Mathematical Modelling and Corrosion Inhibition Studies of Psidium Guajava Extracts on Mild Steel in Industrial Environments

ABSTRACT

This study investigated the effect of *Psidium guajava* extracts as a green corrosion inhibitor on mild steel in different media (0.5 M NaOH and 1.0 M NaOH) environments. The mild steel samples were preweighed in each of the media with different inhibitor concentrations. The logarithmic, quadratic and cubic models were developed using a computer-aided statistical modelling technique. A critical analysis of the different models in terms of the coefficient of determination (R^2) value shows that the cubic models had the best correlation of 1.0 (perfect correlation). Consequently, the various cubic model equations for corrosion rate profiles of leaf extracts in 0.5 M and 1.0 M NaOH environments were further transformed into two generalized forms using MATLAB 15.0 and the cubic model equations with a coefficient of determination (R^2) value of 1.0 showing perfect correlation of the data obtained. Confirmatory, corrosion rates were calculated using the developed equations, compared with the experimental data and found satisfactory. The predicted corrosion rate of the samples was found to be close to the experimentally observed values. The results of the model equations showed that the trend represented in the experimental data was almost perfectly captured by the cubic function. The results show good potential for application in nanomaterials, metallurgical systems, biostructure and manufacturing industries. Therefore, controlling the corrosion of mild steel through novel inhibitor systems and developing a modelling tool that can mimic the exact corrosion process instead of costly experiments are important contributions of the work.

Keywords: Mild Steel, Corrosion Rate, Inhibitor, Model, NaOH

INTRODUCTION

Over decades, the use of green natural extracts as corrosion inhibitors has attracted much attention within the oil and gas communities. The renewed interest in this material has arisen out of the development of new green inhibitors that can replace the synthetic inhibitors. Africa is endowed with a variety of leafy vegetable extracts or native inhibitors which are eco-friendly, biodegradable, do not contain heavy metals or other toxic compounds and ecologically acceptable, inexpensive, readily available and renewable. Several methods have been used currently to minimize corrosion of mild steels (Idenyi *et al.,* 2015; Ahamad & Quraishi, 2010; Raviprabha & Bhat, 2023; Minagalavar *et al.,* 2023; Zhang *et al.,* 2023; Emmanuel, 2024; Kenneth,et al., 2016; Ibisi & Amadi, 2015, Wu *et al*., 2022).

The development of model equations has become an important tool in the development of corrosion inhibitors over the last two decades because calculations can provide a large amount of information about a large number of compounds within a reasonable time frame (Rezaeivala *et al.,* 2022; Oloche *et al.,* 2009). Results from such studies can be used as suitable starting points for further experimental studies. Model equations can also be important tools in the development of more suitable compounds for metal protection, starting from already available compounds and through structural modifications to identify derivatives with improved metal protection effectiveness (Nie *et al.*, 2021; Liu *et al.,* 2021; Talo *et al.,* 2013) Recently, there have been numerous studies in the literature on the computational investigation of organic materials useful for metal protection.

The use of statistical models to predict the passivation properties of metals and composites in alkaline and acidic environments has been predicted for decades, but their application has been largely hampered due to the special skills required in analysis (Ikeuba *et al.,* 2024; Fu *et al.,* 2010, Gan *et al.,* 2010; Munn, 1991)

This mathematical model will help to predict the efficiency of corrosion inhibitors, understand their mechanisms, and optimize their application for the prediction of the life span of mild steel or to find the time for the allowable corrosion rate. This model can help simulate the interaction between the inhibitor and the metal surface, estimate the corrosion rate, and determine optimal concentrations. However report on the unification of cubic models equation for corrosion rate profiles of leaf extracts in the alkaline environment is very rare in the literature, hence to the best of our knowledge this research is novel and presents a fundamental step towards identifying other possible pathways of utilizing vegetable extracts for application in different technological industries. Also, these mathematical models are relatively new and less investigated process. As a method of corrosion monitoring, it is simple, and flexible and offers an easy way to examine the morphology and corrosion penetration rate on mild steel.

MATERIALS AND METHODS

Preparation of Psidium Guajava Leaf Extracts

Materials used for the study were mild steel rods of composition (wt %) Carbon (0.2789), Silicon (0.2428), Sulphur (0.0400), Phosphorus (0.0332), Manganese (0.5096), Chromium (0.0114), Molybdenum (0.0114), Copper (0.1196), Argon (0.0015), Tin (0.0102), Cobalt (0.0100), Aluminium (0.0008), Calcium (0.0001) and Iron (0.0027) and dimension, 10×70 mm. Each specimen was degreased by washing in ethanol, dried in acetone, and stored in a desiccator. The composition of the mild steel bars was analyzed using an optical emission spectrometer and the mild steel bars were purchased from Abakaliki Building Material, Ebonyi State, Nigeria. The chemicals and reagents used in this study were of analytical grade and solution water was used for their preparation.

