Information Fusion and Data Augmentation for Risk-based Maintenance Optimization of Hydrogen Gas Pipelines

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ABSTRACT

Demand for energy is increasing every year and hydrogen is being seen as a good alternative to conventional natural gas. The current focus is on the use of existing pipeline infrastructure for the transport of hydrogen gas, and it is necessary for us to ensure the safe and efficient operation of the pipeline infrastructure given the risks posed by hydrogen. Pipeline integrity management is critical for hydrogen transport and there are knowledge gaps for the impact of hydrogen on the pipeline integrity and operational considerations, thus hindering the pipeline operators from adopting hydrogen into their networks. To realize the concept of transporting hydrogen through existing pipeline systems, it is necessary to have reliable risk assessment and maintenance optimization frameworks in place. A Bayesian network methodology is proposed to fuse information from multiple sources obtained by multimodality diagnosis of pipe materials and Bayesian updating will be incorporated to reduce the uncertainty arising from different random variables. Risk assessment of the pipeline systems will be carried out based on the posterior distributions of the random variables. Given the predicted risk level, we then propose a risk-based maintenance optimization framework to minimize the maintenance costs while ensuring the safe operation of the pipeline systems.

1. PROBLEM STATEMENT

Transporting hydrogen through existing pipeline infrastructure is a promising method for solving many energy and environmental challenges worldwide. The integrity and reliability of the existing gas pipeline network for hydrogen transport are of critical concern for operators and regulators due to the degradation of pipeline steels under hydrogen, a mechanism known as hydrogen embrittlement. The objective of this research is to develop a risk-based maintenance optimization framework that includes a Bayesian Causal Network (BCN) for real-time pipeline risk assessment under uncertainty and a dynamic maintenance planning framework. Considering transport of hydrogen through existing pipeline infrastructure, it is necessary to consider the existing corrosion as well as material inhomogeneity caused by strain ageing due to long term operation of pipelines (Amend, 2013). It was previously shown that the chemical composition data from surface-only measurements using NDE techniques can be used to predict the mechanical properties such as yield/ultimate strength of pipelines (Zhang, Xu, Ersoy, & Liu, 2022; Dahire, Tahir, Jiao, & Liu, 2018). In this study focusing on hydrogen transport, we consider data from pipelines exposed to hydrogen and a complete dataset from six such pipes is obtained from open literature. It consists of chemical composition, yield/ultimate strength as well as a parameter known as hydrogen sensitivity factor (detailed in section 3.1). Information from various sources will be fused together and statistical inference through Bayesian network will be achieved in this research work, ultimately guiding the risk-based maintenance optimization framework.

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2. EXPECTED CONTRIBUTIONS

This research develops a Bayesian causal network using existing risk models for conventional gas transport and fuses information from various sources such as NDE diagnosis data (crack size, chemical composition, hardness etc.), pipeline anomalies/defects, pipeline operating pressure etc. The factors influencing pipeline safety and their relationships will be identified and encoded into the BCN, and new nodes accounting for hydrogen transport will be augmented to the network. Finally, a risk-based maintenance optimization framework for pipeline integrity management (PIM) will be developed. The expected contributions are:

1. Development of a Bayesian causal network for hydrogen-transporting pipelines using transfer learning approach as mentioned above and augmenting it with hydrogen-related information that is known to affect the pipeline operation and integrity.

2. Proposing a reinforcement learning-based maintenance scheduling framework that is solved as an optimization problem to reduce maintenance costs.

3. RESEARCH PLAN

To implement risk-based maintenance optimization framework for hydrogen transporting gas pipelines, this research is divided into two stages. First, a Bayesian causal network will be developed based on previous knowledge, NDE diagnosis data, and new knowledge from hydrogen impact augmented to the network. Information fusion of multimodality data is performed and the causal relationships among the different nodes in the directed acyclic graph structure is learned to improve the quality of inference process. This is followed by Bayesian updating to obtain posterior distributions for the random variables by leveraging NDE diagnosis data. Doing so, the system uncertainty and prognosis accuracy are improved.

