A Sensitivity Analysis of Key Parameters in a Probabilistic Risk Assessment Model for Transmission Pipelines

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Abstract

Pipelines play a critical role in transporting fluids, and the assessment and mitigation of associated risks are paramount. Over the past decades, pipeline risk models have evolved from empirical, index-based approaches to more quantitative, data-driven models, providing insightful results for operators to make decisions regarding inspection, mitigation, repair, or replacement efforts. However, data uncertainty and limited data availability have consistently posed challenges in quantitative or probabilistic risk assessment models. Therefore, efficiently improving data quality and completeness becomes necessary, which requires a judicious decision on allocating limited resources for data collection efforts. To meet this goal, a sensitivity assessment on pipeline risk models becomes critical.

This research focuses on identifying and understanding the sensitivity of crucial input factors spanning from pipeline specifications to environmental conditions. A data-driven probabilistic risk assessment model was selected, and the baseline parameters were set up based on a selected pipeline. By systematically varying the model parameters in a reasonable range, and observing their impact on the likelihood of failure, the study aims to prioritize factors significantly influencing the likelihood of failure. After determining the range of the selected factors, a Monte Carlo simulation up to a million iterations was conducted with random sampling inside the defined distribution, and the correlation coefficients between these factors and the risk results were analysed. As a result, a ranking of the criticality of these factors is summarized. Additionally, a threat-based sensitivity analysis was conducted, specifically on pipeline threats such as corrosion, mechanical damage, incorrect operation, etc., to evaluate which factor affects the likelihood of a specific threat more.

The results contribute to informed decision-making and resource allocation for risk mitigation strategies. Additionally, the research emphasizes the importance of iterative sensitivity analyses, considering uncertainties, and continuous refinement of the risk assessment model to enhance its accuracy and relevance in dynamic operational environments. The findings of this study offer valuable insights for stakeholders involved in pipeline management, safety, and regulatory compliance.

Introduction

Pipeline risk assessment is critical for the safe operation of oil and gas pipelines. Over the last decade, the risk assessment model has evolved from empirical, index-based approaches to more quantitative, data-driven models, providing insightful results that help operators to make decisions regarding inspection, mitigation, repair, or replacement efforts. A typical pipeline risk model takes inputs including pipeline properties such as outside diameter, wall thickness, material type, as well as operating conditions like pressure, temperature, and flow rate. Furthermore, environment conditions such as sensitive area, lightning exposure rate, and earthquake threat are also included. The output of a quantitative pipeline risk model should include the likelihood of failure and the

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consequence of failure. Per the ASME B31.8S standard [1], a pipeline risk assessment model should cover the following threats – internal corrosion, external corrosion, stress corrosion cracking, manufacturing defects, welding issues, equipment, third party / mechanical damage, incorrect operation, weather-related factors and outside force. Therefore, a comprehensive risk model should account for the available information of the pipeline, as well as consider the interactions between threats. This requires a model that incorporates many factors. A widely accepted approach for risk assessment is the E/M/R approach [2], which categorizes the factors into is exposure, mitigation, and resistance. Specific factors for each of these categories must be defined for every threat introduced above.

A thorough pipeline risk assessment model can be complex, requiring high-quality and comprehensive datasets as inputs. Much research has been dedicated to pipeline risk assessment, covering various threats faced by pipeline operations. [3-5]. However, the inputs for pipeline risk assessment models are often constrained by their accessibility and level of accuracy. The data completeness issue is a major challenge when implementing a pipeline risk model. Therefore, it is important to have a robust method for handling missing data and fill in the gaps with reasonable assumptions or estimations. A common solution is to use subject matter expert (SME) inputs and/or default values in risk assessment models when some factors are missing. This approach allows pipeline risk engineers to generate meaningful results, despite the potential introduction of significant uncertainty or a conservative bias. Another approach is to collect more data to feed into the risk model. However, with limited time and budget, it is critical to determine which missing factors have the strongest impact on the risk assessment results to improve the efficiency of data collection efforts. A sensitivity analysis of the pipeline risk assessment can answer the question of "which factors should be collected first".

