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Deep Learning-Based Reliability Model for Oil and Gas Pipeline Subjected to Stress Corrosion Cracking: A Review and Concept

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Abstract: Stress corrosion cracking is considered one of the major causes of failures in oil and gas pipelines. This is why modeling the reliability of oil and gas pipelines subjected to stress corrosion cracking is very important; at the same time it is very complex due to various parameters affecting the stress corrosion cracking. Modern modeling approaches include physical-based and data-driven models that are still not competitive to cope with the complex nature of the stress corrosion cracking mechanism. In today's research, researchers prefer machine learning oriented algorithms and models to address such complex mechanisms due to their increasing popularity. These algorithms and models have the capability of tackling multiple factors and their impact on output response, allowing a prediction of the probability of failure. This research proposes some extensive simulations that lead eventually to a rich dataset that will define some significant factors on which stress corrosion cracking depends. In addition to this, the proposed research not only involves the correlation of derived dataset with the already published dataset but will also provide a comprehensive validation in between the proposed experimental work and machine learning based simulations. This research aims to propose a model that considers the most frequent parameters so that the performance of the proposed technique can be evaluated robustly and may provide a better understanding to upcoming researchers, including oil and gas personals.

Keywords: corrosion, finite element, reliability, machine learning, artificial intelligence.

基于深度学习的油气管道应力腐蚀开裂可靠性模型：回顾与概念

摘要：应力腐蚀开裂被认为是油气管道故障的主要原因之一。这就是为什么对应力腐蚀开裂的油气管道的可靠性进行建模非常重要的原因。同时由于各种参数影响应力腐蚀开裂，因此非常复杂。现代建模方法包括基于物理的模型和数据驱动的模型，这些模型仍然无法应对应力腐蚀开裂机制的复杂性。在当今的研究中，研究人员更喜欢面向机器学习的算法和模型来解决这种复杂的机制，因为它们越来越受欢迎。这些算法和模型具有解决多个因素及其对输出响应的影响的能力，从而可以预测失败的可能性。这项研究提出了一些广泛的模拟，最终导致了一个丰富的数据集，该数据集将定义应力腐蚀开裂所依赖的一些重要因素。除此之外，拟议的研究不仅涉及派生数据集与已经发布的数据集的相关性，还将在拟议的实验工作和基于机器学习的仿真之间提供全面的验证。这项研究旨在提出一个考虑最频繁参数的模型，以便可以对所提出技术的性能进行稳健的评估，并可以为即将到来的研究人员（包括石油和天然气行业人士）提供更好的理解。

关键词：腐蚀，有限元，可靠性，机器学习，人工智能。

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1. Introduction

Oil and gas pipelines are considered the lifeline for the oil and gas industry. They are regarded as the most economical mode of transporting hydrocarbons from one destination to another compared to other methods, such as train, road vehicles, and air [1]. These pipelines, which carry very expensive oil and gas, are also very dangerous if the pipe leaks or bursts, which could cause a massive financial and human loss. Therefore, it is critical to predicting the integrity of oil and gas pipelines to make proper maintenance strategies. Integrity management of oil and gas pipelines consists of three main steps: 1) corrosion detection, 2) corrosion growth, and 3) risk assessment. According to a report by the Conservation of Clean Air and Water in Europe (CONCAWE), factors causing pipeline failure are 1) corrosion, 2) mechanical damage, 3) natural, and 4) third party [2]. Among the causes of failure, corrosion is considered one of the significant reasons for pipeline failure, contributing 30.3% after third party (33.3%) and other causes contributes as Mechanical (25.25%), Operational (7.7%), Natural (4.4%) and others (1.1%), as shown in Fig. 1. According to the Pipeline and Hazardous Material Safety Administration (PHMSA), which is part of the United States Department of Transportation, an average of 287 pipeline incidents, 14 deaths, and 59 injuries happen every year [3].