3.1. Work Performed

We have performed a preliminary reliability analysis and the demonstration of Bayesian updating for a system of hydrogen transporting gas pipeline. Considering a range of pipeline steels (X52, X70 and X100) along with literature data on their fatigue crack growth behavior under hydrogen (Slifka, Drexler, Nanninga, Levy, McColskey, Amaro, & Stevenson, 2014; Drexler, Slifka, Amaro, Barbosa, Lauria, Hayden, & Stalheim, 2014), we first developed an empirical model to capture the hydrogen effect. This is entirely premised upon the Paris' constant *'C'* in the commonly used Paris law (Eq. 1) as follows:

$$\frac{da}{dN} = C\Delta K^{m} \quad (1)$$

$$C_{hydrogen} = C_{air} \times \left[1 + \left(\{4.6 - 4.6\, exp^{-0.05P}\} \times 3^{2(1+R)} \times f^{-0.08} \times q\right)\right] \quad (2)$$

This includes the effect of hydrogen gas pressure, stress ratio and loading frequency. The variable *'q'* is a hydrogen sensitivity factor that quantifies how susceptible a particular grade of steel is to hydrogen embrittlement.

We obtained a relationship between the chemical composition, yield strength and the sensitivity factor *'q'* by simple multivariable regression:

$$q = 1.072 + 0.00011(YS) - 0.5161(Mn) \quad (3)$$

Later, we performed the reliability analysis by direct Monte Carlo simulation technique, where failure condition(s) is usually expressed in terms of a limit state function (LSF). We formulated the LSF as the difference between the total damage the material can accumulate before failure and the total accumulated damage up to a certain number of loading cycles. When the $LSF \leq 0$, it is considered as failure. From this, the probability of failure is calculated as:

$$PoF = \frac{Number\ of\ runs\ when\ LSF \leq 0}{Total\ number\ of\ simulation\ runs} \quad (4)$$

The obtained results are tabulated in Table 1, and it should be noted that these are just preliminary results based on several simplifications made due to lack of sufficient data under hydrogen.

Table 1. Probability of failure estimates for various steels.

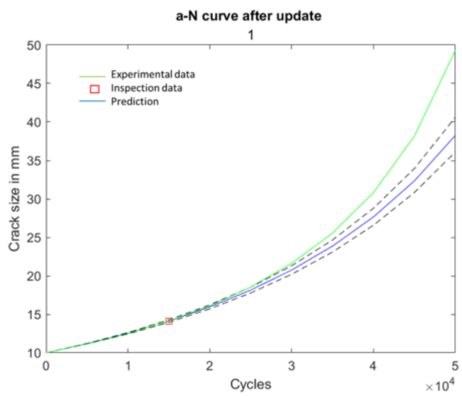
Steel	Probability of Failure
X52	0.06507
X70	0.00763
X100	0.01485

Identifying several sources of uncertainty that affect the overall prediction accuracy and system level risk assessment, it is necessary to reduce them, and we achieve this by Bayesian updating where the priors for the random variables can be updated with new information from NDE diagnosis data (such as crack length) to obtain the posteriors. The updated posteriors can be used in the prognosis step to estimate the remaining useful life and the corresponding probability of failure for risk assessment of the pipeline systems.

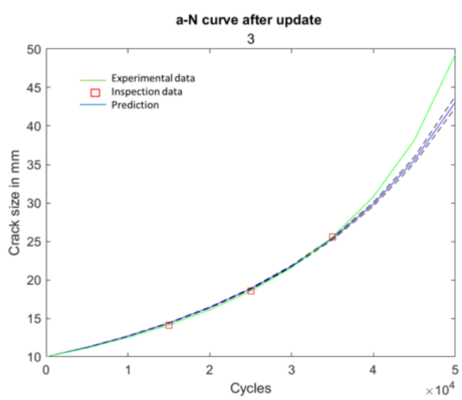
We also demonstrated Bayesian updating based on Bayes' theorem for an X52 pipeline steel by assuming a hydrogen gas pressure of 5 MPa. Suppose $p(\theta, M)$ is the prior distribution for a vector of parameters $'\theta'$ in a model *'M'*, then the posterior is given as:

$$q(\theta, M) = \frac{p(x'|\theta,M)\, p(\theta,M)}{\int p(x'|\theta,M)\, p(\theta,M)} \quad (5)$$

Here $p(x'|\theta, M)$ is the likelihood function which refers to the probability of observing x' given the vector of parameters θ and the model M. The denominator is just a normalizing constant and is difficult to calculate when the vector of parameters is large, which leads to obtaining the posterior distribution only up to the proportionality limit. Markov Chain Monte Carlo (MCMC) sampling is used to obtain the complete posterior distributions. By incorporating Paris' law and assuming its constants *(C, m)* as random variables, we updated the priors with NDE inspection data (synthesized) for crack length and obtained the corresponding posterior distributions. Following this is the prognostics step where the total life until critical crack size is calculated, and the corresponding crack size vs cycles (a-N) plots are obtained (Figure 1). The green and blue curves in the plots correspond to experimental data and model predictions, respectively, and the red squares are the NDE inspection data points used for Bayesian updating. After the third update, the model predictions converge with the experimental data reflecting a reduction in uncertainty.



a)



b)

Figure 1. a-N curves after a) update – 1, b) update – 3.