Corrosion Rate Determination

The leaves of Psidium guajava were collected from Nkalaha town, Ebonyi State and identified by a laboratory technician in the Department of Applied Biology, Ebonyi State University, Abakaliki. 50 g of Psidium guajava leaves were added to 500 ml of distilled water and boiled for about 2 hours at a temperature of 80 ° C and then carefully filtered. From the weight of the extracted leaves, extracts of different concentrations of 25, 50, 75 and 100 cm3 of the plant extracts were filled separately into four beakers. The first beaker was kept empty without adding any extract (control experiment). Four coupons were then suspended with a rope in each of the cups and left for different time intervals (168, 336, 504, and 672 hours, respectively). The above procedure was also done for mild. Weight loss was used to calculate the Corrosion Penetration Rate (CPR) in milligrams per square centimeter per hour. The mathematical calculation of CPR is based on the formula

$$CPR = \frac{\kappa \Delta W}{\rho A t} \qquad (1)$$

Here ΔW is the weight loss after the exposure time t, ρ and A are the density or the exposed sample area and K is a constant whose size depends on the system of units used. For example, if K is 87.6, the CPR is expressed in mm/year and ΔW, t, ρ and A are expressed in mg, hr, g/cm3 and cm^3, respectively (Callister, 2007)

In a bid to carry out mathematical modelling of the test data, SPSS and MATLAB software for correlation and regression analysis of data were used for this study. The mathematical functions were employed because the data obtained was compared with the experimental data. The model equation was used to evaluate the effect of inhibitors on the behaviour of metals in the corrosion systems and to predict the corrosion rate. For the corrosion rate prediction, the input layer admitted the variables of exposure time, inhibitor concentration, media concentration, initial weight and final weight and it was used with 672 experimental measurements taken every seven days for 28 days for the weight loss experiment.

RESULTS AND DISCUSSIONS

Corrosion Penetration Rate Analysis

Experimental results obtained in the course of this study include weight loss and corrosion rates used after seven-day intervals for twenty-eight days. Figures 1 to 2 show the corrosion rates depending on the exposure time for different amounts of *Psidium quajava* leaf extract in alkaline medium.

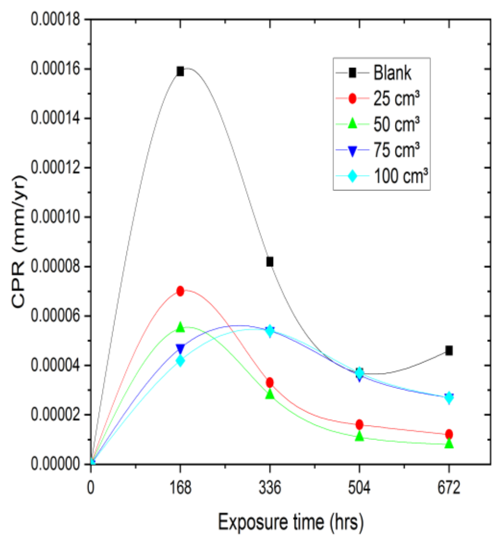

Fig. 1: Variation of corrosion rate with exposure time for corrosion of mild steel in 0.5M NaOH solution containing different volumes of *psidium quajava* leaf extract

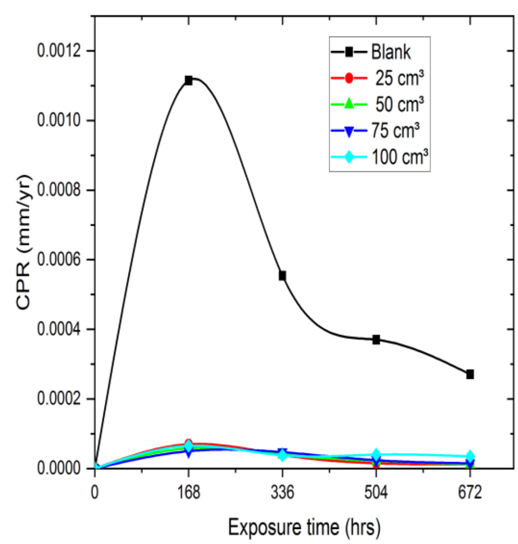

Fig. 2: Variation of corrosion rate with exposure time for corrosion of mild steel in 1.0M NaOH solution containing different volumes of *psidium quajava* leaf extract

Generally, corrosion rates of most materials increase with exposure time. In this case, as the exposure time of the mild steel to the corrosive media was increased, corrosion rates were found to decrease in the time interval of 168-672 hours as evidenced in Figure 1.

Figure 1, it can easily be shown that all the samples showed the usual corrosion rate profiles associated with passivating metals. In significant terms, the control experiment showed high corrosion rates at the early stages of immersion, the rates became very low as the exposure time increased; while 25- 100 cm^3 of leaf extracts had same corrosion rates throughout the experimental period. Another significant observation in the behaviour of the samples is the fact there was no undulations in the trends showing that the influence of extraneous factors were highly insignificant. This is consistent with the results in the literature (Idenyi *et al.*, 2015; Belkhaouda *et al.*, 2013; Fekkar *et al.*, 2020; Ime, 2016; Idu *et al.*, 2015; Durowaye *et al.*, 2014; Verma *et al.*, 2018).