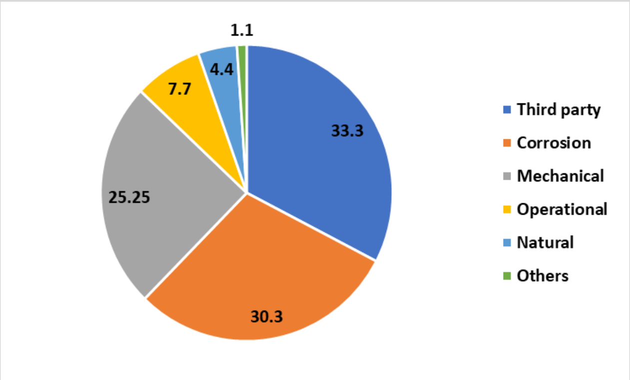

Fig. 1 Percentage of causes of damage in oil and gas pipeline [4]

Corrosion is very complex phenomenon caused by various factors, including electrochemical reaction, material properties, environmental factors, stresses and the properties of the medium flowing in the pipe.

Below are several types of corrosion, such as 1) CO2 corrosion, 2) microbiological induced corrosion, 3) pitting corrosion, and 4) stress corrosion cracking (SCC), which is different from other corrosion failures [5] because it is caused by the combined effects of environment [6, 7], stresses (applied or residual) [8] and material properties [9]. SCC is among the most dangerous types of failures because the prediction of its failure before its occurrence is challenging. Until the present, three modeling approaches have been widely used for the development of a model to predict corroded oil and gas pipe integrity. These are deterministic models, probabilistic models, machine learning models, and hybrid models [10]. But no mode currently can predict corroded oil and gas pipeline reliability in an accurate and realistic manner [11, 12].

Deterministic models based on the physics behind the process can provide its details, but they are very complex to compute and consider only a few parameters, making the model conservative in nature. Keeping in view the conservative and complex nature of these models, as well as scientists' attempts to adopt machine learning models, machine learning has successfully used in the field of reliability of engineering systems, including oil and gas pipelines. Hybrid models are the combination of both model-based and machine learning models, taking advantage of both models.

Various researchers have successfully modeled the corrosion integrity of oil and gas pipelines using machine learning approaches presented in the literature part of this proposal. From the literature, it is found that deep learning is receiving more attention from researchers in the integrity of engineering systems. Deep learning aims to learn higher-level abstractions from the raw data [13, 14]. Deep learning models require no hand-crafted features. Instead, they will automatically learn a hierarchical feature representation from raw data [15-17]. In deep learning, a deep architecture with multiple layers is built up for automating feature design. Specifically, each layer in deep architecture performs a nonlinear transformation on the outputs of the previous layer, so that through deep learning models the data are represented by different levels of hierarchy of features. Convolutional neural network, auto-encoders and deep belief network are the mostly known models in deep learning. Depending on the usage of label information, the deep learning models can be learned in either a supervised or an unsupervised manner. Deep learning models achieve remarkable results in reliability of various engineering applications including batteries [18], bearings [19] and aero engines [20] and turbines [21]. A recent survey indicated that the deep learning models have not been exploited in the field of integrity estimation for oil and gas corroded pipelines, even though deep learning models can improvise the integrity estimation significantly [22]. Similarly, after a comprehensive literature analysis, we found that the deep learning models can act as major contributors to predict integrity estimation in corroded oil and gas pipelines.

Therefore, this research study is focused on developing the deep learning-based corroded oil and gas pipeline integrity prediction model, more specifically for subjected to stress corrosion cracking. After its successful development, the model can be used as a simulation-free reliability model for oil and gas pipelines subjected to stress corrosion cracking.