3.2. Remaining Work

The following are the remaining tasks in this research study:

1. Until now we worked with the physics-based model parameters as random variables and limited material property data. Next, we shall extend the information fusion framework by including data on surface roughness, NDE diagnosis data such as crack size and defect geometry, and hydrogen operational data as shown in Figure 2. Following this will be learning the causal relationships among the various nodes in the Bayesian network.
2. After the extensive development of the BCN, data from prior knowledge will be used to update the posterior distributions of all the random variables and use in the limit state function for risk level quantification.
3. Perform sensitivity analysis to identify the sources that affect the pipeline integrity the most and obtain a precise risk level assessment.
4. The maintenance framework is proposed to be solved as an optimization problem that aims to minimize the maintenance costs subject to certain constraints such as a threshold of the failure probability. We plan to incorporate a reinforcement learning method (Hu, Wang, Pang, & Liu, 2022) for maintenance scheduling.

   Initially assuming a condition vector $\boldsymbol{D}$, after a time Δt with maintenance activity, the new condition vector can be calculated as:

$$\boldsymbol{D_{new}} = \sum_m \boldsymbol{D}.\times \boldsymbol{X}(m,:) \times \boldsymbol{M_m} \times \boldsymbol{P} \tag{6}$$

   where $\mathbf{X}$ is the maintenance decision matrix, $\boldsymbol{M_m}$ is the maintenance transition matrix, and $\boldsymbol{P}$ is the transitional probability matrix. The elements of the maintenance decision matrix $\boldsymbol{X}(i,j)$ denote the percentage of pipes that are in condition j have maintenance method i done. The cost for a maintenance decision $\boldsymbol{X}$ can be evaluated as:

$$\boldsymbol{Cost} = \sum_m \boldsymbol{Q} \times \boldsymbol{D}.\times \boldsymbol{X}(m,:) \times \boldsymbol{C}(m,:) \tag{7}$$

   where the elements of the cost matrix $\boldsymbol{C}(i,j)$ denote the expense of applying a maintenance method i for a pipe that is in condition j.

4. CONCLUSION

This research aims to develop a risk assessment model to quantify the risk levels of pipeline systems transporting hydrogen gas and propose a risk-based maintenance optimization framework. We propose to achieve this objective by building a Bayesian causal network based on existing risk models and augmenting it with new knowledge on hydrogen impact on pipeline operation and safety. So far, we have demonstrated estimating failure probabilities with random model parameters and updating the priors of random variables to obtain the posteriors with reduced uncertainty. The remaining work is to consider several other sources of information and incorporate them into the Bayesian network.

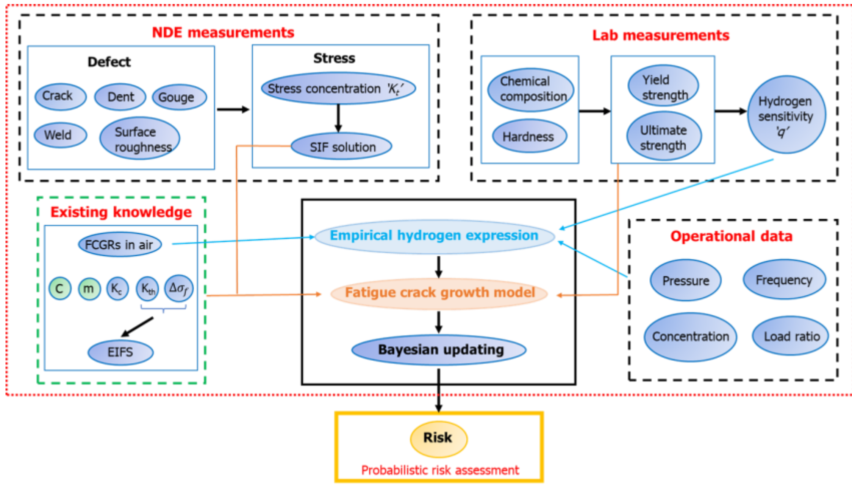


Figure 2. BCN for pipeline risk assessment.

The causal relationships among the different variables will be learned and the risk levels for the pipeline systems will be quantified. Following this will be the development of a risk-based maintenance optimization framework by incorporating reinforcement learning technique. With this work, pipeline operators will have a tool to perform risk-based maintenance scheduling for pipelines transporting hydrogen and make appropriate decisions assuring safety and pipeline integrity, thus promoting the incorporation of hydrogen gas into their networks on a large scale.

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