Sensitivity Analysis in Oil and Gas Pipeline Risk Assessment: A Comprehensive Review and Comparative Study

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Abstract

Sensitivity analysis is of paramount importance for improving the accuracy and robustness of semi-quantitative, quantitative, and probabilistic risk models in oil and gas pipeline risk analysis. For gas pipelines, a sensitivity analysis of the risk models is a requirement under 49 CFR Part 192 192.917(4)c. The inherent complexity and interdependency of factors influencing pipeline risk require an in-depth comprehension of sensitivity analysis methods available. Fitness-for-service calculators have been integrated in some quantitative models; though extensive validation work has been reported, a formal sensitivity analysis has been often omitted in any benchmarks and reviews. The primary objective of this paper is to provide an in-depth review of various sensitivity analysis techniques, highlighting their strengths, limitations, and practical applications in pipeline risk assessment. The comparative analysis is conducted based on multiple criteria, comprising accuracy, robustness of methods, applicability to different risk models and calculators, linear/non-linear compatibility, computational requirements, ability to capture interactions between risk variables and handle uncertainty, and variabilities that impact pipeline risk assessment. The findings of the comparative study provide valuable insights into the strengths and limitations of various methods, allowing practitioners to select techniques based on their modelling objectives and data availability. Two cases are provided to illustrate the practical application of some of these techniques and their incorporation into risk models.

Introduction

Risk models are prominent pipeline integrity management (PIM) tools used to make data-driven decisions. As computing power has increased and data acquisition methods have proliferated, risk models have become more complex. Moreover, the transition to Quantitative Risk Assessment (QRA) techniques and the heightened intricacy of the corresponding risk models requires a greater amount of specific high-quality information to be provided as inputs for the risk models, including meta data generated during their production. The PIM personnel is not necessarily informed on the information requirements. Therefore, a good understanding of the effect of data uncertainty upon the risk model results is crucial to effectively and ethically apply the model in any decision-making process. In the United States, 49 CFR 192.917(4)c [1] specifies the implementation of a Sensitivity analysis (SA) on the factors used to characterize both the likelihood and consequence of failure for gas pipelines.

Two types of uncertainties arise in complex risk models: (i) stochastic uncertainty [2], which is the inherent randomness of the model, and (ii) subjective or epistemic uncertainty, which is equivalent to incomplete knowledge [3]. In pipeline risk modelling, stochastic uncertainty occurs due to the numerous assessed threat scenarios. On the other hand, epistemic uncertainties arise from the numerous uncertain parameters involved in estimating the probabilities and consequences of these threat scenarios[4,5]. Epistemic uncertainty can be broken down into vagueness, ambiguity, and subjectivity inherent in mathematical models [5–7].

Sensitivity analysis and uncertainty analysis are the primary methods utilized to investigate and assess the epistemic and stochastic uncertainties of complex mathematical models respectively [8]. Sensitivity analysis (SA) has been defined by Saltelli, et. al. [9] as “the study of how the variation in the output of a model (numerical or otherwise) can be apportioned, qualitatively or quantitatively, to different sources of variations, and of how the given model depends upon the information fed

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into it". However, uncertainty analysis is defined as characterizing the uncertainty associated with model predictions without attributing the uncertainty primarily to particular assumptions [10–12]. In other words, the purpose of uncertainty analysis is to ascertain the overall level of uncertainty in the results of an analysis, whereas the goal of SA is to determine the relative importance of each uncertain input to that overall level of uncertainty. The inputs of interest in sensitivity analysis, often called 'factors', can encompass various elements such as model parameters, forcing variables, boundary and initial conditions, choices of model structural configurations, as well as assumptions and constraints. The outputs can consist of various aspects of the model's responses, including those that exhibit spatial and temporal variations. They can also include objective functions, such as production or cost functions in cost-benefit analysis, or error functions used for model calibration [13].

SA provides the following benefits to risk modelling: (i) identifying the most significant factors or parameters that have a substantial impact on the output of a risk model [14–17]; (ii) exploring interactions and casualties within the risk models [5,13,18]; (iii) enabling efficient resource allocation for further investigation or data collection [7,8,13,17]; (iv) validating and verifying the mathematical model; (v) reducing dimensionality of risk models by removing redundant variables[15]; (vi) determining direction of change and marginal behaviour of the model with respect to one or more inputs of interest [19]; and (vii) assessing the reliability and robustness of the models [17]. Generally, sensitivity analysis seeks to utilize the notion of 'sparsity of factors' principle which suggests that, frequently, only a small subset of factors in a system have a notable impact on a specific system output. Several SA techniques search the input space by traversing one-dimensional corridors, leaving most of the input factors unexplored. According to recent research [8], a considerable proportion of highly cited papers (i.e., 42 percent) fail to adequately search the input parameters space. SA is crucial, however, its implementation often encounters various issues that are prevalent across all research disciplines, such as ambiguity in terminology and statistically flawed data acquisition and processing methods that may lead to underestimate the model uncertainty. In addition, though SA and uncertainty analysis are distinct practices, modelers frequently mix the two and perform an uncertainty analysis and present it as a SA or vice versa.