A sensitivity analysis of pipeline risk assessment is also recommended or required by multiple industry standards. In ASME B31.8S, "Data Collection for Risk Assessment" section clearly specifies that "*If significant data elements are not available, modifications of the proposed model may be required after carefully reviewing the impact of missing data and taking into account the potential effect of uncertainties created by using required estimated values*" [1]. PHMSA Risk Model Working Group suggests that Pipeline operators should "*take ongoing actions to improve and update data quality and completeness over time*" [6]. Beginning in February 2024, Part 2 of the Pipeline and Hazardous Materials Safety Administration (PHMSA) Gas Mega Rule (RIN2) requires pipeline operators to ensure the risk assessment methods include "*a sensitivity analysis of the factors used to characterize the likelihood and the consequences of an incident*" [7].

In this research, the authors implemented a probabilistic risk assessment (PRA) model for a transmission pipeline. This comprehensive pipeline risk model consists of hundreds of factors. The objective of this research is to perform a sensitivity analysis of this probabilistic risk assessment and identify the impact of individual factors on the likelihood of failure and final risk score. This study first selects the factors to include in this sensitivity analysis; second, defines the input distribution of

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these selected factors based on the previous risk run and SME knowledge; third, runs a Monte Carlo simulation to assess the sensitivity.

Methodology

Transmission Pipeline Risk Model

A probabilistic risk assessment model for transmission pipelines is selected for this study. This model is developed by DNV, following the elements of pipeline risk assessment [2]. The model covers the eight essential elements in pipeline risk assessment including measures in verified units, probability of failure, consequence of failure, integration of pipeline knowledge, sufficient granularity, controlling the bias and unmasked aggregation [8]. The transmission pipeline probabilistic risk assessment model allows users to connect it to a GIS database and pull the linear referenced pipeline properties (e.g., diameter, wall thickness). The model is implemented in a web-based platform that allows the integration of GIS-based information, unsourced data templates such as an Excel table, as well as the SME knowledge. Figure 1 shows the high-level overview of the probabilistic risk assessment model used in this study. For each covered threat, the frequency of failure is calculated in events per mile per year. The consequence of failure is calculated in dollar values. The basic analysis item included in the model is dynamic segments. For each dynamic segment in the model, the results provide the frequency of failure, consequence of failure, and overall risk value.

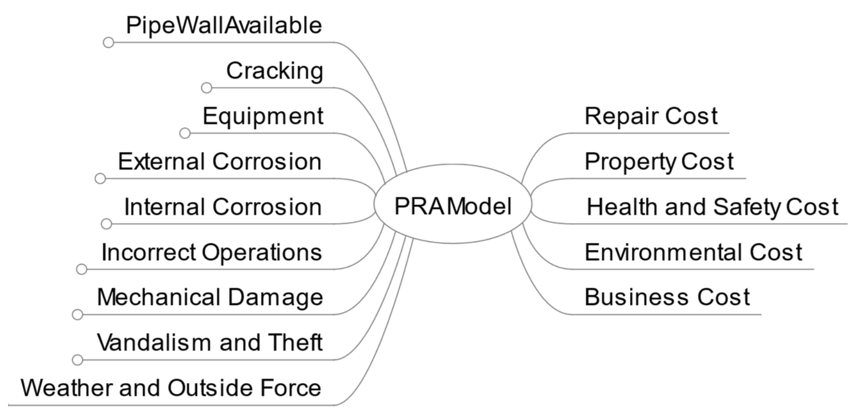

Figure 1. Overview of the probabilistic risk assessment model.