Analysis result of Models.

The results of the statistical models were presented in Table 1-4, Figures 3 - 6 showed the graphs of corrosion rate for the experimental data and model predicted data for mild steel in the NaOH in the absence of the *Psidium guajava* leaf extracts and with the addition of 25-100 cm^3 of the *Psidium guajava* leaf extracts and Figure 13 to 14 show the plots of the cubic model equations of concentrations of *Psidium guajava* leaf extract in 0.5 M NaOH and 1.0 M NaOH at different exposure time.

Table 1: Variation of Model Equations and Coefficient of Determination of Mild Steel in Different Volumes of *Vitex doniana* Leaf Extract in 0.5 M NaOH at Different Exposure Time.

Model Equations	Regression Model for Control with Goodness of Fit (R^2)	R^2
Quadratic	$Y_c = 2.8450\times10^{-4} - 8.6845\times10^{-7}t + 7.6176\times10^{-10}t^2$	0.997
Cubic	$Y_c = 2.4599\times10^{-4} - 5.0396\times10^{-7}\ t - 2.1258\times10^{-10}\ t^2 + 7.7329\times10^{-13}t^3$	1.0
Logarithmic	$Y_c = 6.059\times10^{-4} - 8.8697\times10^{-5}\log(t)$	0.923
	Regression Model for 25 cm^3 with Goodness of Fit (R^2)	R^2
Quadratic	$Y_{25} = 7.7250\times10^{-5} - 2.2589\times10^{-7}t + 1.8601\times10^{-10}t^2$	0.995
Cubic	$Y_{25} = 9.3\times10^{-5} - 3.75\times10^{-7}\ t + 5.8461\times10^{-10}\ t^2 - 3.1635\times10^{-13}t^3$	1.0
Logarithmic	$Y_{25} = 1.7955\times10^{-4} - 2.6661\times10^{-5}\log(t)$	0.965
	Regression Model for 50 cm^3 with Goodness of Fit (R^2)	R^2
Quadratic	$Y_{50} = 6.8500\times10^{-5} - 2.2321\times10^{-7}t + 1.8487\times10^{-10}t^2$	0.992
Cubic	$Y_{50} = 8.6000\times10^{-5} - 3.8889\times10^{-7}\ t + 6.3776\times10^{-10}\ t^2 - 3.5149\times10^{-13}t^3$	1.0
Logarithmic	$Y_{50} = 1.5322\times10^{-4} - 2.3184\times10^{-5}\log(t)$	0.931
	Regression Model for 75 cm^3 with Goodness of Fit (R^2)	R^2
Quadratic	$Y_{75} = 6.0250\times10^{-5} - 2.0327\times10^{-7}t + 1.8601\times10^{-10}t^2$	0.980

Cubic	$Y_{75} = 8.3000\times10^{-5} - 4.1865\times10^{-7}\ t + 7.6176\times10^{-10}\ t^2 - 4.5695\times10^{-13}t^3$	1.0
Logarithmic	$Y_{75} = 1.2489\times10^{-4} - 1.8694\times10^{-5}\log(t)$	0.880
	Regression Model for 100 cm^3 with Goodness of Fit (R^2)	R^2
Quadratic	$Y_{100} = 4.9249\times10^{-5} - 1.5744\times10^{-7}t + 1.3287\times10^{-10}t^2$	0.989
Cubic	$Y_{100} = 6.5000\times10^{-5} - 3.0655\times10^{-7}\ t + 5.3146\times10^{-10}\ t^2 - 3.1635\times10^{-13}t^3$	1.0
Logarithmic	$Y_{100} = 1.1589\times10^{-4} - 1.7681\times10^{-5}\log(t)$	0.95

Table 2: Variation of model equations and coefficient of determination of mild steel in different concentrations of *Psidium guajava* leaf extracin 1.0 M NaOH at different exposure time.