SA is commonly understood as a procedure wherein one or more variables in a given model are altered with the intention of assessing their impacts on a desired outcome. Local Sensitivity Analysis (LSA) is the common name for these types of evaluations, as they only determine the sensitivity of the problem in the vicinity of a "nominal point" within the problem space [13]. LSA is straightforward, intuitive, and suitable for extremely particular situations. LSA techniques have been criticized for providing only a localized view of the problem space, particularly when applied to investigate parameter importance in mathematical modelling [8]. Moreover, they are not valid for nonlinear models. Furthermore, LSA techniques fail to consider the interrelationships that exist between variables of risk models.

In recent years, there has been a notable emphasis in the field of SA on a concept known as "Global Sensitivity Analysis (GSA)"[8,13]. GSA aims to offer a comprehensive view of the ways in which various factors operate and interact throughout the entire problem space to impact a specific function of the system output. Among all GSA techniques, eFAST (Extended Fourier Amplitude Sensitivity Test) is highly recommended in many scenarios due to several notable strengths: (i) handling non-linear models; (ii) evaluates the entire input space; (iii) distinguishing between the effects of different input variables based on their unique frequency signatures; (iv) Efficiency in handling many input variables; (v) improved accuracy over FAST; (vi) improved convergence over Sobol; and (vii) capability to identify interactions.

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The rest of the paper is organized in the following sections: (i) a brief review of both local and global SA techniques highlighting gaps, (ii) a comparative study and discussion about the right criteria when choosing a technique, and (iii) two case studies to illustrate the practical use of global simulation-based SA method (i.e., eFAST) for quantitative risk models.

Sensitivity analysis techniques

Local sensitivity analysis (LSA) or one-at-a-time (OAT) techniques

One way to conduct SA is to vary one input parameter of the model at a time while holding the others constant. This is arguably the simplest SA approach available for deterministic models, but it is not fit for probabilistic models. The nominal values of the input parameters are often used for this type of one-at-a-time (OAT) sampling. The extreme values of the distribution are one of the most common ways to determine the sampling points of interest, although there are many more possibilities.

LSA(a): Pearson correlation coefficients

The most basic form of LSA involves determining the linear correlation between two variables: an input x_i and an output $f(x_i)$ derived from data that is quasi-randomly sampled [9]. The idea is to approximate the full risk model with a linear surrogate, i.e. $f(x_i) = Ax_i$. Pearson's correlation coefficient (Equation 1) is the covariance of the two variables divided by the product of their standard deviations. The widely used Pearson correlation coefficient, Spearman rank correlation coefficient, and Partial correlation coefficient are typical local sensitivity methods.

The Pearson correlation coefficient is symmetric. A key mathematical property of the Pearson correlation coefficient is that it is invariant under separate changes in location and scale in the two variables.

$$\rho_{x_i, f(X_i)} = \frac{cov\,(x_i, f(x_i))}{\sqrt{V\,[x_i]\,V\,[f(x_i)]}} \tag{1}$$

where V denotes the variance and cov the covariance.

LSA(b): Spearman rank correlation coefficients

In contrast to the Pearson correlation coefficient, the Spearman rank correlation coefficient, shown in Equation 2, imposes less stringent data condition requirements. A correlation between the observed values of the two variables is sufficient, or a monotonic relationship derived from a substantial quantity of continuous data is sufficient, irrespective of the two variables.

$$\rho_i = 1 - \frac{6\sum_{j=1}^{k}\left(R_{X_{i,j}} - R_{f(x_i)_j}\right)^2}{k(k^2-1)} \tag{2}$$

where R is the rank of $f(x_i)$ and x_i. As a normalized sensitivity measure, the square R_i^2 of the Pearson coefficient also indicates the proportion of the output variance attributable to the input x_i.

$$R_i^2 = \frac{cov\,(x_i, f(x_i))^2}{V\,[x_i]\,V\,[f(x_i)]} \tag{3}$$

where the sensitivity measure R_i^2 accounts for the contributions of x_i.

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LSA(c): Partial correlation coefficients

A partial correlation coefficient is utilized to assess the degree of dependence between two variables in a population or data set that contains more than two characteristics. This strength of dependence is not considered when both variables change in response to variations in a subset of the other variables. Therefore, the Partial Correlation Coefficient (PCC) is the correlation coefficient where the linear effect of the other terms is removed, i.e. for $S_i = \{x_1, x_2, \dots, x_{j-1}, x_{j+1}, \dots, x_n\}$ we have:

$$PCC_{i|S_i} = \frac{\text{cov}\left(x_i, f(x_i)|S_j\right)}{\sqrt{v[x_i|S_i]\, v[f(x_i)|S_i]}} \tag{4}$$

The result of correlation coefficient indices is a number between –1 and 1 that measures the strength and direction of the relationship between two variables. As with covariance itself, the measure can only reflect a linear correlation of variables and ignores many other types of relationships or correlations. The method demonstrates a comparatively low computational cost that is nearly unaffected by the number of inputs. The quantity of model iterations necessary to achieve satisfactory statistical accuracy is model-dependent.

Global sensitivity analysis (GSA) techniques

GSA(a): Morris method

The Morris Method employs finite difference approximations for SA and operates on the principle that estimating derivatives by moving in one dimension at a time and using sufficiently large steps can yield robust contributions to the overall sensitivity measurement. The procedure involves:

1. Selecting a random starting point in the input space.
2. Choosing a random direction and altering only the corresponding variable by Δx.
3. Estimating the derivative based on this single-variable perturbation and repeating the process.

Continuing this process through numerous iterations allows the mean of these derivative estimates to serve as a global sensitivity index. This approach enhances computational efficiency by utilizing each simulation for dual derivative estimates, offering a more resourceful alternative to other methods. While it focuses on average changes rather than dissecting total variance, its computational advantage is compelling for preliminary global sensitivity assessments.