Sensitivity Analysis Approach Overview

The main steps of the sensitivity analysis include selecting and defining the distribution of input factors, identifying the baseline value in the risk assessment, running the Monte Carlo simulation, and generating and organizing the results. Figure 2 shows the steps covered in this sensitivity analysis study. In this study, the tool used to run the Monte Carlo simulation is @Risk® software, which allows user-defined on the input factors and subsequently performs the Monte Carlo simulation on

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the correlation between these input factors and the sensitivity output. The baseline model simulation is defined by referring to a completed transmission PRA risk assessment for an actual pipeline.

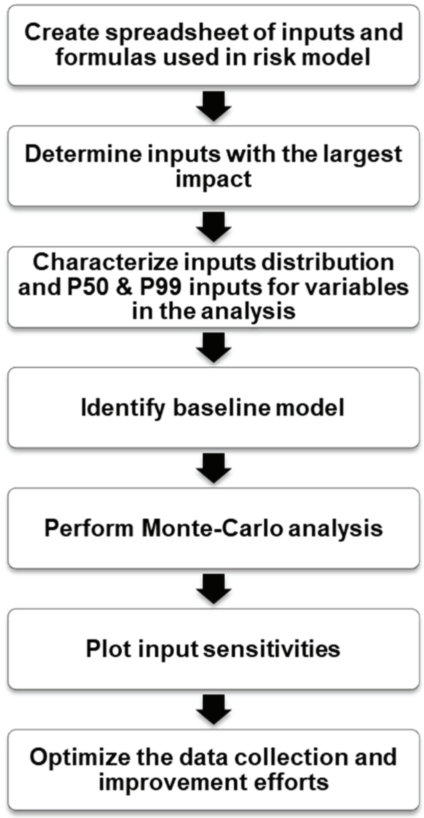

Figure 2. Sensitivity analysis approach in steps.

Input Factors Selection

There are over 300 distinct input variables in the transmission pipeline PRA model. These inputs come from GIS pipeline database, questionnaires, data templates, and analytical models. Running a complete iteration to perform a sensitivity analysis of every input is not feasible with the current computing power. With each new variable that is added to an iteration, there is an exponential increase in the number of unique scenarios that need to be tested. For example, if we are evaluating two discrete variables (either 1 or 0) there will be 4 (2^2) scenarios that will be evaluated (00, 01, 10, 11). When we add a third discrete variable, the number of scenarios increases to 8 (2^3) scenarios that will be evaluated. This exponential growth will require over 1 million scenarios with just 20 variables. Similarly, the computing power needed to properly evaluate each scenario will increase factorially, which will quickly overtake the computing power of our machines. This manifests in a Monte Carlo simulation in a similar way. As the number of evaluated variables increases, there will be an exponential growth of simulations that are required to produce statistically sufficient results. As such, if a 1 million simulation Monte Carlo were run on a system with hundreds of unknowns, the results will not be representative of the true distribution of risk because the sample size is too small.

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In this study, this issue is approached in two ways: by narrowing the focus down to around 20 variables that are deemed most likely to have the greatest effect on risk; and by dividing up each threat and running simulations to determine how each input affects the corresponding frequency of failure. The factors are selected by running a parametric study – changing one factor at a time to evaluate its impact on the risk results. The list is then reviewed and verified with the pipeline engineers. It is worth noting that the factors in this model are not necessarily independent. However, for the efficiency of this sensitivity study, the possible interdependencies between the input factors are not taken into consideration. In this study, the preliminary list of the selected factors included in the sensitivity analysis is shown in Table 1:

Table 1. The factors selected for the sensitivity analysis

Factor	Description
Outside Diameter	Pipeline Diameter.
Max Distance IBC Building	Maximum distance to pipeline for business buildings.
Distance IBC Building	Minimum distance to pipeline for business buildings.
Distance Resid Building	Minimum distance to pipeline for residential buildings.
PIR 1%	Potentially impacted area of building within the 1% fatal region.
PIR 100%	Potentially impacted area of building within the 100% fatal region.
Valve Present	If there is a valve present.
Corrosion Threshold	The corrosion threshold in %.
Depth of Cover	The depth of cover from GIS.
MAOP	The MAOP in GIS.
Normal Operating Pressure	The discharge pressure.
Pipeline Grade	The pipe grades.
Pipeline Install Date	The pipeline install date from GIS database.
Wall Thickness	The wall thickness from GIS database.
Wall Loss Feature Count	The wall thickness from UPDM database.
Annual Surge Event	The number of surge events per year.
Overpressure Value	The pressure value (in psi) over the stated MAOP.
Surge Pressure	The delta pressure between MAOP and the surge pressure.
Critical MD Wall Thickness	The wall thickness with 90% effective against puncturing the wall.
Wall Puncture Resistance	The max resistance.
Frost Heave Factor	Frost line critical depth % reduction to the wall thickness.

Inputs Distributions and Baseline Values

After the factors are selected, the distributions of the factors are defined, based on the available risk assessment run, industrial defaults, as well as the SME's knowledge. For example, to evaluate the impact of valves being present on the risk results, a yes/no distribution is defined. The Monte Carlo software allows multiple types of probability distributions on the input factors, including normal distribution, uniform distribution, discrete distribution, etc. Figure 3 shows a few examples of the

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distributions that are included in this sensitivity analysis. The normal distribution is used when the most likely valve (defined as P50) and worst-case value (defined as P99) are both available in the risk model (e.g., the critical wall thickness). A uniform distribution is applied when the desired lower limit and upper limit are known (e.g., the operating pressure). Discrete distributions are used for yes/no factors such as whether a valve is present on a pipeline.

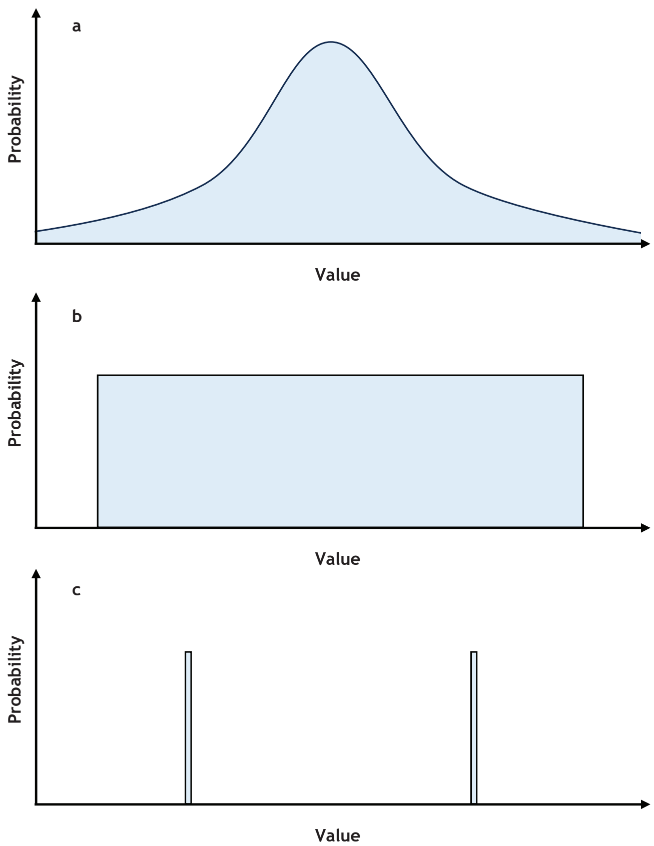

Figure 3. Distributions used to define the range of the input factors (*a.*, normal distribution, *b.*, uniform distribution, *c.*, discrete distribution)

Baseline Value Selection

As discussed above, there are over 300 factors in the risk model. For the factors that are not selected for the sensitivity analysis, a baseline value needs to be assigned to generate the Monte Carlo simulation results. In this study, the baseline value is selected by referring to an actual risk assessment result that was generated on a representative line in the system. It is important to note that the baseline value affects the sensitivity analysis results significantly, meaning that a sensitivity analysis result on a specific line may not apply to all the pipelines in the system, nor should it be reduced to the segment level.