2. Literature Review

Ren, Qiao et al. [23] predicted the internal corrosion rate of underground natural gas pipelines in China using Back-Propagation artificial neural network (BP ANN). The experimental run collects the inputs used in this model. Natural gas pipeline mileage, elevation difference, pipe inclination, pressure, liquid holdup, and Reynolds number are considered in this study as inputs. The research finding is that the BP neural network can predict the natural gas pipeline rate, and the model showed an excellent convergence ability [23].

Liao, Yao, et al. [24] used ANN-GA, ANN-PSO, and only ANN to predict the internal corrosion rate of natural wet gas pipelines. Among these three models, ANN-PSO outperformed the rest. The Grey relational analysis (GRA) technique was used before feeding the data into the model to check the collected data's input variables' importance. The model's inputs are gas maximum wall stress, liquid holdup, heat transfer coefficient of the inner wall, deposition rate, superficial velocity total liquid film, maximum wall shear stress, and pipe angle [24].

Chamkalani, Nareh'ei et al. [26] predicted the CO_2 corrosion rate of oil and gas pipelines using ANN. The inputs considered in the study are pH, velocity, temperature, and partial pressure of CO_2. The dataset of experimental research of Dugstad, Lunde, et al. [25] was used as the training dataset for the model. This dataset contains seven hundred and eighteen (718) data points. A sensitivity analysis was also performed that closely matched the experimental model results [26].

De Masi, Vichi et al. [27] predicted internal corrosion rate, metal loss, and defect area of a 20 km subsea oil and gas pipeline by using ANN and highlighted the portion of the pipeline that had a high risk of corrosion. The model combines the geometrical profile of a real pipeline, flow simulation, physical-based corrosion models and the De-waard model. After trying various learning algorithms, the Lavenberg-Marquadt (LM) algorithm was chosen as the best, with 20 as the highest number of hidden neurons found. This model performed better than the deterministic models [27, 28]. This model has the significant drawback that the operation needs to be stopped for inspection of the pipe. Also, the size of the dataset is smaller, which can decrease the model's accuracy.

Gabetta, De Masi et al. [29] used ANN for the prediction of internal corrosion rate, metal loss and area of defects for onshore gas pipelines. The inputs to the model considered in this study are geometrical features (elevation, inclination and concavity) and fluid dynamic multiphase variables (temperature profile, pressure profile, velocity profile of each phase, flow regimens and phase holdup). This model has the drawback of having a small dataset [29].

Din, Ithnin et al. [30] applied ANN to predict corrosion rate in carbon steel oil and gas pipelines. The inputs in this study were orientation, depth, length, and width of the corrosion defect. In-line inspection (ILI) data has been used to develop the model. The model predicts the pipe defect's length and depth, which can be used to predict the corrosion rate [30]. Although the prediction results obtained from ANN models have acceptable accuracy, the variables' uncertainty due to the deviation of test equipment measurements and the uncertainties in the natural gas system are neglected.

Mazzella, Hayden et al. [31] used ANN to estimate underground oil and gas pipeline corrosion rates. A North American pipeline operator dataset was used for the development of the model. The inputs considered in this study are related to the environment (sulfide pollution, chloride pollution, time of wetness, annual average temperature, number of years below 0 degrees) and pipeline parameters (actual diameter, year of mill run, pipe manufacturer) [31].

Nayak, Anarghya et al. [32] used ANN to predict the CO2 corrosion rate of the pipeline. The inputs to the model considered in this study are pH, the partial CO2 pressure, velocity and temperature. The dataset in this study was generated using an experimental setup. The optimum model was selected at five hidden neurons [32].

Sinha developed a probabilistic neural network to predict the probability of failure. This model can predict POF directly from the ILI data without extensive calculation of the conventional reliability methods, e.g., Monte Carlo simulations. The purpose of this model is to replace the traditional MC simulation. The data set for the neural network training was obtained by the simulation method [33]. This model can maintain the oil and gas pipeline, and benefit from reducing overall repair and maintenance costs.