To refine the Morris Method for practical applications, certain adjustments are necessary. It is important to account for the potential nullification of positive and negative changes, which suggests the use of absolute or squared differences for a more accurate variance measure. Moreover, it's critical to ensure comprehensive exploration of the input space. This can be achieved by defining the distance between trajectories as the cumulative geometric distance between corresponding point pairs. By generating an excess number of trajectories and selecting those with the greatest distances, the method attains a broad coverage of the input domain. When the implementation and computational cost of a model is high, the relative affordability of this technique makes it a viable option for conducting SA.

GSA(b): Derivative-based global sensitivity measures (DGSM)

To surpass the limitations of a linear model, successive linearization may be desired. Given that derivatives involve linearization, it is possible to evaluate derivatives on an average. The Morris OAT sensitivity measure is contingent upon a nominal point x_i and it varies in response to a change in x_i.

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To address this inefficiency, one can calculate the average of $E(x_i)$ across the parameter space which is a unit hypercube $\mathrm{H_d}$. Therefore, new sensitivity measures known as Derivative-based Global Sensitivity Measures (DGSM) can be defined.

Consider a function $f(x_1, \dots, x_d)$, where $x_1, \dots, x_d$ are independent random variables, defined in the Euclidian space R^d , with cumulative density functions (CDF) of $F(x_i)$. The following DGSM was introduced[20].

$$v_i = \int_{R^d} \left(\frac{\partial f(x_i)}{\partial x_i}\right)^2 dF(x_i) = E\left[\left(\frac{\partial f(x_i)}{\partial x_i}\right)^2\right] \tag{5}$$

Then the mean measure can be simply defined as:

$$w_i = \int_{R^d} \frac{\partial f(x_i)}{\partial x_i} dF(x_i) = E\left[\frac{\partial f(x_i)}{\partial x_i}\right] \tag{6}$$

Therefore, a global variance estimate is:

$$v_i - {w_i}^2 \tag{7}$$

GSA(c-1): Variance-based methods: Sobol method

Variance-based approaches rely on the premise, proposed by Saltelli et al., [17], that the variance alone is enough to characterize the uncertainty of the output. Variance-based GSA techniques determine the effect on model outcome as a function of an appropriate parameter probability density function by decomposing the uncertainty of outputs for the corresponding inputs.

Sobol's method [21] is a genuine technique for nonlinear decomposition of variance, making it highly regarded as one of the most reliable approaches. The approach partitions the variance in the system's or model's output into fractions that can be allocated to individual inputs or clusters of inputs. First order and total order effects are the two primary sensitivity measures used in this method. The first order effects consider the primary effects for variations in output caused by the respective input. The total order effects represent the total contributions to the output variance related to the corresponding input, which include both first order and higher order effects owing to interactions between inputs.

The objective is to represent the output variance as a finite sum of elements that are arranged in ascending order. Each of the terms denotes the proportion of the output variance attributable to one input variable (first order terms) or the interaction variance of multiple input variables (higher order terms). Subsequently, the Sobol's sensitivity indices are established by normalizing these partial variances by the output variance.

GSA(c-2): Variance-based methods: FAST and eFAST methods

Two widely used and well-established GSA methodologies are the Fourier Amplitude Sensitivity Test (FAST) and the extended FAST (eFAST) which are faster ways of estimating the total order sensitivity indices [17,22]. The FAST method modified Sobol method allowing faster convergence. The FAST method allocates the variance through spectral analysis, following which the input space is explored with sinusoidal functions of varying frequencies for each input factor or dimension [10,14,17].

FAST transforms the variables x_i onto the space [0,1]. Then, instead of the linear decomposition, it decomposes into a Fourier basis:

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$$f(x_i, x_2, \dots, x_n) = \sum_{m_1=-\infty}^{\infty} \dots \sum_{m_n=-\infty}^{\infty} C_{m_1 m_2 \dots m_n} \exp\left(2\pi i(m_1 x_1 + \dots + m_n x_n)\right) \quad (8)$$

where

$$C_{m_1 m_2 \dots m_n} = \int_0^1 \dots \int_0^1 f(x_i, x_2, \dots, x_n) \exp\left(-2\pi i(m_1 x_1 + \dots + m_n x_n)\right) \quad (9)$$

The analysis of variances decomposition partitions the total variance of the model as a sum of variances of orthogonal functions for all possible subsets of the input variables.
The first order conditional variance is thus:

$$V_j = 2 \sum_{m_j=1}^{\infty} \left(A_{m_j}^2 + B_{m_j}^2\right) \quad (10)$$

where $C_{0 \dots 0 m_j 0 \dots 0} = A_{m_j} + iB_{m_j}$.
FAST can be implemented using the Ergodic Theorem which is defined as:

$$X_j(s) = \frac{1}{2\pi}\left(\omega_j s \ \ mod 2\pi\right) \quad (11)$$

According to the Ergodic theorem, if ω_j are irrational numbers, the dynamical system will not repeat values and will thus provide a solution that is densely distributed across the search space. This means that the multidimensional integral can be approximated by the integral over a single line.

One can approximate this to obtain a more simplified expression for the integral. By considering ω_j as integers, it can be observed that the integral is periodic. Therefore, it is sufficient to integrate throughout the interval of 2π.

