at two different locations. This index is defined as the average of the ratio of the estimated depth of one pit and another pit. We use augmented particle filtering and hierarchical Bayesian method to fuse available inspection data for those pits. The results will be used to inform the selection of maintenance actions and also the optimal next inspection interval.

Introduction

The high cost of failure and maintenance in oil and gas pipelines necessitate developing a model to optimize maintenance policy (e.g., inspection frequency and method). This policy needs to take into account both cost minimization as well as maximization of the reliability of the pipeline.

Among different failure mechanisms, pitting corrosion is of most concern because of its high rate of growth [1]. Based on historical failure data, 15% of all transmission pipeline incidents between 1994 and 2004 in the US [2] and 57.7% of oil and gas pipeline failures in Alberta, Canada between 1980 and 2005 [3] were due to internal corrosion. Hence, developing a condition-based degradation model for internal pitting corrosion is a key step in developing an optimal maintenance policy for oil and gas pipelines.

A proper degradation model should account for all uncertainties, including epistemic uncertainty, variability in the temporal aspects, partial heterogeneity and measurement errors. Specifically for pitting corrosion, the degradation model should also reflect these facts that pits' depth growing rate decrease over time and a pit with larger depth has a higher growing rate [4]. To the best knowledge of the authors, dynamic operational conditions of the pipelines has not been addressed in the present internal pitting corrosion degradation models for oil and gas pipelines. However, in practice, it is not unusual that the operational conditions of the pipeline change over time to react to market forces due to changes in the supply of and demand for products transported by hazardous liquid and gas pipelines [5]. These changes can be one of the following types: flow reversal, product change (e.g. crude oil to refined products), or conversion to service (e.g. convert from natural gas to crude oil) [5]. Therefore, the objective of this research is to introduce a framework to consider change in operational conditions in developing a condition-based degradation model to estimate RUL of a corroded pipeline due to internal pitting corrosion.

Problem definition

The integrity assessment of corroded pipelines is commonly performed based on in-line inspection (ILI) (smart pigging) data. ILI technologies usually use magnetic flux leakage or ultrasonic testing to assess damages. These data are used to evaluate the condition of the pipeline and subsequently to make an optimal decision about maintenance activities. In practice, ILIs are performed every three to ten years and [6] and the sequences of change in operational conditions are not detected in real time. One of these sequences is change in the depth growing rate of the internal pits. Hence, relying on a degradation model developed based on the earlier operational conditions and pit depth measurements is inaccurate and increases the uncertainty of RUL estimation. This uncertainty leads to unpredicted failures or unnecessary maintenances of the pipeline. In this paper, a two-phase data fusion approach is proposed to consider the change in operational conditions in RUL estimation of a pipeline.

Proposed framework

This situation is illustrated with an example here. Assume that a pipeline is in operation since time t_0 and *m* pits are initiated at this time. Also, assume that four ILI operations have been performed at t_1, t_2, t_3, and t_4. PHM analysis based on these four datasets gives us an estimation of RUL (subsequently an optimal maintenance policy) for each pipeline segment at time t_5. But operational conditions change at time T ($t_4 < T < t_5$). Therefore, previous RUL estimation (and previous optimal maintenance policy) might not be valid (and optimal) anymore.

In order to detect the change in the operating conditions (i.e. growing rate of pits) one on-line sensor (e.g. ultrasonic testing, magnetic flux leakage) is installed at one specific location to detect pit depth growing rate of a known active pit, *M*. The optimum location for this sensor is investigated in another research in this project (PSIM project) to have the highest probability of detection. The next step is to map the change in growing rate of pit *M* to the growing rate of other pits along the pipeline. In this step, a similarity index is defined between pit *i* (i=1,…,m) and pit *M*. This similarity index is the average of the ratio of the estimated depth of pit *i* and pit *M* at ILI times. This index is modified by some modification factors, such as location factor, in order to take into account the local heterogeneities. For instance, the location factor reflects the effect of the circumferential location of a pit on its depth growing rate (e.g. top of line). The above-mentioned estimated maximum pit depth of pit *i* and *M* are obtained in the proposed two-phase data fusion framework.

In phase I, a hierarchical Bayesian model based on gamma process is used to fuse ILI data of m pits and estimate the maximum depth of pit *i* at ILI times. Also, in this phase augmented particle filtering is used to estimate the maximum pit depth of pit *M* by using OLI data of this pit.

In phase II, dummy measurements are simulated for pit *i* by multiplying OLI data of pit M and the above-mentioned similarity index. These dummy measurements are used in augmented particle filtering analysis to estimate RUL at any point in time in the future for a pipeline segment which includes pit i^{th}.

Conclusions

In this paper, a novel two-phase data fusion framework is proposed to estimate RUL of a corroded pipeline by fusing more accurate on-line inspection data of one pit with more uncertain in-line inspection data of other pits along the pipeline. In phase I, a hierarchical Bayesian model based on gamma process is used to fuse ILI data of *m* pits to have an estimation of the maximum pit depth of those pits at ILI times. In addition, augmented particle method is used to estimate maximum pit depth of a specific known active pit by using its available online inspection data.

In phase II, the detected change in growing rate of pit *M* after time *T* (the time of the last ILI) is mapped to the growing rate of other pits by simulating dummy measurements for those pits. Those dummy measurements, for each pit, are defined as online inspection data of pit M, multiply by the similarity index between pit M and that pit.

That similarity index is the average of the ratio of the above-mentioned estimated depth of pit *i* and pit *M* at ILI times. By using those simulated dummy measurements of each pit in augmented particle filtering analysis, RUL of each pipeline segment will be estimated. This framework will facilitate the integrity assessment of a corroded pipeline when operational conditions change over time.

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