Model Equations	**Regression Model for Control with Goodness of Fit (*R*^{2})**	R^2
Quadratic	$Y_c = 1.8340\times10^{-3} - 5.0542\times10^{-6}t - 4.0923\times10^{-9}t^2$	0.990
Cubic	$Y_c = 2.3450\times10^{-3} - 9.8919\times10^{-6}\ t + 1.70245\times10^{-8}\ t^2 - 1.0264\times10^{-11}t^3$	1.0
Logarithmic	$Y_c = 4.2303\times10^{-3} - 6.1718\times10^{-4}\log(t)$	0.968
	Regression Model for 25 cm^3 with Goodness of Fit (*R*^{2})	R^2
Quadratic	$Y_{25} = 1.1185\times10^{-4} - 3.2619\times10^{-7}t + 2.4802\times10^{-10}t^2$	0.995
Cubic	$Y_{25} = 9.3999\times10^{-5} - 9.4246\times10^{-8}\ t - 3.7202\times10^{-10}\ t^2 + 4.9209\times10^{-13}t^3$	1.0
Logarithmic	$Y_{25} = 2.9551\times10^{-4} - 4.4186\times10^{-5}\log(t)$	0.977
	Regression Model for 50 cm^3 with Goodness of Fit (*R*^{2})	R^2
Quadratic	$Y_{50} = 2.8450\times10^{-4} - 8.6845\times10^{-7}t + 7.6176\times10^{-10}t^2$	0.997
Cubic	$Y_{50} = 6.7999\times10^{-5} - 1.9841\times10^{-8}\ t - 2.8345\times10^{-10}\ t^2 + 2.8119\times10^{-13}t^3$	1.0
Logarithmic	$Y_{50} = 2.3134\times10^{-4} - 3.3522\times10^{-5}\log(t)$	0.986
	Regression Model for 75 cm^3 with Goodness of Fit (*R*^{2})	R^2
Quadratic	$Y_{75} = 5.8500\times10^{-5} - 3.1547\times10^{-7}t - 5.3146\times10^{-11}t^2$	0.935
Cubic	$Y_{75} = -1.0000\times10^{-6} + 5.3175\times10^{-7}\ t - 1.5589\times10^{-9}\ t^2 + 1.1951\times10^{-12}t^3$	1.0
Logarithmic	$Y_{75} = 1.8856\times10^{-4} - 2.6116\times10^{-5}\log(t)$	0.835
	Regression Model for 100 cm^3 with Goodness of Fit (*R*^{2})	R^2
Quadratic	$Y_{100} = 9.3999\times10^{-5} - 2.1607\times10^{-7}t + 1.9487\times10^{-10}t^2$	0.887
Cubic	$Y_{100} = 1.5700\times10^{-4} - 8.1250\times10^{-7}\ t + 1.7893\times10^{-9}\ t^2 - 1.2654\times10^{-12}t^3$	1.0
Logarithmic	$Y_{100} = 1.6797\times10^{-4} - 2.0862\times10^{-5}\log(t)$	0.824

Table 3: Corrosion Rate of Mild Steel in different Concentrations of *Psidium guajava* leaf extract in 0.5M NaOH at different Exposure Time

Exposure time (hrs)	Corrosion Rate (mm/yr)	Model predicted data for logarithmic	% Error	Model predicted data for cubic	% Error	Model predicted data for Quadratic	% Error
Control							
168	0.000159	0.000409	-156.93	0.000159	0.005	0.000160	-0.75
336	0.000082	0.000382	-365.64	0.000082	0.008	0.000079	3.91
504	0.000037	0.000366	-889.74	0.000037	0.013	0.000040	-9.16
672	0.000046	0.000355	-672.00	0.000046	0.006	0.000045	2.19
25 cm^3							
168	0.000070	0.000192	-175.47	0.000070	-0.002	0.000069	0.50
336	0.000033	0.000179	-444.78	0.000033	-0.001	0.000034	-3.18
504	0.000016	0.000172	-975.91	0.000016	-0.02	0.000015	6.58
672	0.000012	0.000167	-1289.4	0.000012	-0.025	0.000012	-2.88
50 cm^3							
168	0.000055	0.000157	-184.54	0.000055	2.424	0.000055	-0.36
336	0.000028	0.000146	-420.79	0.000028	38.09	0.000027	2.15
504	0.000011	0.000139	-1168	0.000011	327	0.000012	-5.44
672	0.000008	0.000135	-1589	0.000008	1066	0.000008	2.54
75 cm^3							
168	0.000047	0.000095	-102.39	0.000047	-0.001	0.000049	-3.62
336	0.000054	0.000091	-67.99	0.000054	-0.006	0.000049	9.44
504	0.000036	0.000088	-144.81	0.000036	-0.025	0.000041	-14.1
672	0.000027	0.000086	-219.64	0.000027	-0.064	0.000025	6.29
100 cm^3							
168	0.000042	0.000079	-89.41	0.000042	0.084	0.000044	-4.28
336	0.000054	0.000076	-41.35	0.000054	-0.036	0.000049	9.99
504	0.000037	0.000074	-101.19	0.000037	-0.794	0.000042	-14.59
672	0.000027	0.000073	-170.75	0.000028	-3.409	0.000025	6.66

Table 4: Corrosion Rate of Mild Steel in different Concentrations of *Psidium guajava* leaf extract in 1.0M NaOH at different Exposure Time

