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Predictive Model for oil and gas Pipelines in Nigeria: A Taguchi Design approach

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Abstract
In this paper, Taguchi robust design method has been applied to obtain a robust regression model which optimizes the rate of corrosion in oil and gas pipeline systems. Orthogonal array design for the $L_8 2^4$ was used to establish the process response parameters, also a quadratic regression analysis of the optimal values for the parameters presents us with a quadratic model. Sensitivity analysis on this model displayed temperature (P2) as the most sensitive to the system response. The optimal values of P1 (Mean Ph), P2 (mean temperature), P3 (Mean pressure) and P4 (Mean aqueous CO_2 partial Pressure) were established.

Keywords: Oil & Gas pipeline, Corrosion rate, Taguchi robust design, Sensitivity analysis

1. Introduction

Crude oil is the backbone of Nigerian economy, accounting for over 80% of total foreign exchange revenue at present. Pipelines provide the safest, most convenient and economical means of transporting large quantities of crude oil from one point to another. Deterioration in metallic pipeline usually occurs as a result of the damaging effects of the surrounding environment and for mild steel, one of the most dominant forms of such deterioration is corrosion and this is a major cause of pipeline failure around the world (Callister 1997). The economic consequence of corrosion is a very important motivation for this study. Some of these consequences are; shutdown of facility for repairs, loss of oil and gas through corroded pipelines, loss of efficiency (due to diminished heat transfer or because of the clogging of pipe with rust necessitating increased pumping capacity). These losses amount to billions of Naira and ought to be reduced via a reliable model for prediction of corrosion rate.

Robust design methods over the years have proved to be a reliable method in themodelling of a process. This is because it focuses on eliminating the noise factors in a system, thereby reducing cost of failure and maintenance for the system. To reduce the hazardous effect of corrosion of mild steel in pipeline systems, we would employ Taguchi's Robust Design method. This method presents us with the opportunity to develop an optimal model which can be applied to new or existing processes. This will save the huge loss incurred from pipeline failures.

1.1 Review of related Literature

There are different approaches to CO_2 corrosion modelling for use in the oil and gas industry. Nesic etal. (1997) have classified them into three categories namely: Empirical, Semi-empirical and Mechanistic models. Empirical models are developed from little or no theoretical background (Nesic 2007). They could be linear or non-linear mathematical correlation derived from measured corrosion rate data (Fosbol et al. 2009). The model developed by Dugstad et al. (1994), is one of the commonly used empirical models; other empirical models included the linear multiple regression model by Faustenua and Adams (1996), and the recent non-linear model of Nesic (2007).Purely empirical models have little theoretical backing and most or all the constants have little physical meaning and are just best fit parameters to the available experimental data. Extrapolation of empirical models could be very risky because of the large number of models available and most models are similar to one another with minor modifications.

The semi-empirical models are similar to the empirical models in that they are developed from measured corrosion rate data but differ with respect to the equations used for their derivation (Fosbol et al. 2009). One of the advantages of these models is their simplicity and requires less work in determining the corrosion rate. Unfortunately, like the empirical models they require large datasets and do not easily extrapolate to other systems (Fosbol et al. 2009). They are generally more popular in the oil and gas industry compared to other models because of their successful application. Examples of semi-empirical models include the popular De Waard and collaborators (Nesic 2007) and the recent models of Smith and De Waard, and Teevens et al. (2008), which included a software program.

Mechanistic models have a strong theoretical background. Most of the constant in these models have a clear physical meaning according to Nesic et al. (1997), when calibrated on a reliable experimental database this type of model should generally produce accurate and physical realistic results. They take into consideration the chemical, electrochemical, transport processes and engineering principles and not just measured corrosion rate data (Olsen et al. 2005; Kapusta and Pots 2004). Within their theoretical limits, they can be extrapolated to conditions outside of the database used to develop them with a good level of reliability (Fosbol et al. 2009). However, the main challenge with the mechanistic models is the fact that they are time consuming, difficult to develop and require more work to adapt them to new systems and are therefore not so popular with operators.

