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Application of Adaptive Neuro-Fuzzy Inference System Approach for Modelling and Prediction Corrosion Penetration Rate in Crude Oil Pipelines Based on NORSOK Simulation Software

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ABSTRACT

This study aims to study the effect of several relevant parameters, namely temperature, pressure, flow rate, and pH, on the Corrosion Penetration Rate (CPR) of the process of transporting crude oil through pipelines through simulation. NORSOK software was used to simulate the experiments and calculate the corrosion penetration rate for each experiment. Experiments were designed based on central Compound Experimental Design (CCD) using Minitab 17 software. Adaptive Neuro-Fuzzy Inference System (ANFIS), were employed to predict the corrosion penetration rate. The predictions obtained from this method was then compared to the actual values acquired through simulation. To evaluate the accuracy of the predictions, the Mean Absolute Percentage Error (MAPE) was calculated. The mean absolute percentage of error for prediction models using ANFIS is 0.0%.

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Introduction

The transportation of heavy and extra-heavy crude oils from the head-well to the refinery is becoming important since their production is currently rising all over the world. Such oils are characterized by a low API gravity (< 20) and high viscosity (> 103 cP at 298.15 K) that render difficult oil flow through pipelines. Conventional technology pipelining is designed for light and medium oil crudes, but the pipelining of heavy and extra-heavy crude oils may be challenging because of their high viscosities, asphaltene and paraffin deposition, increasing content of formation water, salt content and corrosion issues [1].

One of the necessities of an effective oil and gas pipeline safety Management Plan (SMP) is the establishment of safe and efficient risk assessment strategy for pipelines where the significant danger is corrosion. Corrosion growth is related to several factors involving pipe material, pipe condition, and defect geometrical imperfection. Thus, the assurance of a proper corrosion assessment requires the prediction and evaluation of corrosion growth rates. The prediction of corrosion growth rate precisely, would minimize the cost of pipelines maintenance through the determination of the deteriorated pipeline segments. In Line Inspection (ILI) has been used to detect the pipelines corrosion, also the corrosion can be detected by other inspection tools such as Magnetic Flux Leakage (MFL) and Ultrasonic Tool (UT). However, there are numerous models have been utilized to anticipate the corrosion growth rate such as deterministic and probabilistic models. Recently, there are conducted researches on the application of artificial intelligence in predicting corrosion growth rate for oil and gas pipelines such as Artificial Neural Network (ANN) and fuzzy logic (FL) [2].

Corrosion in lubricate and vapor enterprises principally handles CO_2 gas as it is the main cause of disappointment in the stream subdivision of the lubricate and smoke manufacturing of pipelines from element fortify that has advantages in conditions of chance, cost, and ease of lie over additional alloys. Unfortunately, element brace has lower fighting to colorless odorless gas disintegration. In addition, some differing bitter classes are present in lubricate field accompanying interplay 'tween ruling class, to a degree temperature, pH, flow rate (m/s), CO_2 partial pressure and tart acid (HAC) and CO_2. The vicinity of element dioxide (CO_2) in the fluid steps up the disintegration rate on account of allure reaction accompanying water that results in making carbonic acid [1].

Based on former experiments, it was proved that when CO_2 is separated in water happen three types of responses concede possibility occur to a degree the assimilation, photoelectric and photoelectric responses, and backlashes superior to the establishment of a group of chemical elements and carbonate (FeCo3) layers upon brace namely famous expected alive in acid answer therefore, water pH is discounted and causes corrosion on element brace [2]. Many research documents are vacant on CO_2 disintegration indicator and the belongings of variety like HAC accompanying several different operating limits containing hotness, pH, and flow rate [3,4]. Most of the indicator models depend particular algorithms to connect individual effect of the communicating species to produce a representative total disintegration rate. The individual effect is persistent from the exploratory routine of property fixed sure variables and changeful the principles of another variable. This exploratory arrangement was wasteful and needs a lot of experiments to process all likely disintegration dossier. In addition, the prophecy does not completely cover representing dossier together [5]. In this paper, a mathematical model was developed to predict the effect of operating parameters of the crude oil transportation process on CO_2 corrosion rate by using RSM.

Literature Review

The study conducted by Senussi and colleagues focuses on the implementation of a backpropagation artificial neural network approach to create a model for accurately predicting the CO_2 Corrosion Penetration Rate (CPR) under specific operating conditions [6]. Their model successfully correlates input parameters such as pH, temperature, pressure, and shear stress to CPR. The backpropagation network (BPN) was able to adjust its weight coefficients efficiently with a small set of examples, indicating reliable output generation. Validation of the developed BPN model using Mean Absolute Errors (MAE) resulted in a value of 0.00457 mm/year, highlighting the model's precision and dependability.