Silakorn, Puncreobutr et al. [34] developed an ANN model to predict metal loss due to Top of Line (TOL) corrosion in the Gulf of Thailand carbon steel three-phase pipeline, using company field data. The inputs of the models considered were the parameters of corrosion rate (log distance, topography, pipe slope, gas flow rate, water flow rate, temperature, pressure, CO2, pipe nominal thickness, no. of sea-line batch treatment (SBT) per year, direction of east, topography series) and the output is the wall loss. In the first phase of this study, three pipelines with a data sample of six obtained from magnetic flux leakage were used to develop the model. Then two other pipelines which were not used during the training were used for testing purpose. The results of the model gave better predictions than the traditional simulation-based models. In the second phase of this project, 15 pipelines were used to develop a model. In this phase, sensitivity analysis for the input parameters was also carried out to check whether the inputs are important or not. The dataset consists of 6 data samples of 3 pipes, and these parameters were generated from the corrosion simulation model. The modes' accuracy was

2.6 to 6.5, greater than the other simulation models. The ANN model is capable of predicting the metal loss for new and existing pipelines [27]. The ultimate goal of the research is to reduce pipeline-associated costs. The model can not accurately predict if the data outside the data used for training is used.

Carvalho, Rebello et al. [35] developed ANN to predict the defects in the pipe weld zone of the API 5L-X65 pipeline. Two ANN models were used. The first was used to predict whether the signal was defective or non-defective. The other model was used to predict whether the defect was Internal Corrosion (IC), External Corrosion (EC), or Lack of Penetration (LP). For the model inputs, the magnetic flux leakage (MFL) signals were obtained from Pipe Inspection Gauge (PIG). The PIG was equipped with 136 hall sensors, and 1,025 data points were used for the ANN inputs. Preprocessing of the MFL signals was carried out using wavelet transformation, moving average filter, Fourier analysis, and Savitzky-Golay filter to improve the performance of ANN. The results showed that the model is 94.2% accurate for classifying defects; 92.5% for corrosion and LP; and 71.7% for classifying the EC, IC, and LP [28].

Tian, Gao et al. [36] used a wavelet neural network to predict the degree of corrosion of submarine oil pipeline that is "no corrosion, mild corrosion, moderate corrosion, and serious corrosion" under laboratory conditions. The inputs to the model used in this study are parameters from ultrasonic sensors and magnetic leakage sensors. The training data in this study were obtained from the experimental setup [29]. The number of datapoints is less. Therefore, this model faced the problem of overfitting.

Pipe failure pressure and burst pressure are significant in most reliability work. The limit state function depends on the pipe's failure pressure. ANN has also been successfully applied to predict the failure and burst pressure of corroded oil and gas pipelines.

Silva, Guerreiro et al. [37] predicted the failure pressure of pipes with interacting defects using ANN. In this study, FEM was used to generate the dataset. The inputs considered in the model were the relation between the defect depth and the pipe wall thickness and dimensionless circumferential spacing. The output is the relative pipe pressure capacity. The results were compared with the DNV-RP-F101. This model successfully associated the corrosion defect depth and length with the failure pressure [37].

Xu, Li et al. [38] used ANN to predict the burst pressure of API X-80 pipe. The model inputs were the ratio of defect length to pipe thickness, the ratio of defect depth to thickness, dimensionless longitudinal spacing, dimensional circumferential spacing, and the model's output was failure pressure. The study found that the model is capable of predicting failure pressure from the interacting pipe defects. The validation of the ANN model was done with the experiment [30].

Chin, Arumugam [39] predicted failure pressure subjected to internal pressure in 2020 by using ANN. The dataset was obtained from the full-scale burst pressure tests of API 5L X42 to X100 collected from various literature. The developed model was further validated with finite element modeling and a full-scale burst pressure test. This model was also used for the failure trend analysis of pipes with varied defect depths and lengths, which indicated that the defect depth is directly proportional to the pipe's failure. The model's inputs were the pipe's true ultimate strength, nominal diameter, nominal thickness, corrosion defect depth, and length [31].