Other Models for CO_2 Corrosion rate

Electrochemical models

Almost two decades later Gray et al. (1989) presented a more complete electrochemical model as a part of their experimental study of CO_2 mechanisms. A number of mechanisms for the electrochemical reactions occurring at the metal surface were adopted from the literature and included into an overall model. The model constants were determined from their own glass cell experiments and flow cell experiments (for higher temperatures). In its scope and approach this was a ‘‘breakthrough’’ study in the field of CO_2 corrosion modeling. The authors ambitiously attempted to cover an unrealistically broad unrealistic range of parameters (e.g. pH 2–11, temperature = 25–125^{0}C) with a rather simple theoretical frame-work which inevitably lead over simplifications and omissions of some key phenomena such as scale formation etc.

Despite its undoubted potential, surprisingly few researchers in the field have continued along this theoretical path. One of the rare follow-up studies is the one by Nesic et al. (1995) where the authors also presented an electrochemical model of CO_2 corrosion. Physical constants appearing in the model were determined from the literature, or when missing, found from numerous rotating cylinder glass cell experiments. Most of the experimental observations and physical constants found in this study confirmed the findings of Gray et al. (1989). The predictions made with the model were successfully compared with independent pipe-flow glass-loop experiments demonstrating the ability of mechanistic models for extrapolation. The authors also compared their predictions with two other popular models at the time: the semi-empirical models of de Waard et al. (1993) and the empirical model of Dugstad et al. (1994) (presented above) obtaining reasonable agreement. In a similar development, Anderko et al. (1999) have continued with the electrochemical modeling approach combining it with advanced water chemistry models. Recently George et al. (2004) have presented an extension of Nesic et al. (1995) electrochemical model which includes the effect of HAc.

All the models of this type can be criticized on the grounds that while they described in detail the electrochemical processes occurring on the metal surface, the treatment of the transport processes and chemical processes in the boundary layer was over simplified. This is particularly important when a reliable prediction of protective scale formation is sought. Therefore, a new generation of corrosion models emerged where the transport and the chemical aspects of CO_2 corrosion were improved.

Transport based electrochemical models

Turgoose et al. (1990) were the first to pave the way for a more realistic way of describing the transport processes in the boundary layer for the case of CO_2 corrosion. While they have oversimplified the effect of electrochemical reactions, this was soon rectified in the subsequent studies of Pots (1995) and others. (Nesic et al.2004; Nordsveen et al. 2003) This new coupled transport/electro-chemical approach is long established in other areas of electrochemistry (Watson and Postlethwaite 1990) and crevice corrosion (Newman 1991), and its essential logic was briefly described. In corrosion, certain species in the solution are ‘‘produced’’ at the steel surface e.g. Fe^{2+})

while others are depleted (e.g. H^+) by the electrochemical reactions. This leads to concentration gradients and diffusion of these species towards and away from the surface. The concentration of each species is governed by a species conservation (mass balance) equation.

Other simpler variations of transport-based models of CO_2 corrosion exist. For example, Dalayan et al. (1998) used a mass transfer coefficient for straight pipe flow instead of the transport equation and neglected the kinetics of chemical reactions. Achour et al. (1993) have used a similar model to simulate pit propagation of carbon steel in CO_2 environments under highly turbulent conditions. The transport-based models outlined above can be readily and logically linked to flow models and in particular multiphase flow models.