Exposure time (hrs)	**Corrosion Rate(mm/yr)**	**Model predicted data for logarithmic**	**% Error**	**Model predicted data for cubic**	**% Error**	**Model predicted data for Quadratic**	**% Error**
Control							
168	0.001115	0.002856	-156.22	0.001115	0.01	0.000869	22.02
336	0.000554	0.002671	-382.2	0.000554	0.02	-0.000326	158.88
504	0.000370	0.002562	-592.5	0.000370	73	-0.001752	573.74
672	0.000271	0.002485	-817.1	0.000271	0.05	-0.003410	1358.47
25 cm^3							
168	0.000070	0.000197	-181.7	0.000070	0.001	0.000064	8.49
336	0.000039	0.000184	-371.5	0.000039	0.002	0.000030	22.43
504	0.000015	0.000176	-1074.0	0.000015	0.004	0.000010	30.32
672	0.000012	0.000171	-1321.5	0.000012	0.006	0.000005	61.23
50 cm^3							
168	0.000058	0.000157	-170.2	0.000058	0.002	0.000160	-176.03
336	0.000040	0.000147	-266.6	0.000040	0.004	0.000079	-96.75
504	0.000022	0.000141	-539.8	0.000022	0.012	0.000040	-83.18
672	0.000012	0.000137	-1038	0.000012	0.037	0.000045	-274.16
75 cm^3							
168	0.000050	0.000130	-160.9	0.000050	-0.005	0.000004	91.99
336	0.000047	0.000123	-160.8	0.000047	-0.017	-0.000054	213.82
504	0.000024	0.000118	-391.6	0.000024	-0.075	-0.000114	574.99
672	0.000015	0.000114	-664.8	0.000015	-0.213	-0.000178	1283
100 cm^3							
168	0.000065	0.000122	-86.99	0.000065	-0.002	0.000063	2.77
336	0.000038	0.000115	-203.33	0.000038	-0.011	0.000043	-14.20
504	0.000040	0.000112	-178.98	0.000040	-0.023	0.000035	13.50
672	0.000035	0.000109	-211.39	0.000035	-0.044	0.000037	-5.14

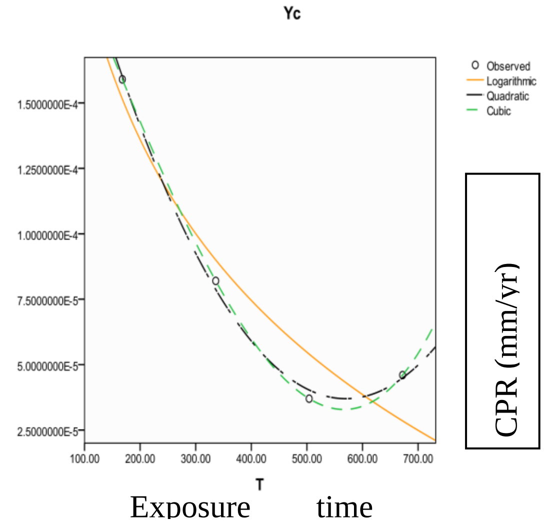

Fig. 3: Corrosion penetration rate plot for experimental data and model predictive data for mild steel without leaf extract of Psidium quava in 0.5 M NaOH at different exposure times

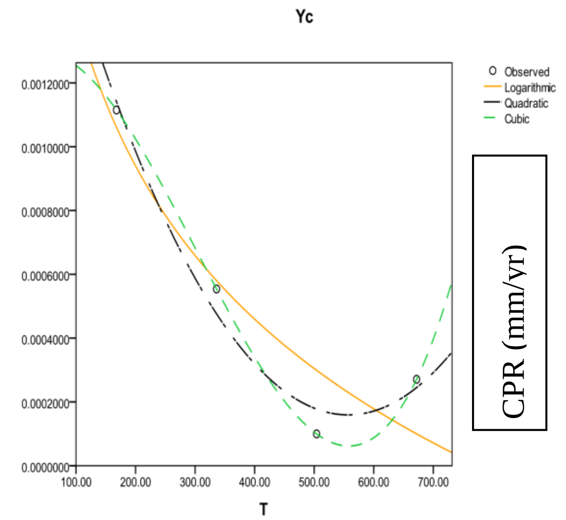

Fig. 4: Corrosion penetration rate plot for experimental data and model predictive data for mild steel without leaf extract of Psidium quava in 0.5 M NaOH at different exposure times

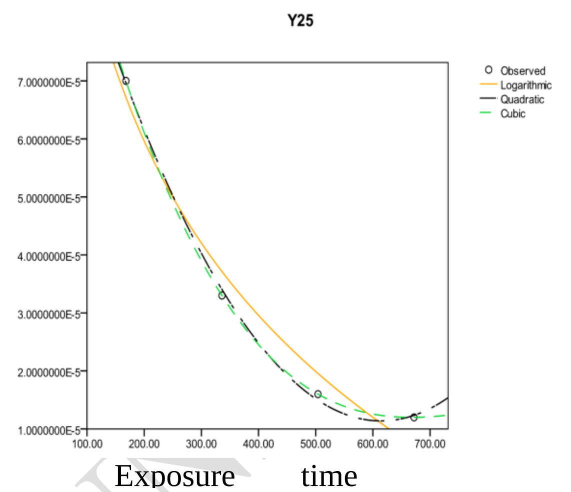

Fig. 5: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 25 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times