In another study, Bushra and team developed a Fuzzy Logic model to forecast CO_2 erosion, sweet environment, and CPR of the steel pipeline at the Libyan Arabian Gulf Oil Company (AGOCO) Sariir-Tobruk [7]. The research encompassed various values of crucial operating parameters like temperature (112-126 °F), pressure (195-494 psi), and pH (5.51-5.65). MINITAB software was employed for Design of Experiments (DOE), while MATLAB (2013) Toolbox was utilized for developing the fuzzy logic model to predict CO_2 erosion penetration rate (CPR). NORSOK M-506 software was used for simulating and calculating CPR for each experiment. The study revealed that the predicted CO_2 corrosion penetration rate closely matched the NORSOK M-506 calculated rate, with a mean absolute error (MAE) of 0.01. This demonstrates the potential of Fuzzy Logic as a reliable technology for predicting CPR during crude oil transportation through steel pipelines.

Furthermore, Sulyman et al. investigated the impact of temperature, pressure, flow rate, and pH on the Corrosion Penetration Rate (CPR) during the transportation of crude oil through pipelines [8]. The study aimed to establish a mathematical model with these parameters as independent variables and CPR as the dependent variable. Response surface methodology was used to determine the optimal values for these parameters. Aspen HYSYS software was employed to simulate experiments and calculate the corrosion penetration rate. The experiments were designed using the Central Composite Experimental Design (CCD) in Minitab 17 software. The mean absolute percentage error was utilized to assess the model's accuracy, resulting in a value of 0.02%, indicating consistency. The Nash Sutcliffe Efficiency (NSE) was also calculated, with a value of 0.999, confirming the model's high efficiency. The study determined the optimal conditions for corrosion penetration rate as temperature (100°F), pressure (360 psig), flow rate (150,000 bbl/day), and pH (5.65), resulting in a minimum corrosion penetration rate of 3.98 mm/year.

Methodology

A Material

Numerous factors play a role in the Corrosion Penetration Rate (CPR). This study delves into the impact of temperature, pressure, shear stress, and pH on CPR by employing Response Surface Methodology (RSM). The focus is on a pipeline associated with AGOCO, extending from the Sarir field to the Hrayqa oil port in Tobruk, covering a total distance of 514 km. The pipeline has a diameter of 34 inches, and the mole percent of CO_2 is considered. The research involves the modeling and prediction of the Corrosion Penetration Rate in a crude oil pipeline using an Adaptive Neuro-Fuzzy Inference System Approach based on NORSOK Simulation Software for the period spanning from January 1, 2019, to January 1, 2023.

B Adaptive Neuro-Fuzzy Inference System Approach

One kind of Artificial Intelligence (AI) that aids in inference, modeling, and prediction is called ANFIS. The Fuzzy Inference System (FIS) known as ANFIS operates in the framework of adaptive networks. It integrates the concepts of Fuzzy Logic (FL) and Neural Networks (NN) into a single framework that performs as a universal estimator and can learn to estimate non-linear functions. It was developed under the name Takagi–Sugeno FIS in the early 1990s. The learning networks of this concept are based on complex mathematical computations that may resolve challenging issues. The adaptive system determines the parameters of fuzzy inference systems of the Sugeno type using a hybrid learning method [9]. An adaptive network is a multilayer feed-forward network made up of nodes connected by directed connections, where each node processes incoming signals according to a specific function to produce an output from a single node. In an adaptive network, each link—which has no associated weights—specifies the direction in which signals flow from one node to another. To be more precise, an adaptive network's configuration applies a static node function to its incoming signals in order to produce a single node output. Each node function is a parameterized function with adjustable parameters, which can be changed to alter both the node functions and the adaptive network's overall behavior.

As there are four input parameters namely, temperature, pH, pressure, Shear Stress. The output response selected for these experiments was tensile strength. The upper (+1) and lower (-1) levels of all the four parameters and their designations are shown in table 1.

Table 1: The Levels of Process Parameters

Variable (Factor)	Units	Notation	Low	High
Temperature	ºF	X1	112	126
Pressure	Psi	X2	195	494
pH	---	X3	5.51	5.65
Shear Stress	Psi	X4	1	30

In this work, the variables considered are those most critical to CPR; temperature, pressure, pH, and Shear Stress. The experimental design was conducted according to the CCD method in Minitab 17 program for four factors and one response. CCD determined total experimental runs of 31 as shown in table 2. To carry out these experiments, the reality was simulated using NORSOK.

