



# Optimization of Operating Conditions Affecting Microbiologically Influenced Corrosion of Mild Steel Exposed to Crude Oil Environments Using Response Surface Methodology

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## Authors' contributions

*This work was carried out in collaboration between all authors. Author SEA reviewed areas related to microorganism behavior, selected the best microorganism for corrosion studies. Authors KKS and AOA designed the experiments, selected the material used and discussed the experimental results. Author IOS gathered all the materials used for the work, reviewed articles, run simulations and documented experimental results. All authors read and approved the final manuscript.*

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## ABSTRACT

In this study, the influence of four operating parameters (pH, salinity, nitrate concentration and immersion time) and their interactions on the microbiologically influenced corrosion (MIC) rate of mild steel in simulated crude oil environments were investigated by response surface methodology (RSM). 4-level historical data design: pH (A) at 4, 6, 8, 10, salinity (B) at 25, 50, 75 and 100 g/l, nitrate (C) at 25, 50, 75 and 100 g/l and immersion time (D) at 168, 336, 504 and 672 h, was employed to correlate the factors with the corrosion rate as response. A polynomial regression model was developed and validated prior to optimization studies. The result showed that pH has the most influential effect on the response and that the predicted data had a reasonable agreement

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with the experimental data with the values of  $R^2 = 0.9660$  and  $Adj-R^2 = 0.9516$ . The optimum conditions of the crude oil environments were observed at: pH (9.37), salinity (94.73 g/l), nitrate concentration (37.97 g/l) and immersion time of mild steel (168 h) in order to achieve minimum corrosion rate of 0.155196 mpy. The study has revealed that the historical data RSM design is an efficient statistical technique for predicting the optimum operating conditions of crude oil environments required to minimize mild steel corrosion in oil pipelines by incorporating all factors under consideration.

*Keywords: Crude oil environment; response surface methodology; historical data design; corrosion rate; optimization.*

## 1. INTRODUCTION

Microbiologically influenced Corrosion (MIC) is a major problem menacing the petroleum industries. It is estimated that 40% of all internal pipeline corrosion in the oil industry can be attributed to microbial corrosion [1]. Corrosion related problems worldwide have been estimated to cost as much as 1.8 trillion US dollars with microbial influenced corrosion contributing to approximately 50% of this total [2]. Throughout the world, pipelines play a highly crucial role in the transportation of petroleum (crude oil) and its allied products at all stages of production ranging from down hole to surface and processing facilities[3], consuming about 8% of metals found in the world accompanied with high rate of corrosion [4]. Mild steel is a very important material in the oil industry due to its usefulness in construction of pipelines as it allows the pipes to not only be easily welded in place, but also permits bending and avoids cracking and breaking under pressure. It is the least expensive and most common steel used due to its hardness and durability [5].

MIC is the process in which microorganisms initiate, enhance, facilitate or aggravate corrosion processes of metals [2,6,7]. Microorganisms seek irregularities on metal surfaces where they can attach themselves and secrete corrosive by-products such as hydrogen sulphide, sticky polymers, enzymatic products and other metabolic substances which can deteriorate metals [2,8,9]. However, it has been reported that microorganisms form biofilms which have two major roles in MIC: its acceleration or inhibition [10]. The major factors involved in the enhancement and inhibition of corrosion (asides biofilm formation), are the properties of the metal in question and the environment in which it is exposed to [9].

Biofilms are complex microbial communities formed from the colonization of different species

of microorganisms. They contain over 90% water, extracellular polymeric substance (EPS) and inorganic matter [11-13]. Studies have shown that bacteria are the primary formers of biofilms [6,7,14]. MIC has been described as an interfacial process in that biofilms alter the properties such as pH, salinity, oxygen levels and nutrients at the interface between the metal and the environment [15]. The influence of biofilms in corrosion of metals in numerous systems such as reservoir, oil pipelines, surface equipment and underground structures have been well documented [3,4,15].

The conventional method of performing experiments is fast becoming out-dated because it involves changing one variable at a time while having other factors fixed at specific conditions. The other option, which involves carrying out experiments with all possible combination of variables, is often impracticable due to the large number of experimental runs it requires. Response Surface Methodology (RSM) is a widely used mathematical and statistical technique for designing experiments, modelling operating parameters, analysing the effects of factors and determining the optimum conditions for desirable responses in various chemical processes [16-24]. It is desirable for conducting multi-factor experiments in that it specifies the most common interactions between various factors for the determination of the most favourable or unfavourable conditions of the processes [18,19,21-24]. RSM is a very useful and robust technique for studying the effect of several variables influencing the responses by varying them simultaneously and performing only a limited number of experiments [17,24].