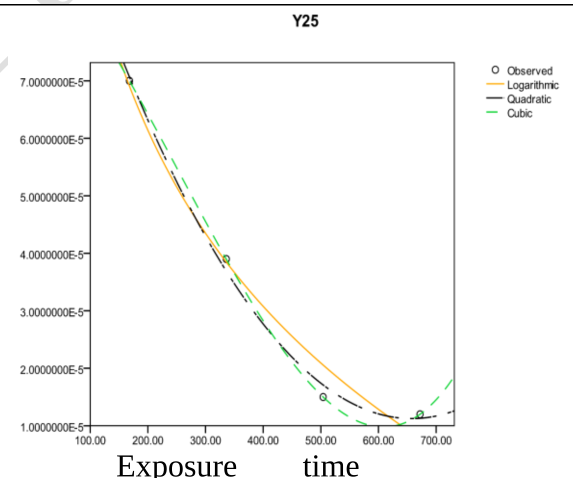

Fig. 6: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 25 cm^3 of *Psidium guajava* leaf extract in 1.0 M NaOH at different exposure times

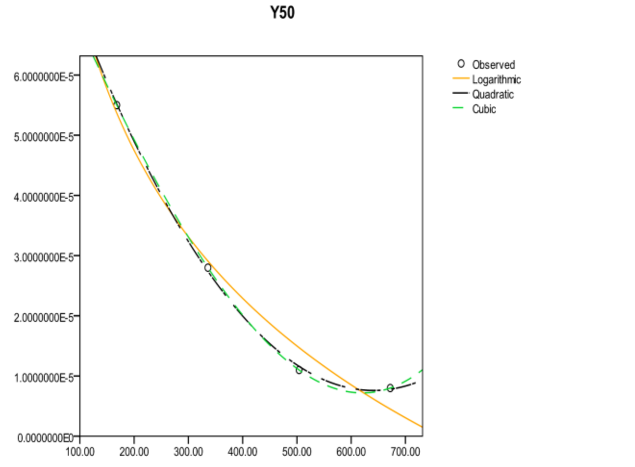

Fig. 7: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 50 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times

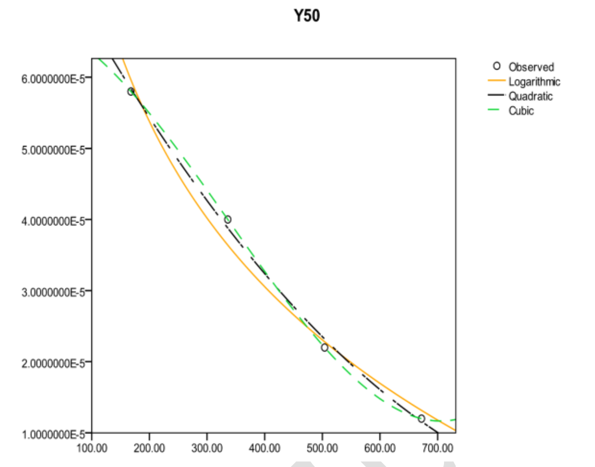

Fig. 8: corrosion penetration rate plotfor experimental data and model predictive data for mild steel with 50 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times

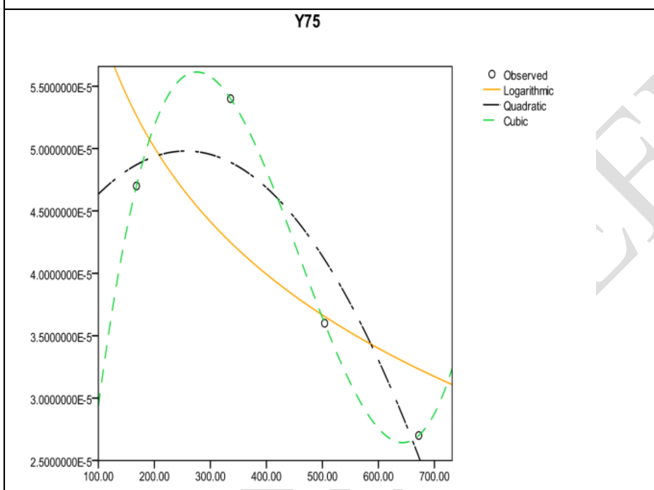

Fig. 9: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 75 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times