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Monte Carlo Simulation

A Monte Carlo simulation was performed using Palisade @Risk® software. For the 21 factors selected for inclusion in the sensitivity analysis, a simulation of 1 million iterations was used to generate the sensitivity report. The authors observed that running a simulation with 10 million iterations returned the exact same ranking of sensitivity results. Therefore, 1 million iterations were chosen to balance the efficiency and precision of the results.

RESULTS AND DISCUSSION

Sensitivity Analysis Results

The Monte Carlo simulation generates a sensitivity rank as shown Table 2.

Table 2. Sensitivity analysis results in tabular format

Rank	Factor Name	Total_Risk / Value Correlation Coefficient
#1	Normal Operating Pressure	0.55
#2	Wall Thickness	0.51
#3	PIR 100%	0.24
#4	Pipe Grade	0.19
#5	Depth of Cover	0.15
#6	Overpressure Value	0.14
#7	Valve Present	0.12
#8	Outside Diameter	0.11
#9	Corrosion Threshold	0.10
#10	Wall Loss Feature Count	0.09
#11	Pipeline Install Date	0.09
#12	PIR 1%	0.06
#13	Frost Heave Factor	0.04
#14	MAOP	0.01
#15	Distance IBC Building	0.00
#16	Distance Resid Building	0.00
#17	Wall Puncture Resistance	0.00
#18	Distance to Comp Building	0.00
#19	Annual Surge Event	0.00
#20	Surge Pressure	0.00
#21	Critical MD Wall Thickness	0.00

Table 2 displays the absolute values of the Spearman correlation coefficient, which measures the strength and direction (positive or negative) of the relationship between two variables (in this study, the author compared ranking indices method including regression coefficient, contribution of

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variance, etc.; the Spearman correlation coefficient was found to provide more reasonable results as it measures both linear and non-linear monotonic relationships). The Spearman correlation coefficient is always between 0 and 1. The correlation evaluated in this table is between the 21 selected input factors and the total risk value. A higher number in the table indicates a stronger impact on the total risk. The positive or negative nature of the correlation is further explained in Figure 4, where the positive value means, the factors are positively related to the total risk, and negative means the opposite way. For example, the higher the operating pressure is, the higher risk is associated with the pipeline. In contrast, a lower wall thickness will lead to a higher risk value. The results align well with the common sense. For instance, the operating pressure affects multiple threats in pipelines, as it determines if the pipeline wall is strong enough to prevent loss of containment. The operating pressure also affects the consequence of failure because higher pressure will lead to a higher impact radius and higher cost. This agrees with the sensitivity analysis results. It is worth noting that the objective of this study is to introduce a method to run sensitivity analysis efficiently on the existing pipeline risk model. Therefore, these positive results suggest that this method is working.