A longer period yields a more accurate representation of the space and hence a more precise approximation, while potentially necessitating a greater number of data points. Nevertheless, this conversion simplifies the genuine integrals into straightforward one-dimensional quadrature that may be effectively calculated.

To obtain the total index using this approach, it is necessary to compute the total contribution of the complementary set, denoted as $V_{c_i} = \sum_{j \neq i} V_j$, and subsequently:

$$S_{T_i} = 1 - S_{c_i} \quad (12)$$

It is important to note that this is a rapid method to calculate the overall impact of each variable, encompassing all higher-order nonlinear interactions, all derived from one-dimensional integrals. The extension is referred to as eFAST which is highly regarded in many scenarios due to several notable strengths:

1. Handling non-linear and non-additive models: eFAST is particularly effective in analysing complex models with non-linear or non-additive effects. It can capture both the main effects and the interaction effects among input variables.
2. Global SA: as a GSA method, eFAST evaluates the entire input space, as opposed to local methods that analyse sensitivity at a specific point in the input space. This comprehensive approach allows eFAST to provide more robust and generalizable insights.
3. Frequency domain analysis: eFAST operates in the frequency domain, using Fourier transforms to decompose the model output into frequency components. This allows it to distinguish between the effects of different input variables based on their unique frequency signatures.

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4. Efficiency in handling many input variables: eFAST is more computationally efficient compared to some other global methods, particularly when dealing with a large number of input variables. This is due to its use of spectral decomposition, which can efficiently separate the effects of each input variable.
5. Improved accuracy over FAST: eFAST extends the original FAST method by incorporating a wider range of frequency harmonics, allowing for the detection of higher-order interactions between variables. This leads to improved accuracy in the sensitivity estimates.
6. Capability to identify non-linear interactions: eFAST is adept at identifying non-linear interactions between input variables, a crucial aspect for many complex systems where such interactions are significant.

GSA(d): Density-based methods

Density-based GSA methods compute the sensitivity of the inputs and their interactions by considering the complete Probability Density Function (PDF) of the model output. Their popularity stems from the fact that density-based SA methods can circumvent certain restrictions associated with interpreting variance-based measures when model input dependencies are present. Nevertheless, in situations involving a substantial number of model inputs (high dimensionality) or computation times of the model or function exceeding a few minutes, their estimation may become impracticable.

Two Density-based GSA methods are DELTA [23] and PAWN [24]. The DELTA (δ) approach is a density-based SA method that is not influenced by the method used to generate the samples. This method calculates the first order sensitivity and the δ (similar to total sensitivity) for each input parameter. DELTA tries to evaluate the impact of the entire input distribution on the complete output distribution, without considering any specific point of the output. PAWN is called after the authors and its purpose is to calculate Density-based SA metrics in a more efficient manner. The main concept is to define output distributions based on their Cumulative Distribution Functions, which are simpler to calculate compared to Probability Density Functions. One benefit of using PAWN is the ability to calculate sensitivity indices not only for the entire range of output fluctuation, but also for a specific sub-range. This is particularly valuable in scenarios when there is a specific area of the output distribution that is of interest.

Sampling strategies and Monte Carlo simulation

It is important to observe that each expectation involves an integral, so the variance is defined as integrals of integrals, which makes this computation quite complex. Therefore, rather of directly computing the integrals, Monte Carlo estimators are frequently employed. Instead of only relying on a pure Monte Carlo approach, it is common practice to employ a low-discrepancy sequence, which is a type of quasi-Monte Carlo method, to efficiently sample the search space.
There are two primary categories of structures for low discrepancy point sets and sequences: lattices and digital nets/sequences. For additional information on these constructions and their attributes, refer to [25]. Sobol sequences [26] are commonly employed as specific instances of quasi-random (or low discrepancy) sequences of a given size.

The low-discrepancy characteristics of Sobol' sequences deteriorate as the dimension of the input space increases. The rate of convergence is adversely impacted if the crucial inputs are situated in the final components of inputs. Consequently, if there is an initial ranking of inputs based on their relevance, it would be advantageous to sample the inputs in decreasing order of importance to improve the convergence of sensitivity estimates.

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The Latin Hypercube sampling (LHS) is another frequently used quasi-Monte Carlo sequence that extends the concept of the Latin Square. In the Latin Hypercube, only one point is assigned in each row, column, and so on, resulting in a uniform distribution across a space with multiple dimensions.

Comparative analysis of SA techniques

A comparative analysis framework was developed to evaluate the different SA methodologies. This framework focused on several dimensions, including accuracy, robustness of methods, applicability to different risk models and calculators, linear/non-linear compatibility, computational requirements, ability to capture interactions between risk variables and handle uncertainty and variabilities in pipeline risk assessment. Each method was assessed based on these criteria to understand its suitability and effectiveness in different risk assessment contexts. Each criterion is defined as follows:

1. **Accuracy**: The degree to which the SA method can correctly estimate the true impact of input variables on the output of the model. High accuracy means the method can provide reliable insights into how input variations affect the output.
2. **Robustness**: The ability of the method to produce consistent results under different conditions, such as the presence of outliers, non-normal distributions, or model non-linearities. A robust method maintains its performance even when the assumptions are violated to some extent.
3. **Applicability to Risk Models**: This criterion assesses how well the SA method can be applied to risk models, which often contain complex interactions and non-linear behaviour. It reflects the method's flexibility and relevance to models used in risk assessment.
4. **Linear/Non-linear Compatibility**: Indicates whether the method is suitable for linear relationships only, or if it can also accommodate non-linear relationships between input and output variables. Non-linear compatibility is essential for analysing systems with complex dynamics.
5. **Computational Requirement**: The computational resources needed to perform the analysis, including time and processing power. Methods with high computational requirements may be prohibitive for models that require numerous or time-consuming simulations.
6. **Ability to Capture Interactions**: The method's capacity to identify and quantify interactions among input variables, which is particularly important in systems where the combined effect of inputs is not simply the sum of their individual effects.