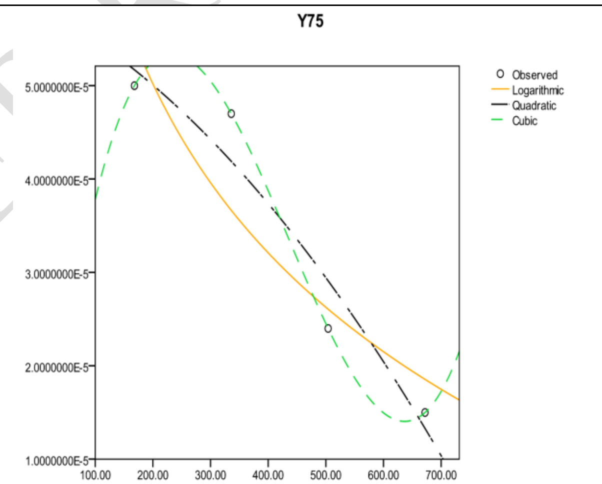

Fig. 10: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 75 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times

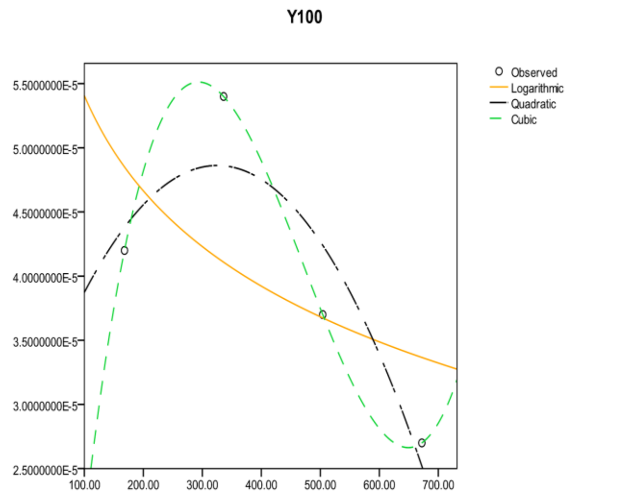

Fig. 11: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 75 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times.

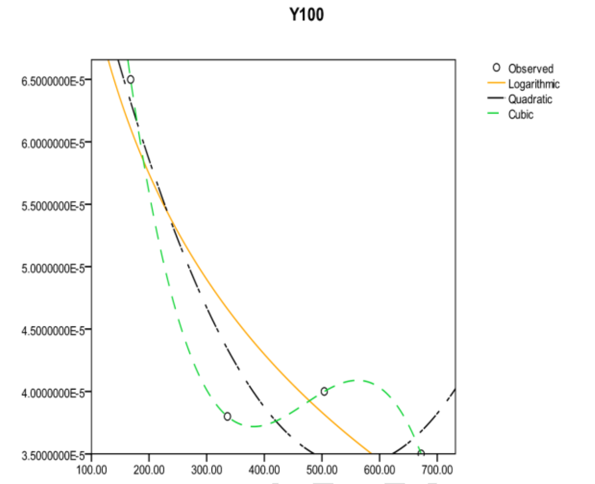

Fig. 12: Corrosion penetration rate plot for experimental data and model predictive data for mild steel with 75 cm^3 of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure times.

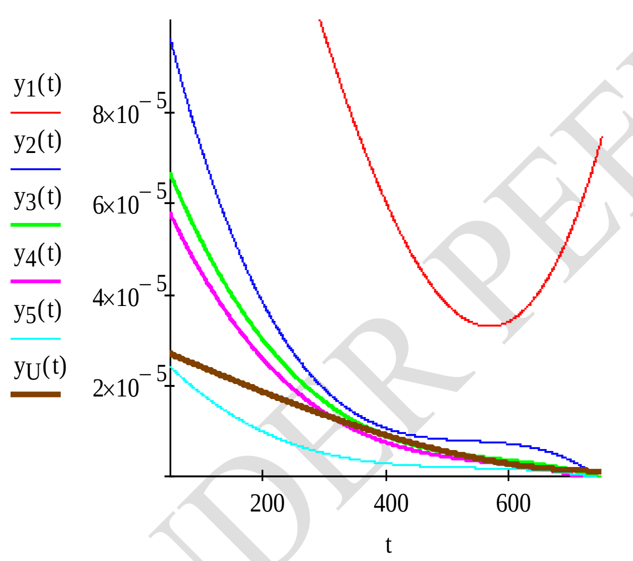

Fig. 13: Plots of the cubic model equations of the concentrations of *Psidium guajava* leaf extract in 0.5 M NaOH at different exposure

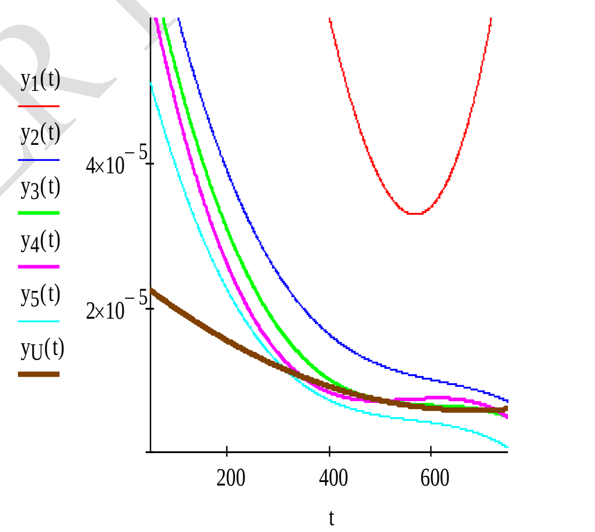

Fig. 14: Plots of the cubic model equations of the concentrations of *Psidium guajava* leaf extract in 1.0 M NaOH at different exposure