RSM has a plethora of design types such as Box–Behnken, central-composite, one-factor, optimal and historical-data [24]. The advantage of historical-data RSM design is that it affords the user the opportunity to define the design points using all or some of the available experimental

data [18]. In contrast to other types of designs in RSM, there is no limitation to the number of design factors that can be supplied in historical-data design. In fact, factor settings and responses of an existing data set can be directly imported to a blank design layout [20].

Abalos et al. [16] utilized  $2^4$  full factorial central composite RSM design at five levels to optimize the culture media for the production of rhamnolipids by *Pseudomonas aeruginosa* AT10. Central composite design (CCD) has been applied for the optimization of textile dye degradation by wet air oxidation [17], as well as the optimization of the experimental variables influencing corrosion rate of aluminium in HCl solution [21]. Jeirani et al. [20] applied historical-data RSM design to predict the optimum aqueous phase composition of a triglyceride micro-emulsion for enhanced oil recovery. Asmara and Ismail [22] experimented on the use of CCD of RSM with three variables to predict  $\text{CO}_2$  corrosion model empirically. Salam et al. [18] employed Box Behnken design of RSM to optimize operating parameters for paraffin-wax deposition in pipelines.

Going by literature, very limited number of studies employed the experimental design and optimization modelling approach of RSM for microbiologically influenced corrosion; hence the need for this study. In line with our previous experimental studies, the optimum condition of crude oil environments can be predicted statistically using design of experiments (DOE), reason being that it has been employed successfully in estimating the optimum conditions required for such processes as minimum  $\text{CO}_2$  corrosion [22] and wax deposition in oil pipelines [18]. The objective of this paper is to estimate the optimum conditions of crude oil environments in contact with mild steel pipelines needed to minimize corrosion using an improved statistical model of DOE.

## 2. METHODOLOGY

### 2.1 Experimental Design

In this paper, Design Expert software version 6.0.8 (Stat-Ease Inc., Minneapolis, USA) was used for RSM. It has the profound ability to optimize the response function and predict future responses after it has developed a regression model statistically from appropriate experimental data.

It has been widely reported that pH, salinity, nitrate and immersion time are significant factors affecting corrosion of metals in the petroleum industries [9,25]. RSM was used in this study to evaluate the simultaneous effects of the four independent variables (pH, salinity, nitrate and immersion time) on the corrosion rate of mild steel in simulated crude oil environments as previously studied experimentally. The RSM was based on historical-data design. Four levels of each variable were chosen namely: pH (A) at 4, 6, 8 and 10, salinity (B) at 25, 50, 75 and 100 g/l, nitrate (C) at 25, 50, 75 and 100 g/l and immersion time (D) at 168, 336, 504 and 672 h. Forty-eight (48) combinations of two (2) variables (with immersion time chosen in all cases) were performed.

### 2.2 Third-order Regression Model

RSM has been applied for developing the mathematical models in the form of multiple regression equations for the MIC process. The main and interaction effects of all possible factor combinations have been estimated. For the development of regression equations related to the corrosion process, a third-order polynomial equation was used to fit the experimental data seen in Equation (1).

$$\begin{aligned}
 Y = & \beta_o + \beta_A A + \beta_B B + \beta_C C + \beta_D D + \\
 & \beta_{AA} A^2 + \beta_{BB} B^2 + \beta_{CC} C^2 + \beta_{DD} D^2 + \beta_{AB} AB + \\
 & \beta_{AC} AC + \beta_{AD} AD + \beta_{BC} BC + \beta_{BD} BD + \\
 & \beta_{CD} CD + \beta_{AAA} A^3 + \beta_{BBB} B^3 + \beta_{CCC} C^3 + \\
 & \beta_{DDD} D^3 + \beta_{AAB} A^2 B + \beta_{AAC} A^2 C + \beta_{AAD} A^2 D + \\
 & \beta_{ABB} AB^2 + \beta_{ACC} AC^2 + \beta_{ADD} AD^2 + \beta_{ABB} AB^2 + \\
 & \beta_{BBC} B^2 C + \beta_{BBD} B^2 D + \beta_{BCC} BC^2 + \beta_{BDD} BD^2 + \\
 & \beta_{CCD} C^2 D + \beta_{CDD} CD^2 + \beta_{ABC} ABC + \\
 & \beta_{ABD} ABD + \beta_{ACD} ACD + \\
 & \beta_{BCD} BCD
 \end{aligned} \tag{1}$$