Multiphase flow models

One of the more complete attempts was recently presented by Nesic et al. (2004). They have presented an integrated CO_2 corrosion/multiphase flow model where mechanistic method were described for predicting various flow regimes (e.g. slug, stratified, annular) as well as the for calculating key hydrodynamic parameters in multiphase flow such as water layer thickness and velocity, wall shear stress, slug frequency, etc. However, the most significant effect of multiphase flow on corrosion in oil and gas pipelines is related to water wetting/entrainment. Rules of thumb or empirical functions were used in the past. The new model of Nesic et al. (2004) builds on a well-established hydrodynamic theory of Brauner (2001) and Barnea (1987). A criterion for forming stable water-in-oil dispersed flow was derived as the means of calculating the critical velocity for water entrainment within the liquid layer. Two main physical properties, maximum droplet size related to break-up and coalescence and critical droplet size related to settling and separation, were compared to deduce this criterion.

The Importance of corrosion rate models for oil and gas pipelines can never be over-emphasized. These models are relevant in the prediction of pipeline failure so as to proffer solution before actual downtime or failure. Corrosion as a threat in oil and gas pipeline systems is an existent challenge that may not be completely eliminated considering the various causes and the chemical processes that leads to it. However, it can be minimized to the least possible rate. This study presents a robust design approach via which an optimum model for a minimum corrosion rate will be achieved. This suggests inculcating at design stage, optimum settings for parameters such that the minimal corrosion rate will be achieved thereby prolonging the life of the pipeline, and also reduce the losses incurred by oil and gas industries as a result of Pipeline failures. These losses are not only monetary but also environmental and, in most cases, human losses.

2.0 Methodology

The design factors in this study have been identified as mean PH (X1), mean Temp (X2), mean pressure (X3) and mean aqueous CO_2 partial pressure (X4) respectively. An $L_8 2^4$ orthogonal array experiment was applied to obtain an optimal corrosion rate. This means 8 experiments for 4 parameters at 2 levels of high and low. The parameter levels are established from past field data. The smaller the better scenario offers the optimal response for corrosion rate and was considered.

Field data collected quarterly over a period of 10 years was put into consideration in establishing the highest and lowest levels for the parameters (table 1). The data collected include pipeline corrosion rate which was evaluated using manual ultrasonic wall thickness measurement technique while the pipeline operating parameters such as the line operating temperature, line operating pressure, pH and aqueous CO_2 partial pressure were obtained from the company's routine monitoring records.

The orthogonal array experiment with the average response for four trials of each of the 8 experiments is shown in table 2. The signal to noise ratios (SN) is derived from the quadratic loss function. The preferred parameter settings are determined through the analysis of the SN ratio where factor levels that maximize the appropriate SN ratio are optimal. There are three standard types of signal to noise ratios depending on the desired performance response. (Phadke 1989).

Table 1: Parameters and Levels

Label	Parameters	Levels	
		Low	High
P1	Mean Ph	7.48	7.86
P2	Mean Temp (^{0}C)	26.24	27.24
P3	Mean pressure (Bar)	17.38	22.88
P4	Mean Aqueous CO_2 Partial Pressure (Bar)	1.39	1.45

Table 2: $L_8 2^4$ Orthogonal Array Experiment

Experiment	P1	P2	P3	P4
1	1	1	1	1
2	1	1	1	2
3	1	2	2	1
4	1	2	2	2
5	2	1	2	1
6	2	1	2	2
7	2	2	1	1
8	2	2	1	2

For this study, the **Smaller the better** scenario for making the system response as small as possible is considered; this signal to noise ratio is given as:

$$\boldsymbol{SN_S = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}(y_i)^2\right)} \quad (1)$$

2.1 Sensitivity Analysis

The experimental data is modelled quadratically so as to accommodate all second order interactions between the parameters. The general quadratic equation for a four-variable problem is given as,

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=d+1}^{2n} a_{i,i} x_i^2 + \sum_{i\neq k} a_{i,k} x_i x_k$$
$$= a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_{1,2}x_1x_2 + a_{1,3}x_1x_3 + a_{1,4}x_1x_4 + a_{2,3}x_2x_3 + a_{2,4}x_2x_4 + a_{3,4}x_3x_4 + a_{1,1}x_1^2 + a_{2,2}x_2^2 + a_{3,3}x_3^2 + a_{4,4}x_4^2 \quad (2)$$