Mathematical modelling and statistical analysis

From Table 1, inhibitor and exposure time are important modeling terms that affect the corrosion rate of mild steel. The coefficient of determination (R^2) is defined as the ratio of the explained variation to the total variation. It is a measure of fitness level. As the coefficient of determination R^2 approaches unity, a better response model results that fits the actual data. The value of R^2 calculated for this model was 1 for cubic, which means that the developed model has a high correlation with the experimental value. It shows that 100% of the variability in the data can be explained by this model. This confirmed that the model explains the relationship between the independent factors and their reactions (cubic equation) reasonably well. Therefore, it was concluded that the influence of inhibitor concentration and exposure time on the corrosion rate was statistically significant. The developed unified models equations for the corrosion behaviour of the mild steel in the alkaline environment in the absence and presence of the extract predict the corrosion failure for the period of time the coupons were immersed in the solution and the level of deterioration of the mild steel were expressed as:

$$Y_U(\mathrm{t}) = 8.1982 \times 10^{-5} - 2.0015 \times 10^{-7}t + 3.1586 \times 10^{-10}t^2 - 2.6450 \times 10^{-13}t^3 \qquad (2)$$

The results of cubic regression model were presented in equation 2 in NaOH environment which gave the actual values of the experimental results in the study.

It has been held for sometimes now that corrosion rate profiles are logarithmic in nature, an argument based on the formula for calculating the corrosion penetration rate.

However, from the point of view of this study, an argument is being presented to the effect that corrosion rate profiles could be looked at as a special case of logarithmic, quadratic and cubic equations if and only if an assumption is made that all samples are assumed to have zero corrosion at the instance of being introduced into the corrosion medium. That being case, the graph would start at the origin. It is this assumption that has been employed in this study. Similar inferences have been reported by other researchers for prediction of corrosion rate profiles by logarithmic and quadratic model equations (Nwoye *et al.,* 2013; Nwankwo *et al.*, 2013; Kochure *et al.,* 2012)

Accordingly, from Table 1 and Figures 2-6, the extent of correlation of the observed corrosion rates with the expected mathematical models has been established for all the mild steel samples in various corrosion environments studied. Close observation of the cubic model equation revealed that the best fit line is obtained from the plots of all model equations presented in Tables 1–4 and shown in Figures 3–12. The cubic model equation clearly shows that the determination coefficient R^2 of 1 is very high, which similarly indicates that about 100% of the determining factors depend on the exposure time of the corrosion process. The standard error of the estimate was between 0.021

and 0.054, which is significantly less than 0.1 and showed that the model equation was significant. This very narrow margin of error implies that the use of cubic models to characterize the corrosion rates of mild steel in alkaline environments is justified and therefore could be used. This established a classic departure from the long-held assumption that the behaviour of the corrosion rate is quadratic and logarithmic. These claims are confirmed by the line patterns in Figures 3-12, where the lines of best fits match the perfection of the obtained correlation data. This result is consistent with the findings of Gan *et al.*, 2010., Ekuma *et al.*, 2007; Ekuma *et al.*, 2010).

In general, the summary graphs (Figures 3–12) showed that the model equations obeyed the cubic, logarithmic and quadratic functions, but the cubic function provided the best fitting line, followed by the quadratic function, while the logarithmic function provided a poor fitting line in the corrosion model equations in selected surroundings.

CONCLUSION

On the basis of this study, the following conclusions are drawn:

i. Experimental data showed that Psidium guajava leaf extracts at different concentrations (25–100 cm^3) inhibited the corrosion of mild steel in alkaline medium.

ii. that the results obtained by regression equations are closely correlated with each other, which validates the developed regression equations. A good agreement between the predicted and actual corrosion rates was observed. This is in qualitative agreement with recent literature.

iii. that the results of the statistical analysis agree well with the experimental results for the inhibitor and time. The rate of corrosion has been found to increase with increasing use of inhibitors and exposure time.

iv. that the developed model equations can be used to predict the corrosion values in relation to anti-corrosion process parameters obtained from any combinations within the studied ranges and can also be used to optimize the process parameters of mild steel in relation to anti-corrosion values.

v. that the weight loss method agrees well with the statistical analysis and this improves the validity of the overall results obtained.

vi. Using these three model equations (cubic, quadratic and logarithmic) we can predict the corrosion rate for each time point and for the different test conditions. To determine the allowable time, cubic expressions for the allowable corrosion rate have also been developed and the allowable time to failure or system life can be estimated for the allowable corrosion rate.

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Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Details of the AI usage are given below:

1.

2.

3.

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