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Probabilistic finite element-based reliability of corroded pipelines

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The structural reliability of corroded pipelines subjected to internal pressure is generally assessed with explicit Limit State Functions. However, such closed-form burst pressure models lead to conservative reliability estimates, resulting in significant challenges in maintenance and risk management. This study presents a pathway for an implicit limit state approach that employs probabilistic numerical modelling, surrogate modelling, and a sample-based reliability method to provide computationally efficient probability of failure estimates for corroded pipelines. Machine learning approaches such as polynomial chaos-Kriging, sector vector machine regression, and Kriging methods were employed to develop a surrogate model based on the design and response points from the generated design of experiments. The reliability estimates from this approach are compared with simulation-based reliability methods to evaluate the efficiency and computational cost of these approaches. It is observed from the sensitivity studies, that the failure pressure of the corroded pipe depends more on the pipe's tensile strength properties than the yield strength. It is worth noting that the corrosion defect length and depth have greater influence on the failure pressure than the defect width. The insignificant contribution of pressure loading is ignored in the development of the surrogate model as it confirms Det Norske Veritas' explicit burst pressure formulation. The proposed approach improves the probability of failure estimates while reducing the simulation cost, thereby enhancing the opportunities for efficient risk considerations.

Keywords: corroded pipelines, uncertainty quantification, probabilistic numerical model, sensitivity studies, surrogate model, structural reliability.

1. Introduction

The structural reliability of corroded pipelines is commonly evaluated by probabilistic methods with closed-form formulations by considering uncertainties in the pipe and metal loss geometry, pressure loading, and mechanical material properties. The developed probabilistic based methods by researchers and industry standards such as Teixeira et al. (2008), Bhardwaj et al. (2019), and the Det Norske Veritas F101 (2019) to provide reliability estimates of corroded pipelines used explicit limit state functions. However, these closed-form solutions lead to conservative reliability estimates as underscored by Amaya-Gómez et al. (2019). The conservative nature of these approximations in the explicit burst pressure models of corroded pipelines subjected to internal pressure affects the computational costs and predictability, resulting in challenges for implementing the risk- based management philosophy.

Therefore, this research provides a probabilistic finite element-based reliability approach to improve the computational efficiency as well as the predictability of the reliability estimates, in comparison with the explicit burst pressure solutions. This proposed approach couples probabilistic numerical modelling with surrogate modelling and surrogate-based reliability methods to compute the probability of failure of corroded pipelines.

The paper is structured as follows: Section 1 introduces the justification and the proposed reliability approach to evaluate corroded pipelines; Section 2 provides the probabilistic methodology to compute the probability of failure of corroded pipelines to address the conservativeness and computational cost issues. The results and discussions of the numerical method, surrogate modelling and reliability evaluations are described in Section 3. Finally, the main findings of the research, limitations, and future work opportunities are presented in Section 4.

2. Methodology for Probabilistic Finite Element-based Reliability of Corroded Pipelines

To derive the computationally efficient reliability estimates of the corroded pipelines, the probabilistic approach employs a five-stage process, namely the uncertainty quantification, probabilistic numerical modelling, sensitivity study, surrogate modelling, and finally, reliability evaluation, as shown in Fig. 1.

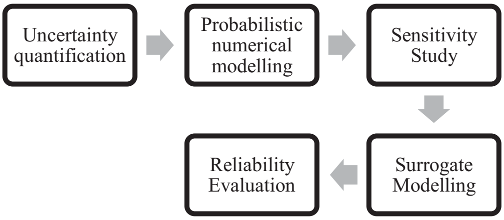


Fig. 1. Flowchart of the probabilistic finite element-based reliability approach.

The probabilistic approach commences by quantifying and selecting the best probability distribution fitting curve to reflect the variability of the critical pipe and corrosion geometric characterizations, material properties, and internal pressure loading. The computed uncertainties utilize the corroded pipe sample data from Teixeira et al. (2008) and recommended distribution curves from Bhardwaj et al. (2019) as given in Table 1. These uncertainties are then implemented in the probabilistic numerical model.