Luo, Hu et al. [40] used Support Vector Machine (SVM) to predict the corrosion rate in offshore natural gas pipes. The inputs considered in the study were angle, pressure, deposition rate, the density of the liquid, the density of the gas, liquid velocity, liquid hold up, pH value, surface tension, flow regime, fluid temperature, superficial velocity of gas, heat transfer from inner wall pipe to fluid, inner wall surface temperature, heat transfer coefficient of the inner wall, the thermal conductivity of gas phase, gas maximum wall shear stress, liquid, and maximum wall shear stress. The author compared the results with the BP network and multivariable regression models, and after analyzing the results, SVM gave better prediction results [32].

Lee, Rajkumar et al.'s [41] applied classification approach by usin Euclidean-SVM and the MATLAB tool to predict the failure of oil and gas pipelines with long-range ultrasonic transducers (LRUT). The Euclidean-SVM performed better than the conventional SVM to classify corrosion defects when using LRUT in terms of accuracy. Also, the need for continuous modification and tuning of kernel function is eliminated in Euclidean-SVM, which makes it less computationally complex [33].

Ossai [42] predicted corrosion defect depth of aging pipelines using a Feed-forward Neural Network (FFNN) with optimized weights by Particle Swarm Optimization (PSO) method, Deep Neural Network (DNN) and Gradient Boost Method (GBM) approach. In this study, the model inputs considered are temperature, CO_2 partial pressure, pH, sulfate ion concentration, chloride ion concentration, iron content, total alkalinity, operating pressure, calcium concentration, basic sediment of water, a million cubic feet per day of gas, the barrel of oil production per day, and the barrel of water production per day. According to the experts, the model can be used for prognostic purposes [42].

Bastian, Jaspreeth et al. [43] used a deep learning model based on a convolutional neural network to predict the level of corrosion in oil and gas pipelines. The input of the model was the image dataset collected from oil and gas pipelines. The main benefit of using vision-based input is that operations can continue without stoppage [34].

2.1. Analysis and Discussion

The literature review found that machine learning is of great interest for researchers to model corroded oil and gas pipeline reliability. Despite the high rate of success in modeling, the majority of models are still reliably conservative and lack the capability of generalization. This issue can be solved by using different types of data sources to build the input data set for the model by developing the deep learning-based model for better accuracy and realistic modeling output. And still deep learning applications have to be implemented with more versions and data.

3. Material and Methods

The proposed model in this study is shown in Fig. 2, with the methodology consisting of two main parts, the data generation part and developing the deep learning model. The first part is mainly focused on the coupling of the physical-based modeling with reliability analysis to predict the probability of failure (POF). The second part is developing and optimizing the deep learning model. The steps to achieve the proposed model in the section below are shown in detail. This study focuses on the development of deep learning models, which is why the data generation part is not discussed in detail.

3.1. Physical-Based Modeling

Finite element analysis (FEA) is considered to be the accepted approach for obtaining the important information in many engineering areas, such as residual stresses and corrosion modeling [35]. Finite element analysis will be used in this study using COMSOL [36] software for obtaining the limit-state function. Pitting—considered as the precursor to stress corrosion cracking—and the cracking mechanism will be solved by getting the stress corrosion cracking results.

3.2. Boundary Conditions

Table 1 Boundary condition for the pipe studied

Parameter	Value
Pipeline	Corban steel
Pipe outer diameter	508 mm
Pipe wall thickness	9.5 mm
Forces	Residual stresses, soil pressure, operating pressure

3.3. Mechanical Model

This section shows the process of determining the strength of a pipeline. To achieve this goal, various standards have been proposed, such as DNV RPF, SHELL, or ASME B31G. The mentioned codes will be used to evaluate the strength of the corroded pipeline and subsequently to determine the failure pressure.