Local SA methods are highly accurate around specific local points but may not accurately represent the system's behaviour in its entirety. Global SA methods, including variance-based techniques like Sobol' indices, generally offer high accuracy across the entire input space, making them invaluable for complex, non-linear models.

Global methods typically provide more robust results than local methods. They are designed to evaluate the impact of input variations across the entire model space, thereby offering insights that are more generalizable. However, methods like the Morris Method, while offering a global perspective, may not be as robust in capturing intricate model interactions as more comprehensive global techniques.

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Local methods are more applicable to simpler or well-understood models, whereas global methods are better suited for complex, multi-input models. Techniques like FAST and eFAST are particularly applicable for evaluating first-order effects and interactions in a wide range of models. While local methods are best suited for linear or mildly non-linear models, global methods like eFAST and variance-based methods are compatible with both linear and highly non-linear models, capable of handling complex interactions effectively.

Computational Requirement is a significant consideration, as global methods are generally more computationally intensive. Variance-based methods, for instance, require a large number of model evaluations. In contrast, local methods and correlation coefficients like Spearman and Pearson are computationally more efficient, though they offer fewer comprehensive insights. Global methods are superior in capturing interactions between variables. Techniques like the PAWN Method and eFAST are specifically designed to identify complex interactions, a feature that local methods and simpler correlation coefficients typically lack. Efficiency is a trade-off between computational cost and the depth of insights provided. Local methods and correlation coefficients are highly efficient but may lack depth in analysis. Global methods provide a more thorough analysis but at a higher computational and time cost. Table 1 summarizes the comparison of these SA methods, providing a clear overview of their characteristics and suitability for different types of risk assessment models.

Table 1. Comparison of GSA and LSA methods

SA Methods	Type	Accuracy	Robustness	Applicability	Compatibility	Computational requirement	Capturing interactions
Variance-based methods	Global	✓✓✓	✓✓✓	✓✓✓	✓✓✓		✓✓✓
Morris method	Global	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
FAST	Global	✓✓	✓✓	✓✓	✓✓	✓✓✓	✓✓
eFAST	Global	✓✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓	✓✓✓
DGSM	Global	✓✓		✓	✓	✓✓	✓
DELTA method	Global	✓✓	✓✓	✓✓	✓✓	✓✓	✓✓
PAWN method	Global	✓✓✓	✓✓✓	✓✓✓	✓✓	✓	✓✓✓
Spearman rank correlation	Local	✓✓	✓✓	✓✓	✓	✓✓✓	✓
Pearson correlation coefficient	Local	✓✓		✓	✓	✓✓✓	
Partial correlation coefficient	Local	✓✓	✓	✓✓	✓	✓✓	✓

Table 1 Legend:

✓✓✓: High or Excellent
✓✓: Moderate or Good
✓: Low or Fair
(Blank): Not applicable or Poor

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The choice of an SA method hinges on the specific requirements of the risk model in question, the nature of the system under study, and the resources available for the analysis. A nuanced understanding of each method's strengths and limitations is crucial for selecting the most appropriate technique for a given risk assessment task.

Case studies

ASME Modified B31G calculator

Most Qualitative Risk Assessment (QRA) models calculate a Probability of Exceedance (POE), or Probability of Failure (POF) based on the In-Line Inspection (ILI) tool capabilities coupled with fitness-for-service (FFS) calculators. For example, a simple probabilistic corrosion model would perform a Monte-Carlo analysis to assess the limit state of the wall loss indications reported by the latest ILI run. FFS calculators, such as Modified ASME B31G and Modified LnSec, have been validated, and their degree of conservatism and application range has been reported. However, a SA is not usually part of the validation process. Yet, a sense of the parameters affecting the estimated burst pressure has been developed from the constant use of the FFS calculators; safety factors affecting the flaw dimensions are commonly introduced to compensate for the inaccuracy inspection technique, and flaw depth is considered to have more impact on the outcome than the other two flaw dimensions.

The ASME Modified B31G Remaining Strength of Corroded Pipeline methodology (Mod B31G) is commonly used for the burst pressure calculations (i. e. the limit state) for corrosion features. Two different domains were considered for the SA of the burst pressure calculator: (1) an extended domain that covers as many combinations as possible of pipe dimensions, material properties and flaw sizes, and (2) selected cases with representative size and material property variations within a single pipe, and flaw measuring errors (i. e. sizing accuracy) representative of the current inspection methods.