Where

$\beta_o$  = offset term,  
 $\beta_A, \beta_B, \beta_C, \beta_D$  = linear effect terms,  
 $\beta_{AA}, \beta_{BB}, \beta_{CC}, \beta_{DD}$  = squared effects  
 $\beta_{AB}, \beta_{AC}, \beta_{AD}, \beta_{BC}, \beta_{BD}, \beta_{CD}$ ,  
 $\beta_{AAB}, \beta_{AAC}, \beta_{AAD}, \beta_{ABB}, \beta_{ACC}, \beta_{ADD}, \beta_{ABB}, \beta_{BBC}$  =  
 interaction  
 $\beta_{BBD}, \beta_{BCC}, \beta_{BDD}, \beta_{CCD}, \beta_{CDD}, \beta_{ABC}, \beta_{ABD}, \beta_{ACD}, \beta_{BCD}$   
 effects  
 $\beta_{AAA}, \beta_{BBB}, \beta_{CCC}, \beta_{DDD}$  = cubed effects  
 $Y$  = fitted response

## 2.3 Variable Coding

The results were analysed by applying the response plots and Analysis of Variance (ANOVA). All experimental data sets of the 48 runs were used as the design points for modelling (Table 1 presents the design summary). The four factors pH, salinity, nitrate and immersion time indicate the conditions of the simulated crude oil environment with their low and high values set according to the range of the experimental data sets. The operational parameters, their designated symbols, response and experimental range are tabulated in Table 1.

The experimental design of the operational parameters with the observed values for the response is depicted in Table 2.

## 3. RESULTS AND DISCUSSION

### 3.1 Regression Model Fitting for Corrosion Rate

A regression model was obtained for the response of corrosion rate from the application of historical data design of RSM which recommended a third-order polynomial model to be fitted to the response data. Model treatment was done since the model contained many insignificant terms [20]. The model is a modified cubic model obtained by manual reduction and simplification of the model which involved excluding larger insignificant terms to give the final empirical model in terms of actual factors as shown in Equation 2.

$$\begin{aligned}
 Y = & +1.80 - 1.37 * A - 0.36 * B - 0.32 * \\
 & C + 0.14 * D + 0.51 * A^2 + 0.13 * B^2 - \\
 & 0.64 * D^2 + 0.095 * B * D + 0.068 * C * D + \\
 & 0.55 * A^3 + 0.23 * B^3 - 0.031 * A * C^2 - \\
 & 0.22 * A * D^2 + 0.13 * B^2 * D - 0.22 * B * \\
 & D^2
 \end{aligned}
 \tag{2}$$

Multiple regression analysis technique included in the historical data RSM design was employed in obtaining the coefficients of the empirical model. The model coefficients with positive sign represent synergistic effect, while negative sign represents antagonistic effect. The coefficients of model factors D, A<sup>2</sup>, B<sup>2</sup>, BD, CD, A<sup>3</sup>, B<sup>3</sup>, and B<sup>2</sup>D positively contribute to the model equation while A, B, C, D<sup>2</sup>, AC<sup>2</sup>, AD<sup>2</sup> and BD<sup>2</sup> have negative impact on the developed model [18]. The most influential model parameter was A as it had the highest coefficient and F-value [18,24].

### 3.2 Analysis of Variance (ANOVA) and Statistical Significance of the Model

ANOVA was another statistical parameter used to analyse the adequacy of the model [23]. The ANOVA results for the model in Equation (2) are tabulated in Table 3. The F-value of 67.02, as well as the p-value (or Prob> F) of < 0.0001 for the model shows that the model is significant. As can be observed in Table 3, ten (10) of the fourteen (14) p-values of the model are less than 0.05, signifying that about 71.4% of the model parameters are significant. As earlier stated, majority of the insignificant terms were deliberately excluded to improve model performance [18].

### 3.3 Model Validation

Fig. 1 shows the predicted corrosion rate against the actual corrosion rate (obtained from experiments).

The regression line gave R<sup>2</sup> of 0.9660 and adjusted-R<sup>2</sup> of 0.9516 which are approximately close to 1; thus indicating a relatively good correlation between the predicted and experimental values of the corrosion rates. Also, residual values of ±20% were obtained for majority of the predicted and actual values of the response showing relatively small discrepancies between them. The adequate precision was another statistical parameter which was analysed for the model. It measures the ratio of signal to noise and it is suitable to have its value to be greater than 4 [17,19-21]. The adequate precision for the model in Equation (2) was 33.695 indicating an adequate signal (high value of adequate precision indicates an adequate signal). The degree of freedom for lack of fit was evaluated at 36, though most of the design points were proximal and equally spaced around the line of fit.