3.4. Reliability Analysis

In this section, pipeline reliability will be analyzed in terms of probability of failure (POF). The information generated from the FEA model will be used for the limit-state function g(x). Then, by using a numerical model for reliability analysis—such as FORM, SORM, or a Monte Carlo simulation—the probability of failure will be predicted.

3.5. Limit State Function

Limit stat function is considered to be the security border, which is conveniently defined by the difference between the pipe pressure resistance and the applied pressure,

$$G(x) = P_r - P, \tag{1}$$

where x is the realization of the random variables of the pipe. This margin is defined such that $G(x) > 0$ represents safety and $G(x) < 0$ shows the failure of the pipe.

3.6. Probability of Failure

For predicting the probability of failure in this study, we will use RELIASOFT Weibul software:

$$POF = \frac{n(LSF \leq 0)}{N} \tag{2}$$

where N is the total number of experiments and $n(LSF \leq 0)$ is the number of experiments that lead to failure. A summary of input data used in the reliability assessment is given in Table 2.

Table 2 Probability distributions of oil and gas pipeline

Variable	Probability distribution
Operating pressure	Normal
Yield strength	Normal
Tensile strength	Normal
Corrosion defect depth	Normal
Corrosion defect length	Normal
Crack growth	To be defined
Nominal wall thickness	Fixed
Outside diameter	Fixed

3.7. Proposed Machine Learning Model

In this research, the purpose is to propose the machine learning-based model for predicting the probability of failure for corroded oil and gas pipelines. From the literature survey during gap finding, it has been found that machine learning has been used effectively for the reliability prediction of corroded pipelines but still advance machine learning and particularly deep learning has not been utilized at a satisfactory level based on the author of this paper. Therefore, in this research, the author has proposed deep learning models, such as Long Term Short Term Memory (LSTM) and Physics Informed Deep Neural Networks (PINN), for the probability of failure predictions. The development of the model will be carried out in future work.