The intervals for the pipe dimensions (D and t) were selected to represent the inventory installed with most operators in North America. And additional condition of $4t < D$ was introduced. There are some limitations to the linear distributions: outside diameter and wall thickness of installed vintage pipe are generally limited to combinations specified in earlier version of API 5L. In addition, some combinations would not be realistic from an engineering perspective, such as thin-walled pipe with a large diameter. Still running such a general case is essential to assess the applicability of the model. The parametrization used for the first scenario is presented in the following Table:

Table 3. Proposed parametrization for Mod B31G scenario 1

Parameter	Variable	Units	Distribution	Min Value	Max Value
X1	D	in	Uniform	2	60
X2	l	in	Uniform	1	100
X3	t	in	Uniform	0.1	0.5
X4	d	in	Uniform	0.05*t	0.8*t
X5	YS	psi	Uniform	20,000	85,000

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Figure 1 presents an array of scatter plots correlating five distinct risk variables (X1 through X5) with the model output (Y). Each plot is annotated with a Pearson correlation coefficient (r), indicative of the strength and direction of the linear relationship between the corresponding risk variable and the output. The values of the Pearson correlation coefficient range from -1 to +1, where +1 implies a perfect positive linear correlation, 0 indicates no linear correlation, and -1 represents a perfect negative linear correlation.

For X1 (the outside diameter), we observe a strong negative linear correlation (r = -0.55), suggesting that as X1 increases, Y (the burst pressure) tends to decrease. In contrast, X2 (flaw length) exhibits an r value of -0.04, which points to a negligible linear relationship with Y. Similarly, X4 (flaw depth) shows an r value of -0.01, further indicating a lack of any significant linear correlation with the output. X3 (wall thickness) and X5 (yield strength), with r values of 0.25 and 0.2, respectively, demonstrate weak positive linear relationships, indicating that higher values of these variables are associated with higher output values to a small degree.

These scatter plots are instrumental in identifying which risk variables have a more pronounced linear influence on the output, thus guiding risk management strategies. Variables with higher absolute values of the Pearson correlation coefficient, such as X1 (outside diameter), are likely to be prioritized for control or mitigation due to their stronger linear association with the output.

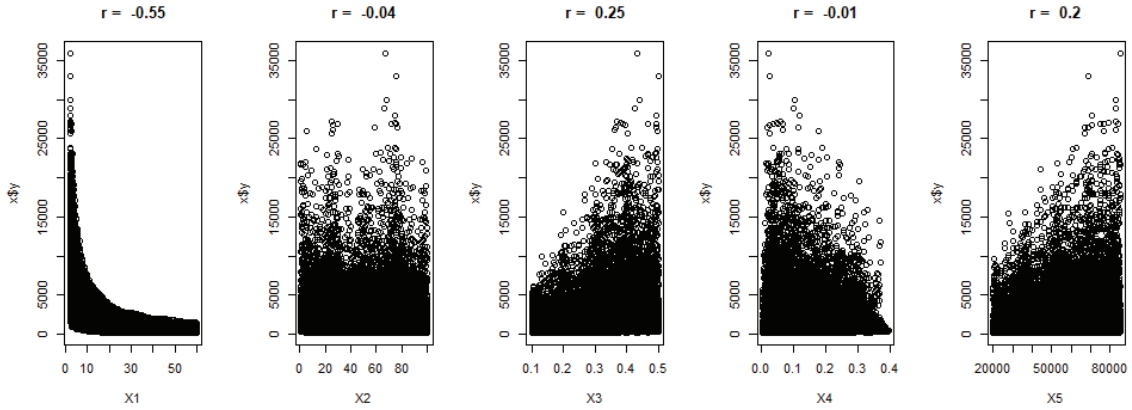

Figure 1. Pearson correlation coefficient plot for Mod B31G scenario 1

The tornado chart in Figure 2 shows the sensitivity indices for the set of input variables, namely X1 through X5, in relation to the output of the Mod B31G model (burst pressure). Each horizontal bar represents the extent of influence that each variable exerts, with the main effects delineated in turquoise and the interaction effects in white.

From the chart, it is discernible that the outside diameter (X1) stands out with the highest total order sensitivity index, demonstrating the most significant combined effect on the model's output. This is evidenced by the turquoise segment of the bar corresponding to X1, which extends considerably further than those of the other variables, coupled with an interaction effect denoted by the white segment, culminating in a total index of approximately 0.8205.

In contrast, flaw length (X2) exhibits the least influence with a negligible main effect and an inconsequential interaction effect, leading to a minimal total sensitivity index close to 0.00692. The other variables, pipe wall thickness (X3) and flaw depth (X4), depict moderate main effects and very minor interaction effects, with total sensitivity indices of approximately 0.19445 and 0.12378,

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respectively. Meanwhile, Yield Strength (X5) presents a slight main effect and a total index of about 0.10766. In this general case, pipe dimensions are the factors with more impact on the outcome (i. e. have higher sensitivity factors), followed by the material properties (YS). On the contrary, the flaw dimensions are the factors with the least impact upon Mod B31G, in the general case.