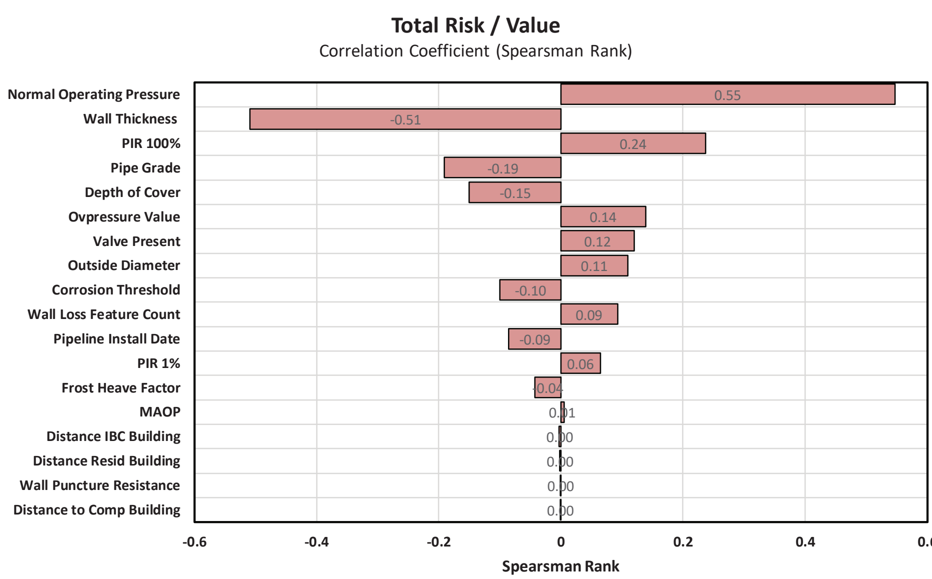

Figure 4. Tornado sensitivity ranking chart of the Spearman correlation coefficient

The Impact of Asset Levels on Sensitivity

The sensitivity results depend on the particular asset. This means that if the baseline pipeline properties are altered, the sensitivity ranking might change. Therefore, the sensitivity ranking for one pipeline shouldn't be used for another pipeline or a larger system of pipelines without assessment. For instance (Figure 5), product water content could affect the internal corrosion likelihood and risk level significantly for a bare steel pipeline, but it has almost no effect on a plastic pipeline because the internal corrosion threat is not relevant for plastic material. When assessing the sensitivity for a certain asset level, the specific inputs should be considered. In Figure 4, the minimum distance to nearby residential buildings is ranked lowest in the sensitivity ranking. This is because the impact radius in this study already overlaps with the nearby buildings. For other pipelines with a lower impact radius, this factor may become more important in the sensitivity ranking.

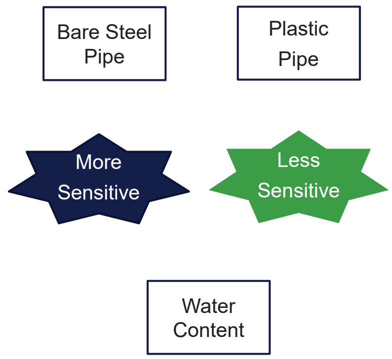

Figure 5. Example of asset specific sensitivity

Threat Specific Sensitivity

PRA models should include the threats required by the standard. This covers threats such as internal corrosion, mechanical damage, and incorrect operation. These threats may have very different mechanisms and sensitivities. As discussed above, internal corrosion threat is sensitive to water content in the product, while mechanical damage is not. The Monte Carlo methodology in this study provides a possibility for threat-specific sensitivity analysis as well. Figure 6 and Figure 7 show two sets of sensitivity analysis results for external corrosion and mechanical damage, with around 20 selected factors for each specific threat. These results serve as a reference for operators to determine threat-specific mitigation measures or maintenance plans in cases where a particular threat is of concern in pipeline operations.