Fig. 2 shows the graphical analysis of the model as carried out by normal plot of the residuals. Apparently, the residuals portray a normal distribution because virtually all the points follow a straight line curve. Also, the residuals show that no further improvement can be done to the model by making changes to the response because the data points are scattered and do not exhibit a "S-shaped" curve [20]. Therefore, these figures and graphs illustrate that the model in Equation (2) can be regarded as the best

possible model of the historical data RSM design of mild steel corrosion in crude oil environment. Hence, they shall be employed in finding the optimum composition of crude oil environments.

**Table 1. Design summary**

Operational parameters	Symbols	Ranges	Low coded	High coded
pH	A	4 – 10	-1	+1
Salinity (g/l)	B	25 - 100	-1	+1
Nitrate (g/l)	C	25 - 100	-1	+1
Immersion time (h)	D	168 - 672	-1	+1
<b>Response</b>	<b>Symbol</b>	<b>Analysis</b>	<b>Minimum</b>	<b>Maximum</b>
Corrosion rate (mpy)	Y	Polynomial	0.152	3.916

**Table 2. Historical data experimental design of the independent variables with the observed values for the response, (Y<sub>i</sub>)**

Std	Run	Factor 1 A: pH	Factor 2 B: salinity (g/l)	Factor 3 C: nitrate (g/l)	Factor 4 D: time (h)	Response: corrosion rate (mpy)
18	1	4.00	0.00	0.00	168.00	1.445
37	2	4.00	0.00	0.00	336.00	1.369
8	3	4.00	0.00	0.00	504.00	1.293
14	4	4.00	0.00	0.00	672.00	0.913
12	5	6.00	0.00	0.00	168.00	1.293
32	6	6.00	0.00	0.00	336.00	1.267
42	7	6.00	0.00	0.00	504.00	1.255
28	8	6.00	0.00	0.00	672.00	0.76
7	9	8.00	0.00	0.00	168.00	1.217
26	10	8.00	0.00	0.00	336.00	1.217
9	11	8.00	0.00	0.00	504.00	1.255
38	12	8.00	0.00	0.00	672.00	0.913
15	13	10.00	0.00	0.00	168.00	0.837
36	14	10.00	0.00	0.00	336.00	1.166
11	15	10.00	0.00	0.00	504.00	1.749
29	16	10.00	0.00	0.00	672.00	0.913
19	17	0.00	25.00	0.00	168.00	0.76
33	18	0.00	25.00	0.00	336.00	0.913
13	19	0.00	25.00	0.00	504.00	1.331
25	20	0.00	25.00	0.00	672.00	0.152
1	21	0.00	50.00	0.00	168.00	0.608
24	22	0.00	50.00	0.00	336.00	0.76
23	23	0.00	50.00	0.00	504.00	1.103
34	24	0.00	50.00	0.00	672.00	0.304
44	25	0.00	75.00	0.00	168.00	0.38
21	26	0.00	75.00	0.00	336.00	0.456
35	27	0.00	75.00	0.00	504.00	1.179
6	28	0.00	75.00	0.00	672.00	1.445
16	29	0.00	100.00	0.00	168.00	1.369
48	30	0.00	100.00	0.00	336.00	1.293
22	31	0.00	100.00	0.00	504.00	0.913
39	32	0.00	100.00	0.00	672.00	1.293
5	33	0.00	0.00	25.00	168.00	1.267
17	34	0.00	0.00	25.00	336.00	1.255
45	35	0.00	0.00	25.00	504.00	0.76
46	36	0.00	0.00	25.00	672.00	1.217
4	37	0.00	0.00	50.00	168.00	1.217
47	38	0.00	0.00	50.00	336.00	1.255

Std	Run	Factor 1 A: pH	Factor 2 B: salinity (g/l)	Factor 3 C: nitrate (g/l)	Factor 4 D: time (h)	Response: corrosion rate (mpy)
43	39	0.00	0.00	50.00	504.00	0.913
41	40	0.00	0.00	50.00	672.00	0.837
27	41	0.00	0.00	75.00	168.00	1.166
20	42	0.00	0.00	75.00	336.00	1.749
10	43	0.00	0.00	75.00	504.00	0.913
40	44	0.00	0.00	75.00	672.00	0.76
3	45	0.00	0.00	100.00	168.00	0.913
2	46	0.00	0.00	100.00	336.00	1.331
31	47	0.00	0.00	100.00	504.00	0.152
30	48	0.00	0.00	100.00	672.00	0.608