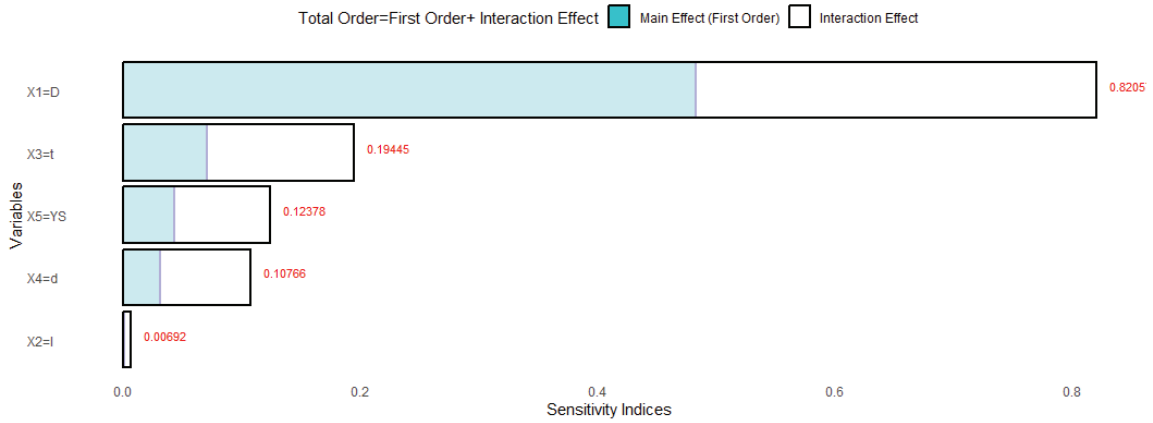

Figure 2. Tornado chart for Mod B31G scenario 1

Three additional scenarios corresponding to actual flaw assessments were considered. The pipe dimensions consider the local variations along a single pipe. The yield strength distribution corresponds to the variations reported for API 5L Grade B and flaw size corresponds to common ILI tool accuracy: the flaw depth accuracy was assumed to be within 10% the size for 99.7% of indications, while the length accuracy was assumed to be within 20% the size for 99.7% of indications.

Scenario A corresponds an API 5L Grade B, 3-in pipe with a wall loss of 50% the pipe wall and a flaw length of 25-in. Scenario B is an API 5L Grade B, 12.5-in pipe with a wall loss of 50% the pipe wall and a flaw only 2-in long. Scenario C corresponds to an API 5L Grade B, 25-in pipe and a 50-in long flaw with a depth of 50% the pipe wall thickness. Table 4 presents the parametrization used for scenarios A, B and C.

Table 4. Proposed parametrization for Mod B31G (scenarios A to C)

				Scenario A		Scenario B		Scenario C	
Parameter	Variable	Units	Distribution	Mean	STD	Mean	STD	Mean	STD
X1	D	In	Normal	3	0.0018	12.5	0.0075	25	0.0018
X2	l	In	Normal	25	0.75	2	0.06	50	1.5
X3	t	In	Normal	0.15554	0.00154	0.22119	0.00219	0.37875	0.00375
X4	d	In	Normal	0.077	0.00513	0.1095	0.0073	0.1875	0.0125
X5	YS	Psi	Normal	38,500	1,225	38,500	1,225	38,500	1,225

The tornado chart in Figure 3 shows the sensitivity indices for Scenario A. The flaw depth (X4) has the highest total order sensitivity index. Yield Strength (X5) comes second, with more influence on the outcome than the pipe dimensions. Pipe wall thickness (X3) depict a moderate effect with total sensitivity index of approximately 0.19445. Outside diameter (X1) and flaw length (X2) have the least impact on the model outcome with a total sensitivity index of approximately 0.015. It can be observed

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that the interaction effect corresponds to less than 10% of the total sensitivity index for the top three factors.

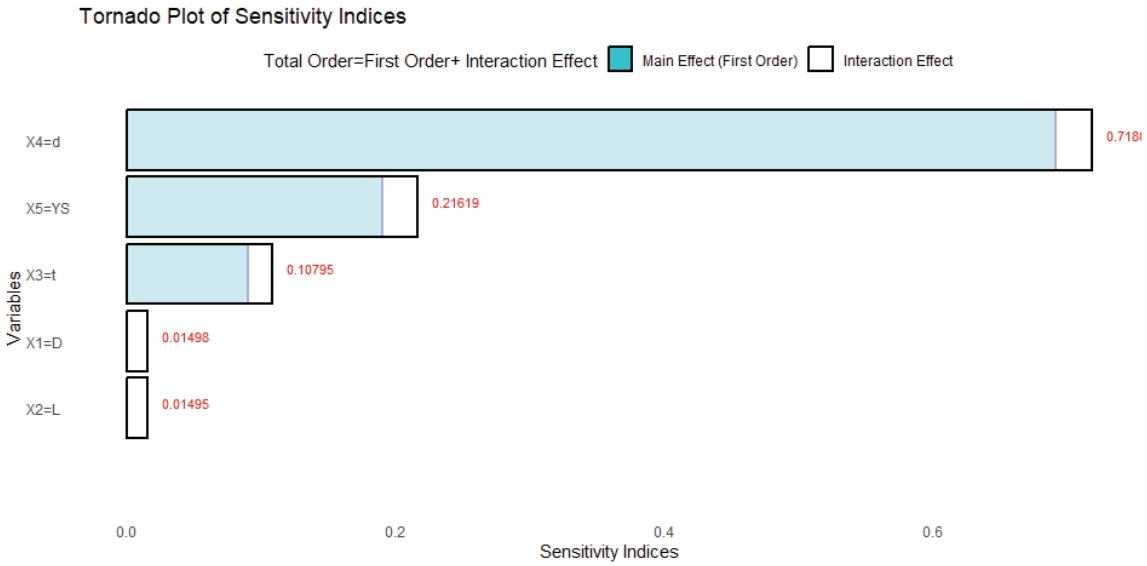

Figure 3. Tornado chart for Mod B31G scenario 1

Table 5 presents the sensitivity factors for scenarios A, B and C. It should be noted that the flaw length has the least impact on the outcome in Scenarios A and C but has the highest sensitivity index for scenario B. Scenario B corresponds to a short wall loss indication in the axial direction while keeping the same size accuracy as the other two scenarios, which might not be realistic since some ILI tools have a threshold for flaw detection an different accuracies depending on the flaw size. However, the mentioned effect of the flaw length parameter in Mod B31G illustrates the need to run SA on multiple cases representative of the operator assets. That is, the general case shown in Scenario 1 does not suffice and the sensitivity cases used for the analysis of one system should be reviewed before using with another system to make sure they are representative.