Where y = rate of corrosion, x_1 = mean pH, x_2 = mean temperature, x_3 =mean pressure and x_4 = mean aqueous CO_2 pressure. Following the method of Dieter (1999), the sensitivity of corrosion rate expressed in equation (3) can be established by taking partial derivatives of both sides of the equation with respect to the four unknown variables.

$$\frac{\delta y}{\delta x_1} = a_1 + a_{1,2}x_2 + a_{1,3}x_3 + a_{1,4}x_4 + 2a_{1,1}x_1 \quad (3)$$

$$\frac{\delta y}{\delta x_2} = a_2 + a_{1,2}x_1 + a_{2,3}x_3 + a_{2,4}x_4 + 2a_{2,2}x_2 \quad (4)$$

$$\frac{\delta y}{\delta x_3} = a_3 + a_{1,3}x_1 + a_{2,3}x_2 + a_{3,4}x_4 + 2a_{3,3}x_3 \quad (5)$$

$$\frac{\delta y}{\delta x_4} = a_4 + a_{1,4}x_1 + a_{2,4}x_2 + a_{3,4}x_3 + 2a_{4,4}x_4 \quad (6)$$

To put the results of equation 3-6 into a meaningful basis, we determine the relative sensitivities. The relative sensitivity of the variables $x_1, x_2x_3\ and\ x_4$is given by:

$S_{x_1} = \frac{\delta y/y}{\delta x_1/x_1}$, $S_{x_2} = \frac{\delta y/y}{\delta x_2/x_2}$, $S_{x_3} = \frac{\delta y/y}{\delta x_3/x_3}$, and $S_{x_4} = \frac{\delta y/y}{\delta x_4/x_4}$

3.1 Results and Discussions

3.2 3.1.1 Taguchi results

Applying equation (1), the signal to noise ratio responses are obtained and is shown in table 3. This was used to obtain the optimal settings for the parameters as P1 (Mean Ph) = 7.48, P2 (mean temperature) = 26.24°C, P3 (Mean pressure) = 22.88bar and P4 (Mean aqueous CO_2 partial Pressure) = 1.45 bar respectively.

Table 3: Response Table for Signal to Noise Ratios; Smaller is better

LEVEL	S/N Averages			
	P1	**P2**	**P3**	**P4**
1	11.2152	11.1997	11.1880	11.1685
2	11.1764	11.1919	11.2036	11.2230
Delta Δ	0.0388	0.0078	0.0157	0.0545
RANK	**2**	**4**	**3**	**1**

Furthermore, the response for the table for means is shown in table 4.

Table 4: The Response for the table for means

LEVEL	S/N Averages			
	P1	**P2**	**P3**	**P4**
1	0.2750	0.2754	0.2758	0.2764
2	0.2762	0.2757	0.2753	0.2747
Delta Δ	0.0012	0.0002	0.0005	0.0017
RANK	**2**	**4**	**3**	**1**

This is used to compute the expected corrosion rate at the optimal settings for the parameters. Corrosion rate for the Parameter P1 at level 1, Parameter P2 at level 1, Parameter P3 at level 2 and Parameter P4 at level 2 is given by:

$$ECR = Average + (P1_1 + P2_1 + P3_2 + P4_2)\ Contributions$$
$$ECR = 0.2756 + (0.2750 - 0.2756) + (0.2754 - 0.2756) + (0.2753 - 0.2756) + (0.2747 - 0.2756)$$
$$ECR = 0.2756 - 0.0006 - 0.0002 - 0.0003 - 0.0009 = 0.2733\text{mm/yr} \quad (7)$$