The probabilistic numerical model is developed from a validated deterministic model in compliance with provisions in British Standards Institution. and European Committee for Standardization BS 7910 (2019), generated using the mean-value estimates of the corroded pipeline features and material properties. The produced design of experiments from the probabilistic numerical model generates the key input random variables of the corroded pipeline system (identified in Table 1) as the design points and the pipeline failure stress as the model response point. The statistical dependency of the design variables in Table 1 is examined by computing the Spearman's rank correlation coefficient and the probability of occurrence for the null hypothesis of no correlation between design variables and an alternative hypothesis of a non-zero correlation. This statistical testing provides the best approach for the sensitivity study and surrogate modelling. The sensitivities of the design points to the true model response from the design of experiments are then conducted to screen and determine the impact of the material properties, pipe and defect geometry as

Table 1. Uncertainty quantification of key random variables for the corroded pipeline (Teixeira et al. (2008); Bhardwaj et al. (2019)).

No.	Key random variables	Mean or location or characteristic value	Standard deviation or shape	Unit	Distribution Fitting curve
1	External diameter of pipe (*D*)	406.40	0.41	mm	Normal
2	Pipe wall thickness (*t*)	12.70	0.13	mm	Normal
3	Metal loss defect depth (*d*)	4.05	2.00	mm	Weibull
4	Metal loss defect width (*w*)	52.00	2.00	mm	Weibull
5	Metal loss defect length (*L*)	323.70	2.00	mm	Weibull
6	Tensile Yield Strength (SMYS)	6.02	0.08	MPa	Lognormal
7	Tensile Ultimate Strength (UTS)	6.26	0.07	MPa	Lognormal
8	Internal pressure loading (*P*)	26.25	3.37	MPa	Gumbel

well as the internal pressure loading on the pipeline failure stress. Machine learning and regression methods such as Kriging, polynomial chaos Kriging and sector vector machine regression are applied on the screened design and response points from the design of experiments to develop the surrogate model.

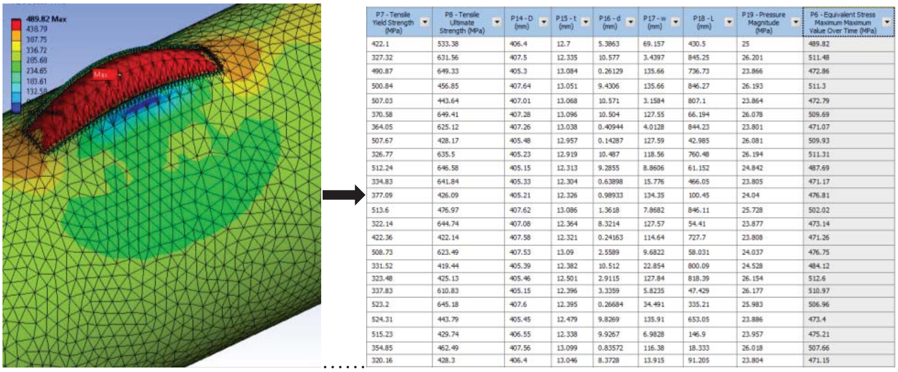
The surrogate model captures the non-linear relationships between the screened predictors and the pipeline failure stress. The probability of failure of the corroded pipe is estimated with surrogate-based reliability simulation methods and their efficiency is determined by comparing the number of samples in the simulation evaluations and the corresponding confidence interval.

3. Results and Discussion of Probabilistic Finite Element-based Reliability of Corroded Pipelines

The results of the probabilistic numerical modelling , sensitivity studies, surrogate modelling and reliability methods are discussed in this section.

3.1.*Probabilistic Numerical Model*

The probabilistic numerical model of the corroded pipe obtained from the mean-value deterministic model and the uncertainties from Table 1 produced a typical design of experiments dataset as shown in Fig. 2. This is achieved by using Kriging interpolation technique to define the sampling design points and response point.