Table 5. Sensitivity factors for Mod B31G (scenarios A to C)

		Sensitivity Analysis		
Parameter	Variable	Scenario A	Scenario B	Scenario C
X1	D	0.015	0.007	0.015
X2	l	0.015	0.724	0.015
X3	t	0.108	0.05	0.079
X4	d	0.718	0.093	0.683
X5	YS	0.216	0.19	0.272

FFS subject matter experts have stressed the importance of flaw depth on the outcome of the burst pressure calculation of corroded pipe; flaw depth is indeed the parameter with most influence on the burst pressure calculation. However, in some cases, the values and accuracies of the other factors, might Hence the importance of performing the SA for each risk model, with cases representative of the system and the inspection tools used, and couple the results with the data uncertainty assessment. YS consistently comes in the top three influential factors. The original Mod B31G model uses SMYS

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rather than YS. The SA presented shows that original simplification has impact on the calculated burst pressure, and that the calculation would benefit from the use of representative mechanical properties rather than minimum specified values.

Sensitivity analysis of an ASME/ANSI B31.8S Compliant risk model

The SA of a risk model was performed. The model considers all threats specified in ASME B31.8S section 2 and the Safety, Environmental and Production Loss for Consequence of Failure (CoF). The final Likelihood of Failure (LoF) is calculated by simple aggregation of the LoF of individual threats. Table 6 shows a summary of the models used for each threat.

Table 6. Basis of the assessed risk model

Threat	Model Basis
External Corrosion	Mod B31G
Internal Corrosion	Mod B31G
Stress Corrosion Cracking	Mod Ln Sec for Axial Cracking
Manufacturing - Defective Pipe Seam	Mod Ln Sec for Axial Cracking
Manufacturing - Defective Pipe	Mod Ln Sec for Axial Cracking
Defective Girth Weld	Simple Limit State Thresholds
Defective Fabrication Weld	Susceptibility Model
Wrinkle Bend or Buckle	Susceptibility Model
Equipment Failure	API 581
Third Party Damage	Impact model by Chen and Nessim coupled with probability of failure given a hit model by Fuglem et al.
Previously Damaged Pipe	EPRG Mechanical Damage Fatigue Model
Incorrect Operational Procedure	CEPA IF Self-Assessment Questionnaires
Weather Related and Outside Force	Geohazard and hydro hazard mapping coupled with lateral strain measurements

Table 7 shows the five factors that have the highest effect on the outcome of the risk model. Outside diameter stands out as the predominant parameter, exerting a significant impact on both LoF and CoF. Yield Strength affects the resistance of the pipe and affects the outcome of the LoF in the majority of the individual threat models. Flaw dimensions (corrosion/crack/gouge depth) were expected to have a significant impact on LoF; however, they rank behind the dimensions of the pipe and the properties of its material in terms of significance.

Table 7. Top 5 influential factors on the risk model

Rank	Symbol	Parameter
1	D	Outside Diameter
2	YS	Yield Strength
3	d	Wall loss/Crack Flaw Depth
4	dg	Gouge Depth
5	MAOP	Maximum Allowable Operating Pressure

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The above results were integrated to develop data quality flags that influenced the calculated risk. Those quality flags controlled if the pipe dimensions and mechanical properties had Traceable, Verifiable and Complete (TVC) files and if the Maximum Allowable Operating Pressure (MAOP) had been reconfirmed. The risk model was modified to adjust the outcome when data pipe dimensions or mechanical properties were deemed uncertain. Flaw dimensions were considered in the probabilistic LoF analysis that incorporates the measuring tool error and did not require further adjustment in the risk model.

Conclusions

This comprehensive review and comparative study have underscored the critical role of SA in risk assessment for oil and gas pipelines. Through the meticulous examination of various SA techniques, ranging from variance-based methods to derivative-based and local approaches, the study has highlighted the unique strengths and limitations of each method in the context of pipeline risk management. A comparative analysis revealed that while some methods like eFAST' method provide a broad and detailed sensitivity spectrum, others, such as the Morris Method, offer a more computationally efficient, albeit less accurate and detailed, perspective. This diversity in SA techniques underscores the necessity of selecting an approach that aligns with specific project requirements, taking into consideration factors such as model complexity, data availability, and computational resources.

The practical case of a SA for ASME Mod B31G model for corroded pipe was presented. Scenarios with an extended domain corresponding to the inventory installed and selected cases for representative corrosion features were reviewed. The factors impacting the outcome of the model are dependent on the parametrization. Hence, a comprehensive SA requires the careful definition of such scenarios to represent the application domain of the risk model.

A ranking of the factors impacting the outcome of a risk model compliant with ASME/ANSI B38.1S were presented: pipe dimensions (outside diameter) and mechanical properties (yield strength) are more influential than flaw dimensions (corrosion/crack/gouge depth). The insights provided by the SA of the risk model were integrated into the model to compensate for data uncertainty.

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