

Decision Making Under Uncertain Erosion Conditions Using the Probabilistic Model

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ABSTRACT

Erosion threatens the integrity of pipeline system through wall thinning. This effect is worsened when corrosion and erosion interact. Therefore, it is necessary to estimate the ranges of possible erosion rates under a set of operating conditions rate for the safe operation of pipeline. However, data uncertainty (including missing data) challenges the erosion rate estimation. This study shows how to use and erosion probabilistic model to (1) gather the most useful data depending on threat mechanism and already collected information about pipeline conditions, (2) help pipeline operators use probabilistic results to inspect for threats in the most useful locations (number of inspection sites is also considered), (3) help pipeline operators optimize inspection time intervals and (4) help pipeline operators tailor erosion mitigation strategies to specific pipeline and operating conditions.

Key words: Bayesian network; Erosion; Pipeline Integrity; Probabilistic Model.

INTRODUCTION

Erosion is one of the major threats of the pipeline integrity¹ when it's transporting liquid hydrocarbon products with solid particles. The erosion process decreases the effective wall thickness and therefore reduces the capacity of the pipeline to contain the pressured product. This can induce serious consequences including property, health and safety, environment, and business costs.² To help maintain the integrity of the pipeline and minimize the erosion threat, there is a need for an effective tool to estimate the erosion rates for pipelines in different operation conditions.³

The traditional guidelines in the industry related to corrosion management include ISO⁽¹⁾ 13703, which suggested a maximum velocity of 5 m/s for single phase liquid transportation line.⁴ For the two-phase flow lines erosion calculation, API⁽²⁾ RP 14E was widely used, with the equation below:⁵

$$v_e = \frac{C}{\sqrt{\rho}} \quad (1)$$

Where v_e is the erosional velocity (ft/s), ρ is the fluid mixture density at flowing conditions (lb/ft³), and C is an empirical constant ($\sqrt{\text{lb}/(\text{ft} \cdot \text{s}^2)}$) which can range from 100 to 125 for solid free two-phase flow (a lower C is suggested when solids are present but the guidance to define this value is not available).

However, the API RP 14E approach faces several limitations.⁶ First, the equation is based on a simple estimation of the liquid density and an empirical constant “ C ”, where the physical meaning of C is ambiguous. Second, the API RP 14E equation does not take consideration many other factors known to affect the erosion, for example the radius of curvature and solid content. This calls for a more comprehensive model to address the erosion estimation.

As steps forward to build more comprehensive erosion models, the University of Tulsa Sand Production Pipe Saver (SPPS)⁷ model (Model T) and the DNV RP-O501⁸ model (Model D) have been proposed by pipeline integrity researchers. These models considered many factors including the pipeline diameter, particle properties, liquid product density/viscosity, etc. Therefore, these models should be able to predict the erosion velocity in a more precise manner than API 14E. However, an ongoing challenge with most of the pipeline models also exists here: the data availability. In the pipeline operation, there are often unknown, limited, or uncertain data for the models. To handle these challenges, uncertainty needs to be handled properly in the pipeline erosion model.

In a reported research, several machine learning technologies was applied to an erosion database to explore the approaches to handle uncertainty.⁹ A Bayesian network model was built for the erosion estimation, where the pipeline properties, product properties and the geometry properties are all included in a single model, using the Bayes' equation shown below.

$$P(A_i|B) = \frac{P(B|A_i) * P(A_i)}{\sum_{j=1}^n P(B|A_j) * P(A_j)} \quad (2)$$

Where $P(A_i|B)$ is the posterior probability (i.e., what we want) of an event A_i given the observation B ; $P(A_i)$ is the prior probability of the event A_i before the observation B , and $P(B|A_i)$ is the likelihood function and is the probability of the observation B given that event A_i occurred (i.e., knowledge).

(1) International Organization for Standardization

(2) American Petroleum Institute

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Figure 1 shows the diagram of this Bayesian network model. The advantage of a Bayesian network model includes its capacity to get probabilistic distributions with limited or uncertain information. The Bayesian network models have been applied to assess multiple pipeline threats including internal corrosion, external corrosion, stress corrosion cracking, *etc.*¹⁰⁻¹⁵ By using the Bayesian network model, the pipeline operators can get suggestions about the pipeline wall flaw/crack depth evolution over time, and also the location of the most severe wall loss. In case there is missing data, the Bayesian network model is able to address the uncertainties in the input and translate it into the probability distribution in the results. This provides the results with the available information, and furthermore, provides guidance about what is the most important data to collect, aiming a more comprehensive and precise prediction. The Bayesian network model was included in the erosional velocity guideline recently developed, as one alternative probabilistic approach to get erosional velocities with uncertain or unknown data.