P7 - Tensile Yield Strength (MPa)	P8 - Tensile Ultimate Strength (MPa)	P14 - D (mm)	P15 - t (mm)	P16 - d (mm)	P17 - w (mm)	P18 - L (mm)	P19 - Pressure Magnitude (MPa)	P6 - Equivalent Stress Maximum Maximum Value Over Time (MPa)
422.1	533.38	406.4	12.7	5.3863	69.157	430.5	25	489.82
327.32	631.56	407.5	12.335	10.577	3.4397	845.25	26.201	511.48
490.87	649.33	405.3	13.084	0.26129	135.66	736.73	23.866	472.86
500.84	456.85	407.64	13.051	9.4306	135.66	846.27	26.193	511.3
507.03	443.64	407.01	13.068	10.571	3.1584	807.1	23.864	472.79
370.58	649.41	407.28	13.096	10.504	127.55	66.194	26.078	509.69
364.05	625.12	407.26	13.038	0.40944	4.0128	844.23	23.801	471.07
507.67	428.17	405.48	12.957	0.14287	127.59	42.985	26.081	509.93
326.77	635.5	405.23	12.919	10.487	118.56	760.48	26.194	511.31
512.24	646.58	405.15	12.313	9.2855	8.8606	61.152	24.842	487.69
334.83	641.84	405.33	12.304	0.63898	15.776	466.05	23.805	471.17
377.09	426.09	405.21	12.326	0.98933	134.35	100.45	24.04	476.81
513.6	476.97	407.62	13.086	1.3618	7.8682	846.11	25.728	502.02
322.14	644.74	407.08	12.364	8.3214	127.57	54.41	23.877	473.14
422.36	422.14	407.58	12.321	0.24163	114.64	727.7	23.808	471.26
508.73	623.49	407.53	13.09	2.5589	9.6822	58.031	24.037	476.75
331.52	419.44	405.39	12.382	10.512	22.854	800.09	24.528	484.12
323.48	425.13	405.46	12.501	2.9115	127.84	818.39	26.154	512.6
337.83	610.83	405.15	12.396	3.3359	5.8235	47.429	26.177	510.97
523.2	645.18	407.6	12.395	0.26684	34.491	335.21	25.983	506.96
524.31	443.79	405.45	12.479	9.8269	135.91	653.05	23.886	473.4
515.23	429.74	406.55	12.338	9.9267	6.9828	146.9	23.957	475.21
354.85	462.49	407.56	13.099	0.83572	116.38	18.333	26.018	507.66
320.16	428.3	406.4	13.046	8.3728	13.915	91.205	23.804	471.15

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Fig. 2. Extracts of the numerical model failure stress and design of experiments.

The pipeline failure pressure is determined from the deterministic numerical model by examining the pressure at which the equivalent Von-Mises stress in the corroded region exceeds the pipeline yield strength and reaches the ultimate tensile strength of the pipeline material. The explicit Limit state function (G) in terms of the DNV failure pressure (Det Norske Veritas F101 (2019)) and prevailing internal pressure (P) is expressed in Eq. (1).

$$G = UTS \times \left(\frac{2t}{D-t}\right) \times \frac{\left(1-\frac{d}{t}\right)}{\left(1-\left(\frac{d}{t}\times\frac{1}{M}\right)\right)} - P \qquad (1)$$

where the Folias factor, M is defined in Eq. (2).

$$M = \sqrt{1 + 0.31\left(\frac{L}{\sqrt{Dt}}\right)^2} \qquad (2)$$

The failure pressure prediction from the deterministic finite element model deviates from the burst pressure equations of Det Norske Veritas F101 (2019), the modified formulation of the American Society of Mechanical Engineers B31G (2012) and ASME by 1.76%, 5.48% and 8.24% respectfully, as shown in Table 2, highlighting the validity of the numerical model.

Table 2. Failure pressure estimates from deterministic numerical model and existing approaches.

Burst Pressure Model	Failure Pressure (MPa)	Deviations from the numerical model (%)
Numerical model	25.00	-
DNV	24.56	-1.76
Modified ASME B31G	23.63	-5.48
ASME B31G	22.94	-8.24

The estimated deviation, Dev is given in Eq.(3).

$$Dev = \frac{(Predicted - Numerical\ Model)}{Numerical\ Model} \times 100\% \qquad (3)$$

The derived sampling design points, comprising of the variability of the input parameters and the corresponding failure stress response point from the numerical model are shown in Fig.3.