Table 3. ANOVA for response surface reduced cubic model

Source	Sum of squares	Degrees of freedom	Mean square	F-value	Prob> F	Remark
Model	33.33	14	2.38	67.02	< 0.0001	Significant
A	7.64	1	7.64	215.08	< 0.0001	Significant
B	0.31	1	0.31	8.70	0.0058	Significant
C	0.91	1	0.91	25.61	< 0.0001	Significant
D	0.055	1	0.055	1.55	0.2216	Insignificant
A <sup>2</sup>	0.85	1	0.85	24.04	< 0.0001	Significant
B <sup>2</sup>	0.057	1	0.057	1.61	0.2133	Insignificant
D <sup>2</sup>	0.60	1	0.60	16.97	0.0002	Significant
BD	0.053	1	0.053	1.49	0.2314	Insignificant
CD	0.080	1	0.080	2.27	0.1418	Insignificant
A <sup>3</sup>	4.09	1	4.09	115.22	< 0.0001	Significant
B <sup>3</sup>	0.25	1	0.25	6.95	0.0127	Significant
AD <sup>2</sup>	0.55	1	0.55	15.35	0.0004	Significant
B <sup>2</sup> D	0.15	1	0.15	4.16	0.0496	Significant
BD <sup>2</sup>	0.30	1	0.30	8.54	0.0062	Significant
Residual	1.17	33	0.036			
Cor total	34.50	47				

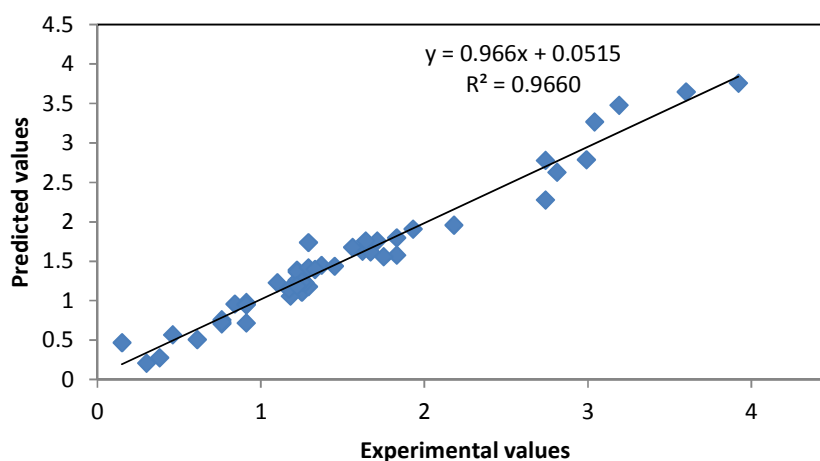
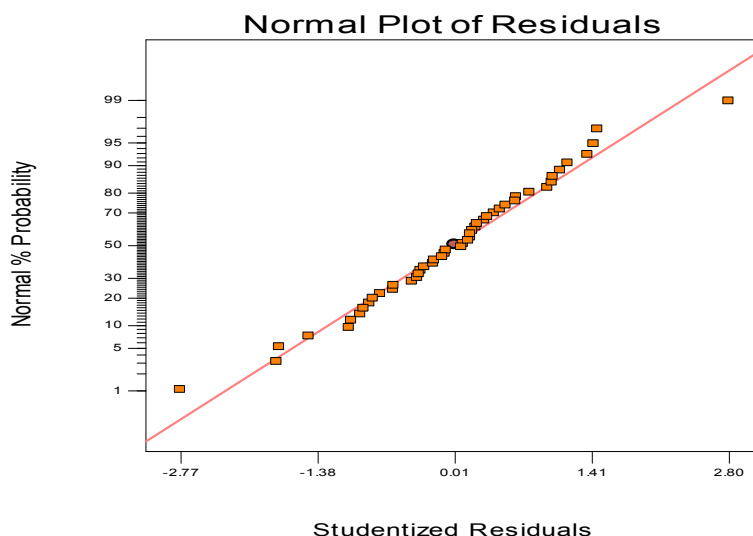


Fig. 1. Cross plot between the experimental and predicted values



**Fig. 2. Normal plot of residuals for the model in equation (2)**

From the model, all the operational parameters have been identified as significant terms and as such influence the response. Therefore, it is proven statistically that the MIC rate of mild steel is dependent on the operational parameters in the following order: immersion time > salinity > pH > nitrate concentration of crude oil environment based on the frequency of occurrence of each parameter in the model. On factor interaction, corrosion was dependent on the operational parameters in the following order: pH > nitrate concentration > salinity > time as can be observed in the values of sum of squares in Table 3.

### 3.4 One Factor Plots

The behaviour of the effect of each of the four variables considered individually on corrosion rate is presented in Fig. 3 (i-iv). Fig. 3 (i) shows the effect of pH (A) on corrosion rate at constant salinity (B) of 62.5 g/l, nitrate concentration (C) of 62.5g/l and time (D) of 420 h. There was a decrease in corrosion rate from 3.13 to 1.20 mpy when A was increased from 4 to 8. However, from pH 8.5 to 10, the corrosion rate slightly increased to 1.49 mpy.