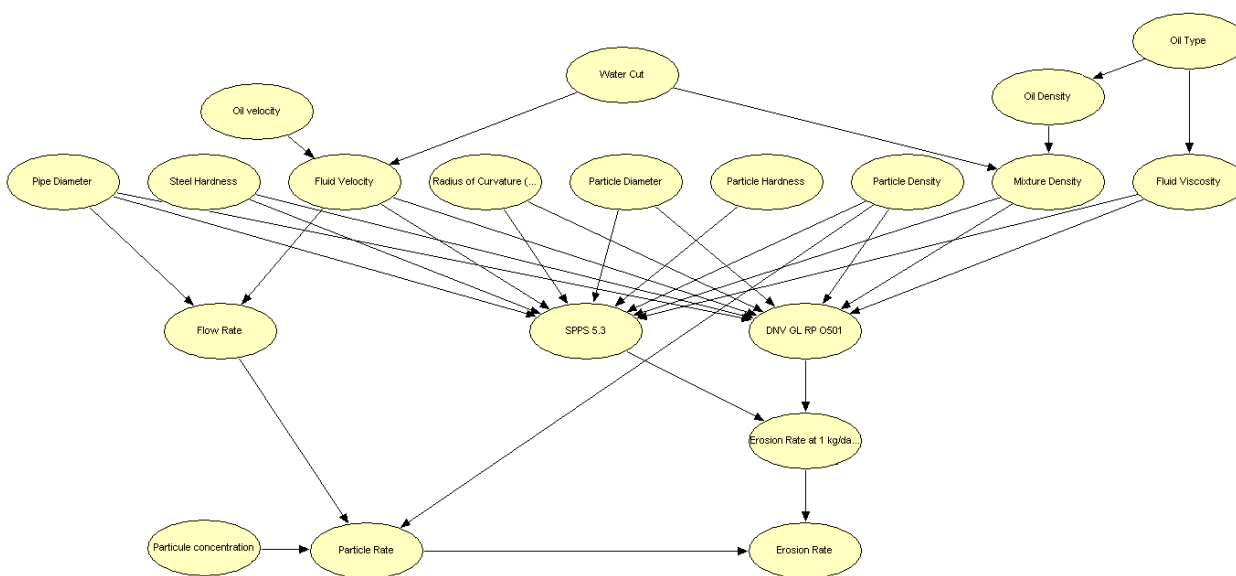


Figure 1: The layout of the Bayesian network erosion model

In this study, the erosion rate estimations under several different scenarios were explored using the Bayesian network model. Furthermore, this paper explains how to use the results to help operators to decide about how to gather the most useful data (the most useful data depends on threat mechanisms and already collected information about pipeline conditions) and make smarter decisions.

METHODOLOGY

The Bayesian network model of erosion threat was established based on a previous published research⁹, where a ~40 million (31, 752, 000 simulations were run for model T, and 15,876,000 simulations for model D) erosion rates database was constructed and served as the foundation to implement multiple machine learning methodologies. Factors including pipeline diameter, steel hardness, fluid velocity, radius of curvature, particle diameter, particle density, fluid viscosity, mixture density and particle hardness were considered in the Bayesian network model. The values within each input parameter's range were clustered into combinations in the erosion database simulation. The total

number of combinations were 63,504 for model T and 31,752 for model D. Then, 500 random points were selected within each combination range to do the simulation and statistically generate the erosion rate probability distribution. The particle rate was treated as a separate factor to scale the final erosion rate. The methodologies to utilize this Bayesian network model in this study are illustrated in the following sections

Bayesian Network Model

Nine factors are included in the Bayesian network model, where the specific range for each factor are reported in another publication.¹¹ The model factors are discretized into smaller bins for the ease of application. Take fluid velocity as an example, where the range of the fluid velocity included in the model was from 1 m/s to 15 m/s. In this case, the factors in Bayesian network were discretized into bins for every 2 m/s gap. This gives us the states like 1-3 m/s, 3-5 m/s, ... 13-15 m/s. These bins were used to handle the uncertainty and generate the probabilistic results from the model. Figure 2 shows how the discrete bins work with known (a), unknown (b) or uncertain (c) data.

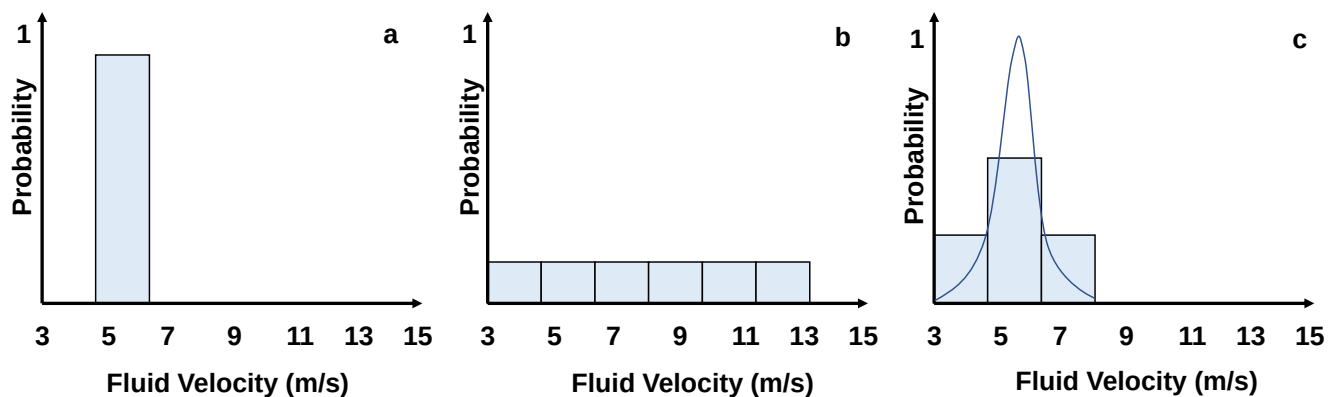


Figure 2: Example of the discretization of the velocity data as an example. (a) known data, (b) unknown data, (c) uncertain data

A statistical analysis was then done on the erosion database to check which discretized bins the final erosion rate falls in. As an example, Table 1 shows the conditional probability table for the erosion rate estimation (the particle rate in the tables is set to 1 kg/day).