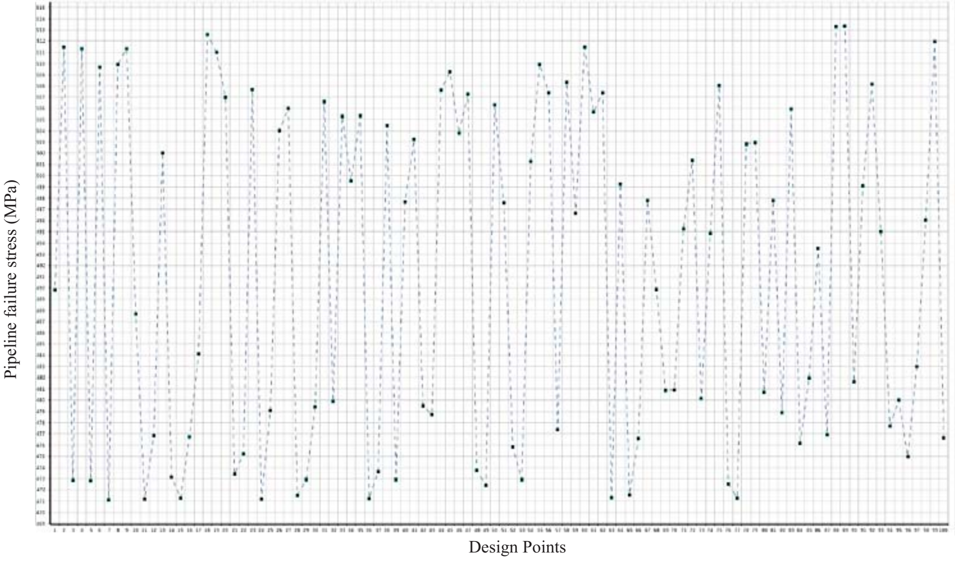

Fig. 3. Typical trendline of design points and failure stress response points from the probabilistic numerical model.

3.2.*Sensitivity Studies and Surrogate Modelling*

The results of the statistical dependence testing utilizing the Spearman correlation method and hypothesis testing of no correlation between the input variables is presented in Table 3. It is observed from Table 3 that the input parameters are statistically independent as the correlation coefficients are negligible and the corresponding p-values are not less than the significance level of 0.05. Hence the hypothesis of statistical independency is accepted. The sample-based sensitivity study of the input variables and model response from the numerical design of experiments revealed that the failure stress of the corroded pipeline is highly influenced by the tensile strength property of the pipe material than the yield strength unlike the yield strength-skewed equation proposed in Teixeira et al. (2008). The failure stress depends on the corrosion defect length than the defect width feature as shown in Fig. 4. The impact of the internal pressure on the failure stress is insignificant unlike the impacts from the defect depth, pipe diameter and pipe wall thickness, as stipulated by the failure stress formulations in Teixeira et al. (2008), Det Norske Veritas F101 (2019), and the American Society of Mechanical Engineers B31G (2012). Therefore, the internal pressure predictor is not included in the surrogate modelling stage. In the surrogate modelling, polynomial chaos Kriging is used to establish the non-linear relationship between the screened input variables and the failure stress of the corroded pipeline, since it produced an acceptable leave-one-out error of 0.04. The sample based-sensitivity, surrogate modelling, and the surrogate based-reliability methods of the corroded pipeline are conducted using UQLab simulation tools developed by S. Marelli and B. Sudret (2014).

Table 3. Estimated correlation coefficient and probability of occurrence using Spearman's correlation method.

Estimated correlation coefficient, rho								
variable	SMYS	UTS	D	t	d	w	L	P
SMYS	1.0000	0.0186	0.0821	0.0052	-0.0679	0.0136	0.0319	-0.1045
UTS	0.0186	1.0000	-0.0486	-0.0070	0.0141	-0.0404	0.0010	0.0843
D	0.0821	-0.0486	1.0000	-0.0312	-0.0053	-0.0609	0.0518	0.0085
t	0.0052	-0.0070	-0.0312	1.0000	0.0003	0.1456	0.0378	0.0730
d	-0.0679	0.0141	-0.0053	0.0003	1.0000	0.0147	0.0861	0.0256
w	0.0136	-0.0404	-0.0609	0.1456	0.0147	1.0000	0.0256	0.0234
L	0.0319	0.0010	0.0518	0.0378	0.0861	0.0256	1.0000	-0.0051
P	-0.1045	0.0843	0.0085	0.0730	0.0256	0.0234	-0.0051	1.0000
Probability of occurrence, p-value								
variable	SMYS	UTS	D	t	d	w	L	P
SMYS	1.0000	0.8544	0.4163	0.9590	0.5013	0.8932	0.7523	0.3004
UTS	0.8544	1.0000	0.6304	0.9447	0.8890	0.6895	0.9922	0.4039
D	0.4163	0.6304	1.0000	0.7574	0.9582	0.5467	0.6081	0.9331
t	0.9590	0.9447	0.7574	1.0000	0.9981	0.1481	0.7081	0.4698
d	0.5013	0.8890	0.9582	0.9981	1.0000	0.8842	0.3939	0.7999
w	0.8932	0.6895	0.5467	0.1481	0.8842	1.0000	0.7999	0.8169
L	0.7523	0.9922	0.6081	0.7081	0.3939	0.7999	1.0000	0.9601
P	0.3004	0.4039	0.9331	0.4698	0.7999	0.8169	0.9601	1.0000