Fig. 3(ii) shows that the relationship between the corrosion rate and salinity has an inverse relationship with constant values of pH of 7, nitrate concentration of 62.5 g/l and immersion time of 420 h. The corrosion rate decreased from 2.07 to 1.65 mpy when the salinity was increased from 25 g/l to 81.25 g/l and a slight increase in

corrosion rate was observed when the salinity was greater than 81.25 g/l, leading to a final corrosion rate of 1.79 mpy at salinity of 100 g/l. Illustrated in Fig. 3(iii) is the effect of increase in nitrate concentration from 25 to 100 g/l at pH of 7, salinity of 62.5 g/l and immersion time of 420 h. The corrosion rate decreased linearly from 2.12 to 1.48 mpy when the nitrate concentration was increased from 25 g/l to 100 g/l. Fig. 3 (iv) shows the effect of increasing time of exposure from 168 to 672 h at constant pH value of 7, salinity of 62.5 g/l and nitrate concentration of 62.5 g/l on corrosion rate. Corrosion rate increased from 0.86 to 1.50 mpy when immersion time was increased from 168 to 420 h and decreased with further increase in immersion time to a final value of 1.14 mpy at the end of 672 h.

### 3.5 3D Response Surface Plot

The surface behaviour of combination of variables on corrosion rate was described in Fig. 4 (i-iii). Fig. 4 (i) describes the behaviour of pH and immersion time at constant salinity and nitrate concentration. From the plot, corrosion rate decreased from 2.56 to 0.246 mpy when the pH was increased from 4 to 8.5 for low immersion time of 168 h and increased to 0.48 mpy on increasing pH value 10. At high immersion time, there was a similar trend to behaviour at low concentration only that the corrosion rate was 2.85 mpy at pH of 4 and 0.77 mpy at pH of 10.

Fig. 4 (ii) shows the behaviour of salinity and immersion time at constant pH and nitrate concentration. It is apparent from the plot that corrosion rate decreased from 1.46 to 0.56 mpy with increase in salinity from 25 to 100 g/l at low immersion time of 168 h. When immersion time increased to 672 h, the corrosion rate increased from 1.46 to 1.82 mpy at salinity of 25 g/l and also increased from 0.56 to 1.30 mpy at salinity of 100 g/l. At high immersion time of 672 h, the corrosion rate decreased from 1.82 to 1.20 mpy on increasing salinity from 25 g/l to 81.25 g/l, and increased to 1.30 mpy at salinity of 100 g/l.

Fig. 4 (iii) depicts the behaviour of nitrate concentration and immersion time at constant pH and salinity. The plot indicated that corrosion rate decreased from 1.40 to 0.63 mpy with increase in nitrate concentration from 25 to 100 g/l at low immersion time of 168 h. When immersion time increased to 672 h, corrosion rate increased from 1.40 to 1.55 mpy at nitrate concentration of 25 g/l and also increased from 0.63 to 1.05 mpy at 100 g/l. At high immersion time of 672 h, the corrosion rate decreased from 1.55 to 1.05 mpy on increasing salinity from 25 g/l to 100 g/l.