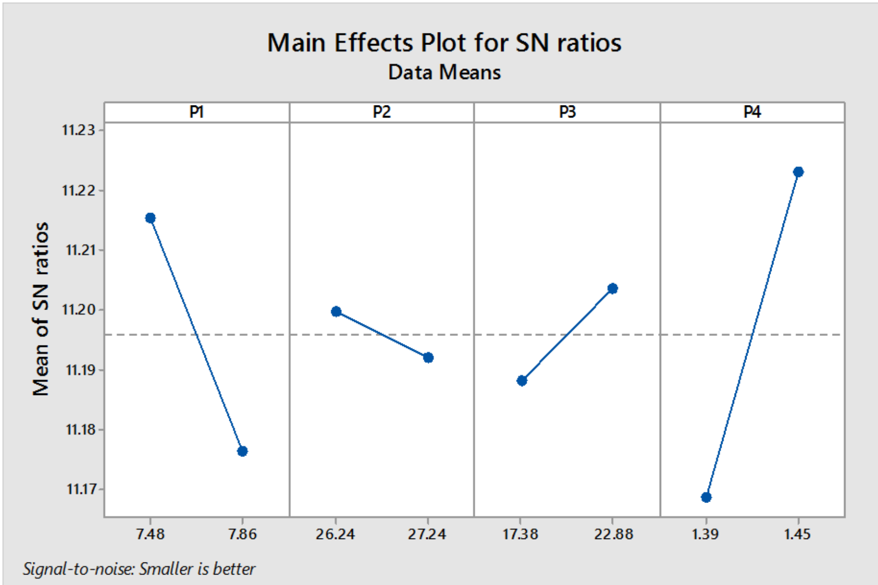

Figure 1: Main effects Plot for SN Ratio

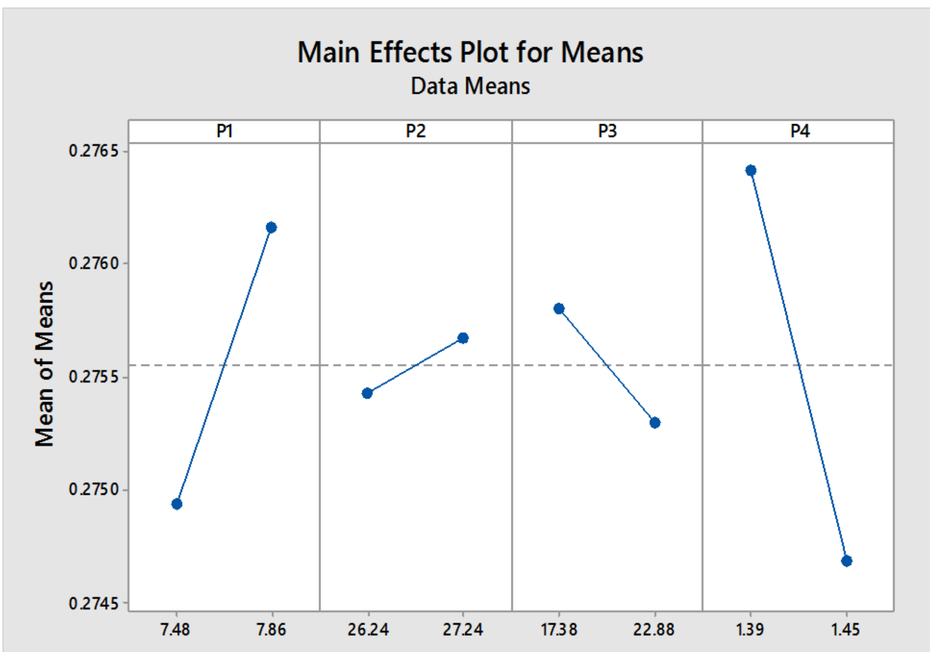

Figure 2: Main effects Plot for Means

The model summary gives R-square value of 0.9925% which indicates that the model has a very good fit and the model equation gotten from regression analysis is given as:

MEAN1 = 0.2868 + 0.003224 P1 + 0.000250 P2 - 0.000091 P3 - 0.02875 P4

3.1.2 Sensitivity results

A solution of a normal equation generated from equation (2) resulted to

$$y = -0.9331 + 0.0876x_1 + 0.0425x_2 + 0.0139x_3 + 0.2339x_4 - 0.0031x_1x_2 - 0.0015x_1x_3 - 0.1197x_1x_4 - 0.0001x_2x_3 + 0.0239x_2x_4 + 0.0028x_3x_4 + 0.0123x_1^2 - 0.0010x_2^2 - 0.0001x_3^2 + 0.0051x_4^2 \quad (8)$$

This model establishes the major effects of factors, the interaction effects of factors and finally the higher order effects of factors accounting for the nonlinear response of corrosion rate. With an R^2-value and correlation (r) of 0.9283 and 0.9635 respectively. The model has satisfactory statistical indices and is therefore used to analyze the sensitivity of the operating parameters. The analysis of the interrelationship between the parameters (X1, X2, X3, and X4 respectively) and their effect on the response factor, y yielded the results displayed in figures 3a-d.

This separate sensitivity analysis shows and explains the effect of each factor on the final response. An increase in PH causes a decrease on the corrosion rate (figure 3a). This is a good response. An increase in temperature on the other hand has a detrimental effect increasing the corrosion rate, (figure 3b). Increase in pressure causes a decrease on corrosion rate (figure 3c) and finally the CO_2 aqueous pressure increases with an increase in corrosion rate (figure 3d).