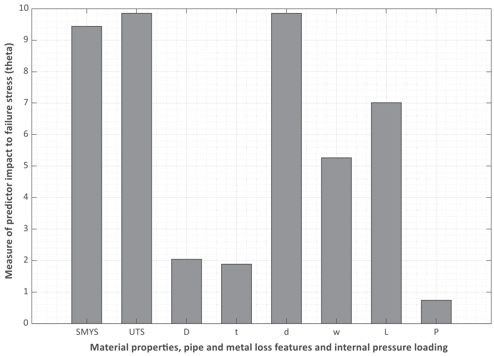

Fig. 4. Sensitivity of design variables using hyperparameters (theta) using polynomial chaos Kriging method.

3.3. *Surrogate-based Reliability Method*

The surrogate-based reliability methods, namely active learning with subset simulation and Monte Carlo simulation (MCS), are performed on the developed metamodel to determine the probability of failure of the corroded pipeline without specifying an explicit failure stress limit state function. The active learning with subset simulation reliability methods of the corroded pipeline based on the surrogate model yields a probability of failure (P_f) estimate of 7.25 x 10^{-2} within a confidence interval (*CI*) of 6.83 x 10^{-2} to 7.68 x 10^{-2} as displayed in Fig. 5.

The MCS produced similar probability of failure estimates but utilizes 10^6 model evaluations within an unreliable CI of 2.96 x 10^{-2} to -9.60 x 10^{-2}. It is observed that the active learning with subset simulation reliability evaluations produced the reliability estimates at a much lower computational cost of 114 model evaluations than the MCS, which uses ten million model evaluations. Additionally, the surrogate-based active learning approach produced reliable estimates with a better confidence range of 0.0085 than the confidence range of 0.126 generated by the MCS.

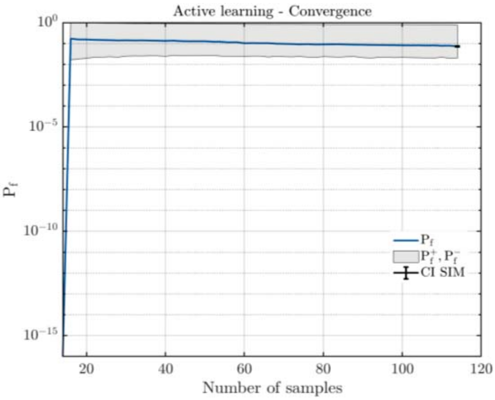

Fig. 5. Surrogate-based reliability estimates of the corroded pipeline.

4. Conclusions

The approximate estimates from the closed-form solutions for failure stress prediction of corroded pipelines require a method that explores implicit limit states from a surrogate model to enhance the computational cost and predictability of reliability estimates of corroded pipelines subjected to internal pressure. This paper provides an approach that employs probabilistic numerical models, surrogate modelling, and reliability evaluations. This section highlights the main findings, limitations, and future research work.

The probabilistic numerical model captures the uncertainties of the critical features of the corroded pipeline using the best distribution fitting models. It produced a validated matrix of design and response points in the design of experiments by using appropriate techniques in the Kriging method. The sample-based sensitivity analysis demonstrates the ability to determine the effect of material properties, pipe and metal loss geometry, and pressure loadings on the failure stress prediction of corroded pipelines. This affirms the inclusion of material properties such as tensile strength responsible for plastic deformation failure of the corroded pipeline in the surrogate model. Significantly, the corrosion defect depth and length, pipe wall thickness, and the pipe external diameter were included in the surrogate modelling stage. However, the applied pressure loading is excluded in the generated surrogate model, similar to the existing explicit burst pressure formulations, although they are conservative in nature.

The use of polynomial chaos Kriging-based surrogate modelling, instead of extensive numerical simulations, sufficiently establishes the non-linear relationship between the screened predictors and the pipeline failure stress of the corroded pipeline by producing an estimated error of 4%. The surrogate-based active learning reliability method produced efficient probability of failure estimates with fewer model evaluations bounded by more predictable results than the computationally expensive Monte Carlo simulation. This approach enhances the predictions of the probability of failure of the corroded pipeline while decreasing the cost of simulation, resulting in effective risk and maintenance management. The next stage of this research will explore approaches to enhance the time-dependent reliability of corroded pipelines.

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