Table 2: Design of Experiment and its Actual Values of CPR

T (F)	P (psi)	Hp	S (psi)	Actual CPR mm/yr
119	344.5	5.58	15.5	2.8
112	195	5.65	30	2.1
119	344.5	5.58	15.5	2.8
119	344.5	5.545	15.5	2.9
112	195	5.51	30	2.4

119	344.5	5.58	15.5	2.8
119	344.5	5.615	15.5	2.7
119	269.75	5.58	15.5	2.4
119	344.5	5.58	15.5	2.8
112	494	5.65	1	2.2
112	494	5.51	30	4.2
126	494	5.51	30	3.9
119	344.5	5.58	15.5	2.8
119	344.5	5.58	15.5	2.8
126	195	5.51	1	1.5
126	494	5.65	30	3.3
112	195	5.65	1	1.4
122.5	344.5	5.58	15.5	2.7
126	494	5.51	1	2.4
115.5	344.5	5.58	15.5	2.8
119	419.25	5.58	15.5	3.1
126	195	5.51	30	2.3
112	494	5.65	30	3.6
119	344.5	5.58	8.25	2.6
126	195	5.65	1	1.2
126	195	5.65	30	1.9
112	195	5.51	1	1.5
119	344.5	5.58	15.5	2.8
112	494	5.51	1	2.6
119	344.5	5.58	22.75	2.9
126	494	5.65	1	2.1

C Results

The response data were calculated by the NORSOK model. Then, the data were entered in the Matlab worksheet, and after that the predicted values of CPR were calculated as shown in table 3.

Tables 3: Actual Values by NORSOK Model and Predicted Values by RSM

T (F)	P (psi)	Hp	S (psi)	Actual CPR mm/yr	Prediction CPR mm/yr
119	344.5	5.58	15.5	2.8	2.8
112	195	5.65	30	2.1	2.1
119	344.5	5.58	15.5	2.8	2.8
119	344.5	5.545	15.5	2.9	2.9
112	195	5.51	30	2.4	2.4
119	344.5	5.58	15.5	2.8	2.8
119	344.5	5.615	15.5	2.7	2.7
119	269.75	5.58	15.5	2.4	2.4
119	344.5	5.58	15.5	2.8	2.8
112	494	5.65	1	2.2	2.2
112	494	5.51	30	4.2	4.2
126	494	5.51	30	3.9	3.9
119	344.5	5.58	15.5	2.8	2.8
119	344.5	5.58	15.5	2.8	2.8
126	195	5.51	1	1.5	1.5
126	494	5.65	30	3.3	3.3
112	195	5.65	1	1.4	1.4
122.5	344.5	5.58	15.5	2.7	2.7
126	494	5.51	1	2.4	2.4
115.5	344.5	5.58	15.5	2.8	2.8
119	419.25	5.58	15.5	3.1	3.1
126	195	5.51	30	2.3	2.3
112	494	5.65	30	3.6	3.6
119	344.5	5.58	8.25	2.6	2.6
126	195	5.65	1	1.2	1.2
126	195	5.65	30	1.9	1.9
112	195	5.51	1	1.5	1.5
119	344.5	5.58	15.5	2.8	2.8
112	494	5.51	1	2.6	2.6
119	344.5	5.58	22.75	2.9	2.9
126	494	5.65	1	2.1	2.1

D Validation Model

To validate the developed model, the Mean Absolute Percentage Error (MAPE) was used to estimate the variation between the actual and predicted CPR. The value of the MAPE is 0.0%, compared with the actual values of Corrosion Penetration Rate, as plotted in Figure 1.

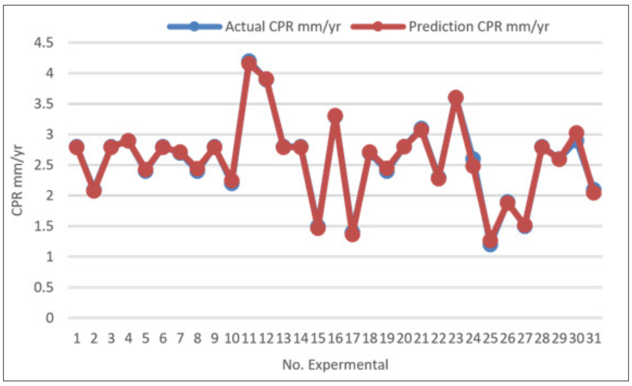

Figure 1: The Actual and the Predicted CPR

Conclusion

In this study, attempts were made to predict the corrosion penetration rate of the pipelines that are used for transporting crude oil between Sarir-Tobruk stations. The corrosion penetration rate values were determined by using NORSOK software. The following points summarize the conclusions of the study: Based on the comparison between the actual values of corrosion penetration rate calculated by using NORSOK software and the predicted values of corrosion penetration rate by using the RSM technique, it can be concluded that the RSM model could be used to predict the values of corrosion penetration rate, under the specified parameters ranges, with a mean absolute percentage error of 0.0% [10].

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