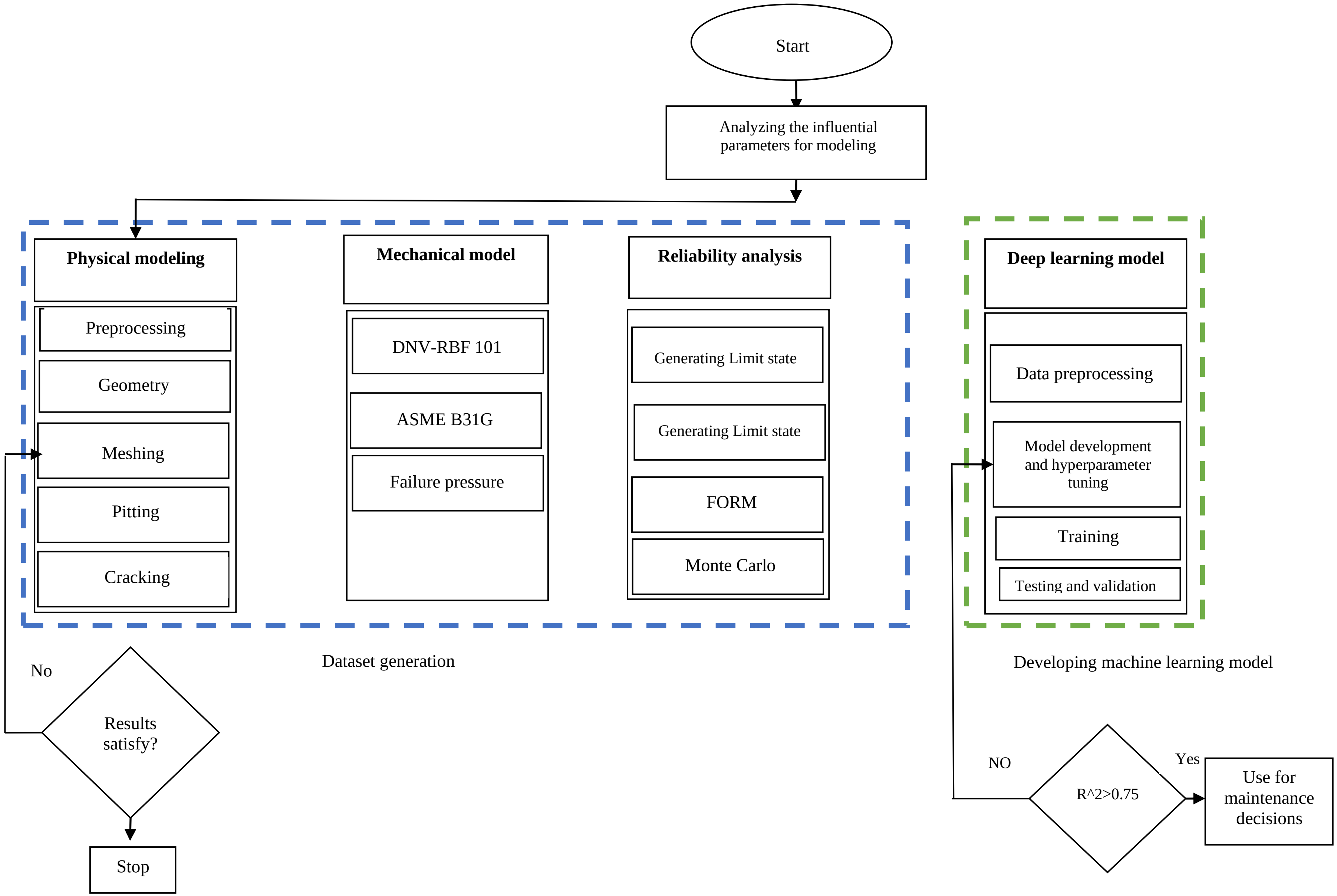
Start
Analyzing the influential parameters for modeling
Physical modeling
Preprocessing
Geometry
Meshing
Pitting
Cracking
Mechanical model
DNV-RBF 101
ASME B31G
Failure pressure
Reliability analysis
Generating Limit state
Generating Limit state
FORM
Monte Carlo
Deep learning model
Data preprocessing
Model development and hyperparameter tuning
Training
Testing and validation
Dataset generation
Developing machine learning model
No
Results satisfy?
Stop
NO
R^2>0.75
Yes
Use for maintenance decisions

Fig. 2 Proposed model for the research

4. Expected Results of the Model and Implications

The expected outcome of the proposed model is as follows:

- The model can predict the probability of failure without extensive simulations.
- The model can be used to consider multiple influential factors at a time.
- The accuracy of the model prediction can be higher than the existing approaches.
- There will be no need to do physical and complex modeling after the successful development of the model.

5. Conclusion and Future Work

5.1. Conclusion

Stress corrosion cracking in oil and gas pipelines is considered one of the major causes of failure. Its complex nature due to the combined effect of stresses and corrosion makes modeling of reliability more difficult. Currently, traditional modeling approaches are not capable of modeling the reliability of the pipelines subjected to stress corrosion cracking. After a thorough literature survey, it has been found that machine learning methods are the best modeling tool to model the reliability of such complex systems. In this research, the advantages of deep learning over these drawbacks have been identified and proposed in the deep learning-based reliability model for oil and gas pipelines. The dataset for stress corrosion cracking parameters will be acquired through simulations using finite element and first-order reliability methods and published literature data. After validation of the dataset, the model will be developed. The proposed model will be able to predict the reliability of the oil and gas pipelines in terms of probability of failure without performing the traditional time-consuming and complex modeling.

5.2. Future Direction

The model proposed in this study will be implemented by using different versions of deep learning and predict the probability of failure in oil and gas pipelines subjected to corrosion. Upon successful validation of the model, the model will be further used for maintenance planning decision making.

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