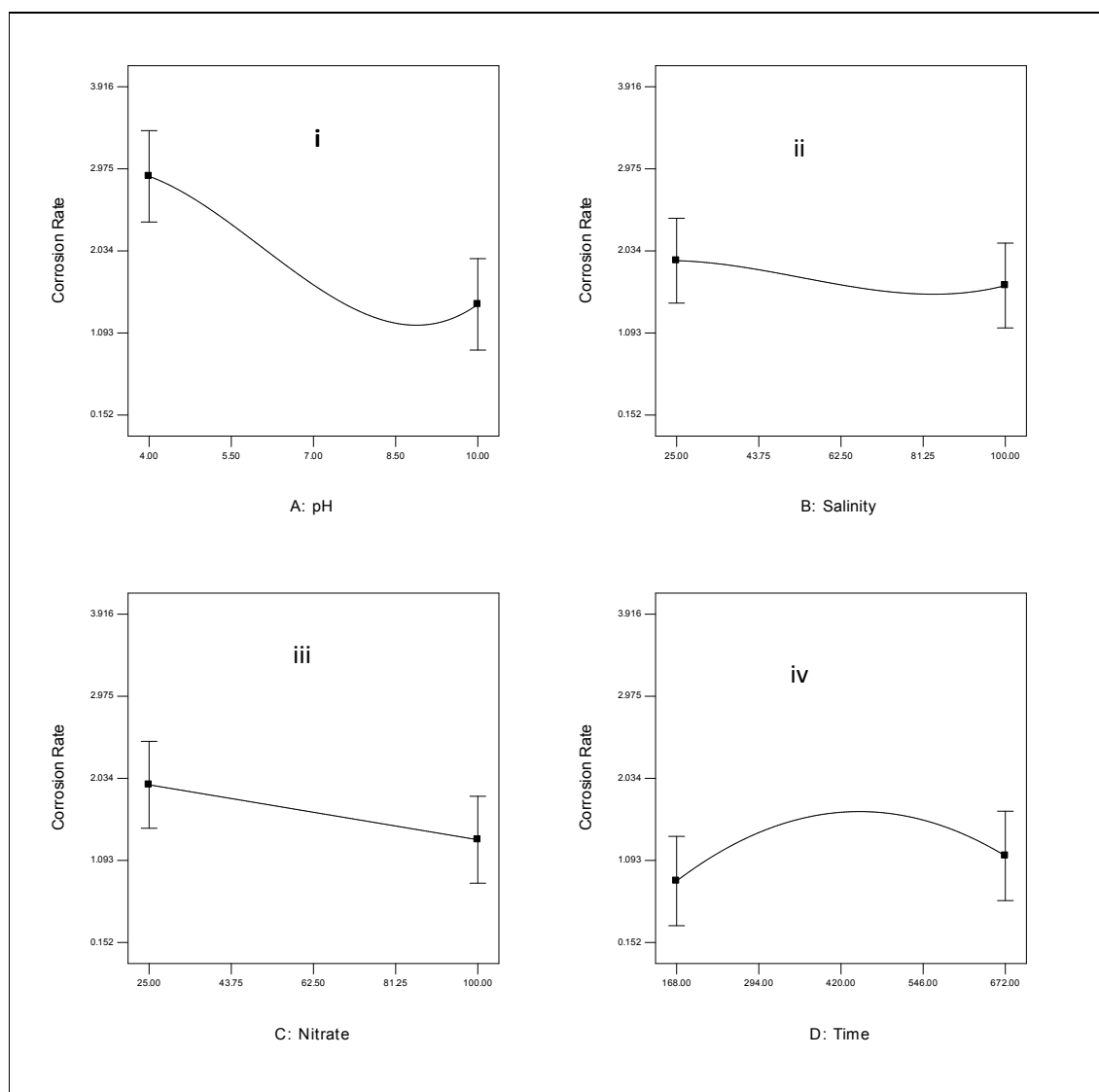
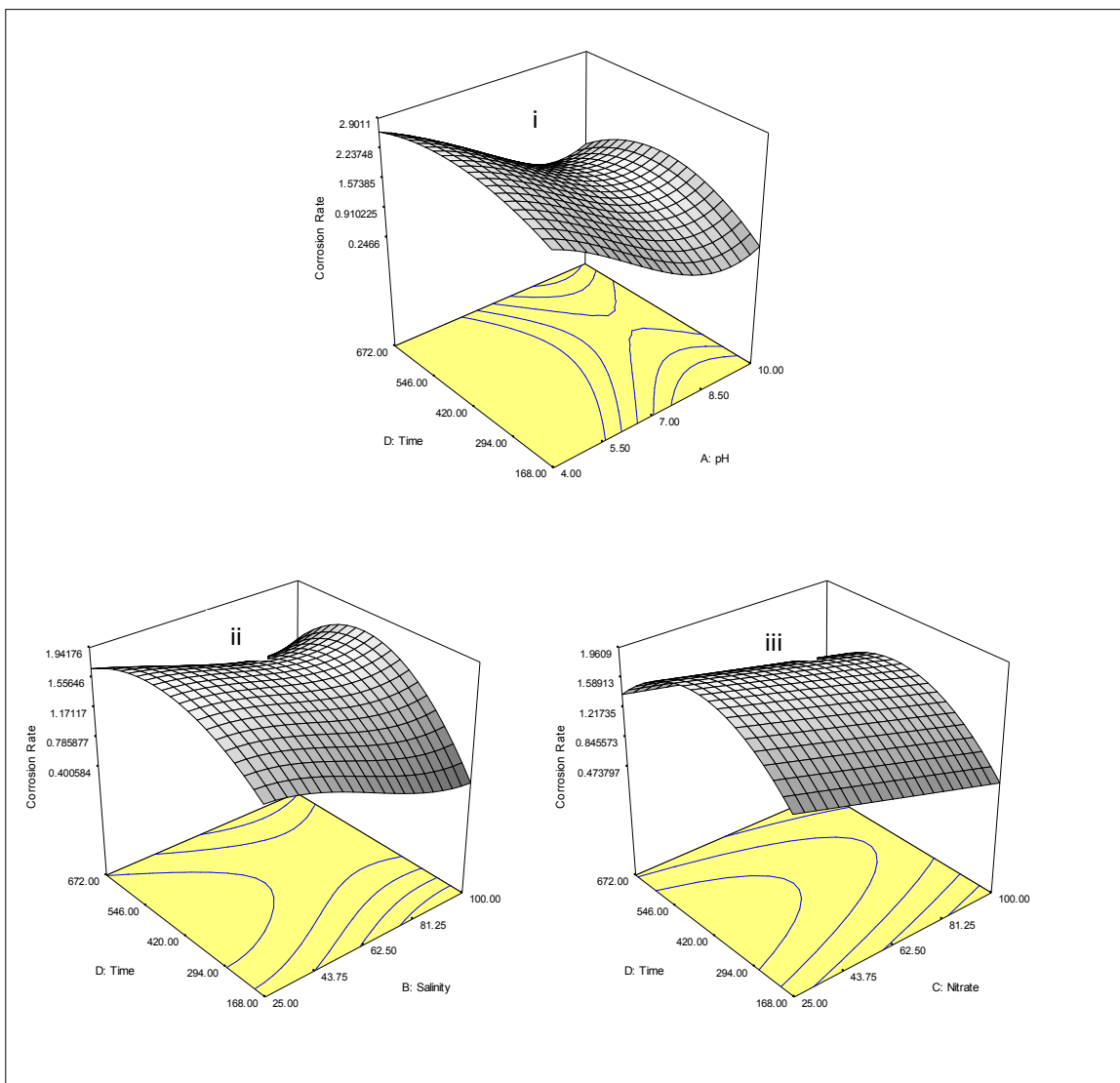