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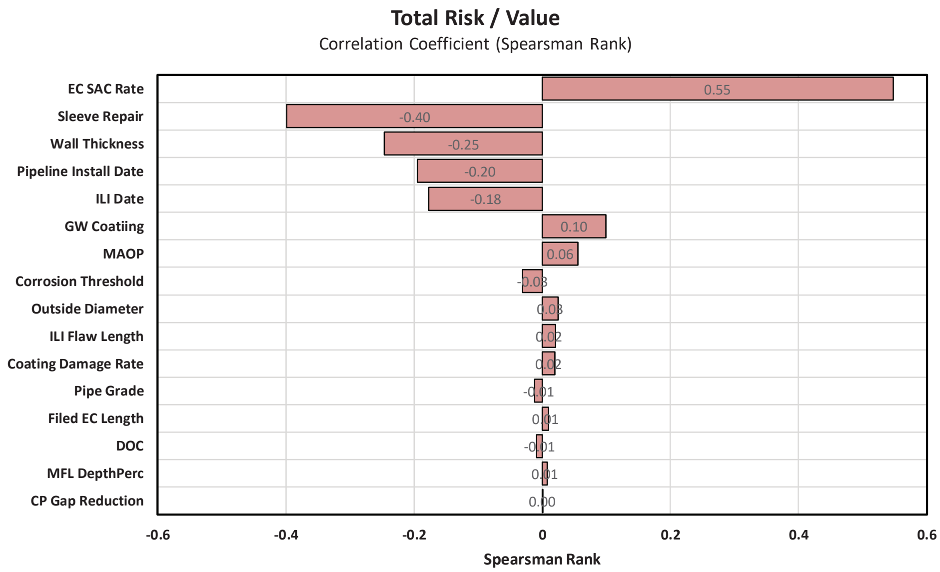

Figure 6. Threat specific sensitivity analysis – External corrosion

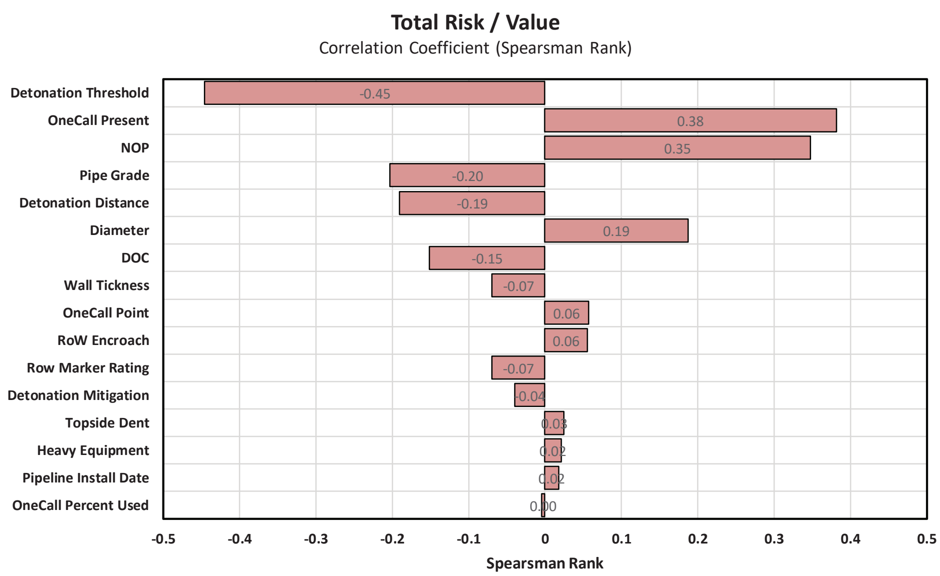

Figure 7. Threat specific sensitivity analysis – Mechanical damage

RESULTS AND DISCUSSION

In this paper, the authors present a sensitivity study (via Monte-Carlo simulation) methodology on a probabilistic pipeline risk assessment model that estimates the risk of pipeline failure. By performing the sensitivity assessment, the operators can identify the most influential parameters affecting the risk results. The sensitivity study ranks of the parameters selected in this study by their impacts on the pipeline risk. The model provides useful information for operators to understand the high-impact factors on the pipeline risk and to optimize the data collection effort to continually improving the precision of the risk results.

The authors emphasize that the objective of this study is to introduce a methodology for risk model sensitivity analysis. The ranking presented in the results is specific to the user-defined asset level, the PRA model baseline value, and the selected factors included in the simulation and are illustrative only. Therefore, this ranking of risk model factors should not be generalized to other pipelines or operators. A specific sensitivity assessment is recommended when factor ranking is needed. Additionally, this ranking should be refreshed by rerunning the sensitivity assessment after possible risk model updates and/or additional data collection efforts.

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