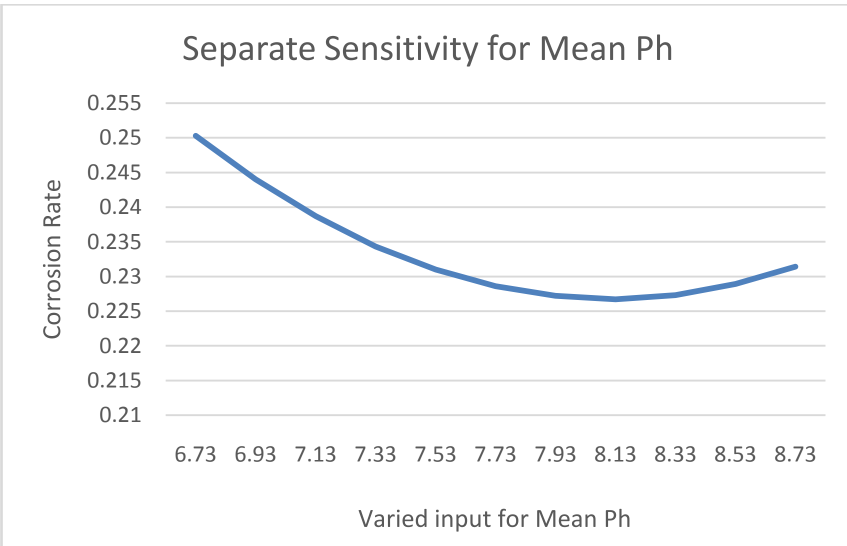

Figure 3a: Effect of Ph on Corrosion rate

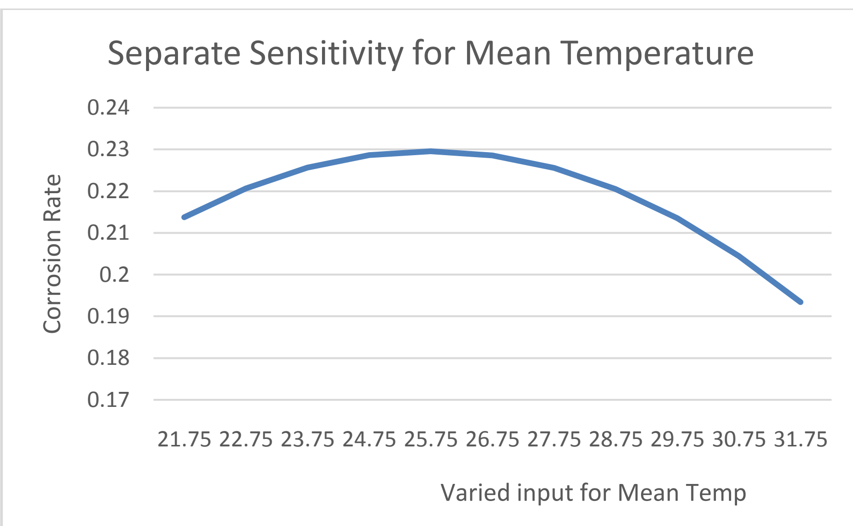

Figure 3b: Effect of Temperature on Corrosion rate

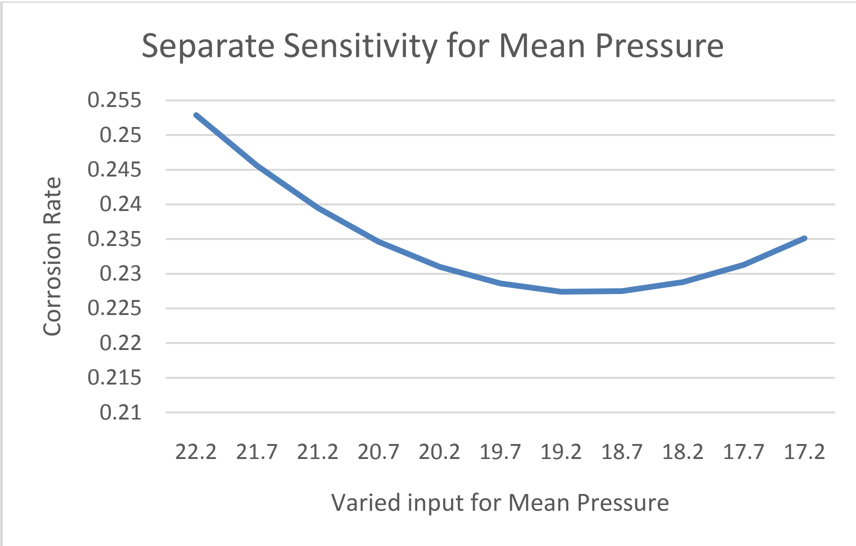

Figure 3c: Effect of Pressure on Corrosion rate

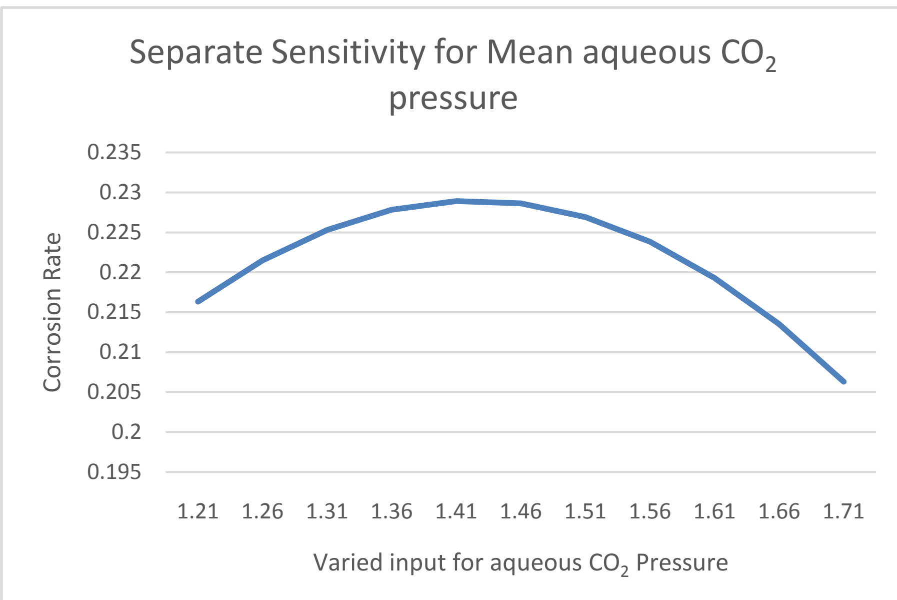

Figure 3d: Effect of Aqueous CO2 pressure on Corrosion rate

Finally, the relative sensitivities of the factors are considered in other to see if the effects of the separate sensitivities are repeatable. The relative sensitivities are given by:

$S_{x_1} = \frac{\delta y / y}{\delta x_1 / x_1} = 0.1888,$

$S_{x_2} = \frac{\frac{\delta y}{y}}{\frac{\delta x_2}{x_2}} = 1.1788,$

$S_{x_3} = \frac{\delta y / y}{\delta x_3 / x_3} = 0.0582,$

and $S_{x_4} = \frac{\delta y / y}{\delta x_4 / x_4} = -0.0753$

From the above results, only the CO_2 aqueous pressure result was inconsistent, hence, we deduce that temperature is the factor that most influences the rate of corrosion. This is depicted in the cumulative graph of sensitivity (figure 4).

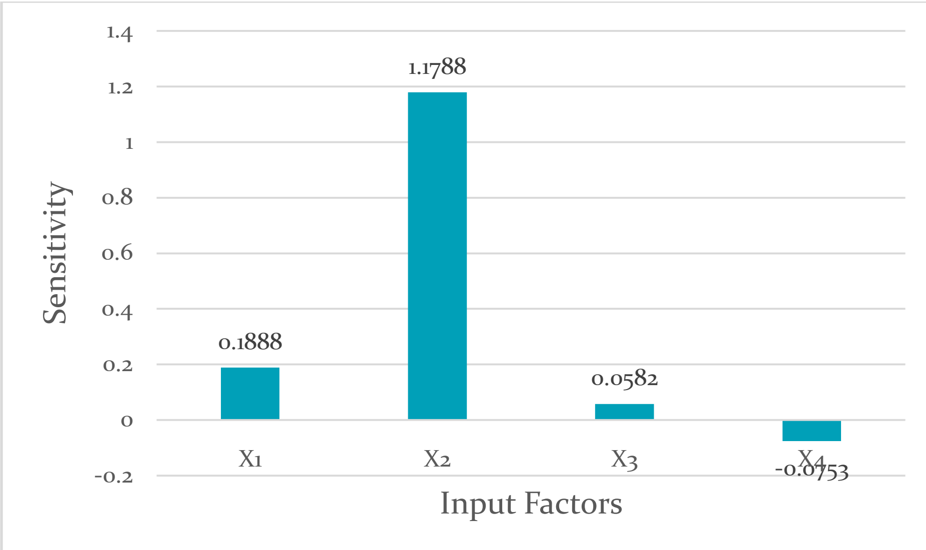

Figure 4: Cumulative graph of sensitivity

4.0. Conclusion

From the study, we establish that;

1. The Optimal values for the parameters are P1 (Mean Ph) = 7.48, P2 (mean temperature) = 26.24°C, P3 (Mean pressure) = 22.88bar and P4 (Mean aqueous CO2 partial Pressure) = 1.45 bar respectively.
2. The expected optimal response, Y which is the minimum corrosion rate is 0.2733mm/yr
3. The optimal regression model for new processes is:
   Y = 0.2868 + 0.003224 P1 + 0.000250 P2 - 0.000091 P3 - 0.02875 P4
4. Temperature (P2) is the parameter that is most sensitive to the response and must be reasonably controlled in practice.

5.0 Recommendation

It is recommended that the pipeline management and quality control make a concerted effort in controlling the effects of temperature in oil pipeline installations bearing in mind that it has the highest contributing effect to the rate of corrosion in internal pipeline systems.

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