Fig. 3. One factor plots





**Fig. 4. 3D Response surface plots of factor interactions**

### 3.6 Model Optimization

Numerical optimization of the model in Equation (2) was done using the Design Expert software to determine the pH, salinity, nitrate concentration and immersion time at which the corrosion rate of mild steel was at minimum. The following steps were taken prior to the optimization in order to identify the criteria of the numerical optimization. First, the goal factors for pH, salinity, nitrate and immersion time were set to “is in range” while that of corrosion rate was set to “minimum”. Table 4 illustrates the summary of the corrosion rate modelling.

The predicted optimum composition of the crude oil environment was estimated to be pH (9.37), salinity (94.73 g/l), nitrate concentration (37.97 g/l) and immersion time of mild steel (168 h). At these optimum conditions, the corresponding predicted corrosion rate was found to be 0.155196 mpy. Experimentally, 75 g/l nitrate concentration and 168 h immersion time was the condition of the crude oil environment at minimum corrosion rate (0.152 mpy) without considering its pH and salinity.

**Table 4. Summary of corrosion rate modelling**

Operational parameter	Goal	Lower limit	Upper limit	Optimized condition
pH	Is in range	4	10	9.37
Salinity (g/l)	Is in range	25	100	94.73
Nitrate (g/l)	Is in range	25	100	37.97
Immersion Time (h)	Is in range	168	672	168
Corrosion Rate (mpy)	Minimize	0.152	3.916	0.155196

#### 4. CONCLUSION

In this study, historical-data RSM was used to model MIC rate of mild steel as a function of the operating conditions pH, salinity, nitrate concentration and immersion time in crude oil environment. After the ANOVA test on the complete modified cubic model, majority of the insignificant effects were excluded in order to improve the predictive performance of the model. The resulting response surface model, obtained as a function of virtually significant effects, was statistically proven to be realistic. The result of the ANOVA demonstrated that the model was highly significant and that immersion time was the most significant factor affecting the corrosion of mild steel. High values of  $R^2$  (0.9660) and adjusted- $R^2$  (0.9516) indicated a good correlation between the predicted and experimental values. The two factor interactions were revealed with 3D response surface plots. In minimizing corrosion rate, the optimum operating conditions of the crude oil environments were obtained at pH (9.37), salinity (94.73 g/l), nitrate concentration (37.97 g/l) and immersion time of mild steel (168 h).

Therefore, it is apparent that RSM not only gives valuable insight on interactions between the factors, but also helps in the recognition of possible optimum values of the same. It is concluded that historical-data RSM is a promising statistical technique that could be used confidently in predicting the optimum operating conditions of crude oil environments that would minimize corrosion rate of metals used in the oil industry.

#### COMPETING INTERESTS

Authors have declared that no competing interests exist.

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