Study of Corrosion Inhibition Potentials of *Eichhornia crassipes* Leaves Extract on Mild Steel in Acidic Medium using Artificial Neural Network

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Abstract

Prediction of corrosion behavior of steel in acidic environments is an essential step towards optimizing the design of equipment in any industrial setting. An artificial neural network (ANN) may be used as a reliable modeling method for simulating and predicting the corrosion behaviour. The present study has been conducted to investigate the corrosion inhibition potentials of *Eichhornia crassipes* (water hyacinth) leaves extract for mild steel in acidic media and to establish an appropriate ANN model for predicting corrosion behavior of mild steel in H_2SO_4 inhibited by *Eichhornia crassipes*. The experimental procedure employed weight loss method for corrosion rate measurements. Results have shown that *Eichhornia crassipes* is an effective inhibitor for corrosion inhibition of mild steel in acidic medium. A Levenberg-Marquardt (LM) ANN with single hidden layer having five neurons was employed to simulate the corrosion behaviour. The neural network was trained using the experimental corrosion database. Finally, validity of the proposed model was tested using standard statistical parameters. Results indicate that the trained ANN model is robust for predicting corrosion behaviour of mild steel in acidic media.

Keywords: Artificial neural networks (ANNs); corrosion rate, simulation, corrosion behaviour

Introduction

The study of corrosion involves the study of the chemical, physical, metallurgical, and mechanical properties of materials as it is a synergistic phenomenon in which the environment is as equally important as the materials involved. Computer modeling techniques can handle the study of complex systems such as corrosion and thus are appropriate and powerful tools to study the mechanism without compromising accuracy. A variety of techniques have been developed to reduce the number of simulations without compromising accuracy. Monte Carlo and the Box-Muller methods are well known. Artificial Neural Network (ANN) is a computational model based on the structure and functions of biological neural networks (Mohanraj *et al.,* 2012). ANNs are considered nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. The operational manner of ANNs is that when inputs are applied to the input neurons the network performs a summation of the weighting factors and then it activates one or more speci?c output neurons that are capable of providing the most suitable answer for the given problem. The use of ANN has grown in popularity during the last few years. The reason for this is that neural networks represent a novel and modern approach that can provide solutions to problems for which conventional mathematics, algorithms and methodologies cannot. These problems are usually very complex and some of the

mechanisms involved have not been fully understood by researchers.

The commonest type of artificial neural network consists of three mathematical groups, layers, or units as shown in fig 1.
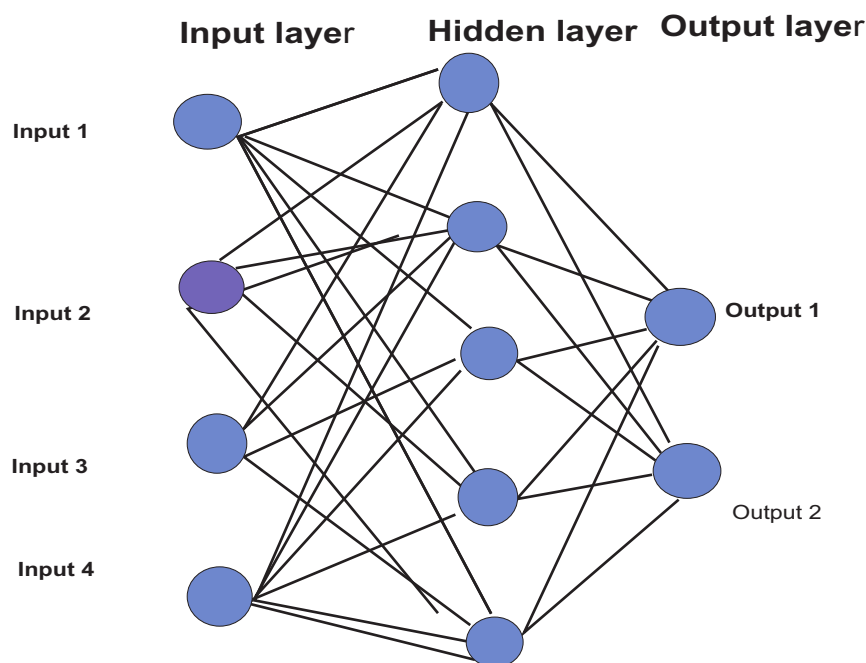

Fig. 1: A schematic illustration of an ANN model.

According to Zhenyu *et al*., (2007) the mathematical units are conventionally constructed with three layers, i.e. input, hidden and output layer. The hidden layer usually contains one or several layers, and the number of neurons in each layer can be different. The behaviour of an ANN depends on both the weights and the input-output function (transfer function) that is specified for the units. According to Mohanraj *et al*., (2012) transfer function consist of algebraic equations which are either linear or non linear. The most commonly used transfer functions are log-sigmoid and tangent sigmoid. The log sigmoid transfer function is used when all the values in input and output layer are positive while tangent sigmoid is used when there are negative values in the input or output layer.

The methodology for implementing ANN comprises four steps (Dou *et al*., 2007) which include Collection and pre-processing of the experimental data, Training the ANN, and optimization of its configuration, evaluating the performance of the ANN and returning to stage 2 if the performance is not satisfactory, and using the trained ANN for simulation or prediction.

Many articles have revealed instances where ANN has been applied in predicting corrosion in engineering systems.

The application of neural network methods to model the pitting corrosion behavior of a stainless steel as a function of solution composition and temperature was presented by Cottis *et al.,* (1999). The ANN prediction exhibited reasonable correlation with data for simple one- and two-component solutions. The use of simulated data to test the neural network method in conditions similar to those being modeled was suggested as one method of obtaining a better assurance of the applicability and performance of the method.

A neural network can provide considerable information on the corrosion behavior of resistant metal alloys. Kamrunnahar and Urquidi-Macdonald (2011) developed an algorithm to predict behavior of corrosion resistant metal alloys using a supervised neural network method as a data mining tool. The data mining results were

categorized and prioritized to certain parameters (i.e. pH, temperature, time of exposure, electrolyte composition, metal composition, etc.) and helped understand the synergetic effects of the parameters and variables on corrosion behavior. The results were in good agreement with the experimental values.

Prediction of low-carbon steel, copper and aluminum corrosion rates according to environmental parameters in the area of São Luis –Maranhão in Brazil using ANN model was developed by Elaine *et al.,* (2009) The area along the "702 – São Luis II –Presidente Dutra" 500 kV transmission line, located in an equatorial region, was employed for the purpose. A specific methodology was developed to determine the local corrosivity rate for these metals. Five atmospheric corrosion stations (ACS) were installed along the 702 transmission line in an extension of 200 km. Along with the meteorological data, local pollutants were collected and analyzed during a period of two years. In the same period, specimens were exposed to the atmosphere and periodically collected for corrosion evaluation. The obtained results indicated that the neural network can be used as a good corrosion estimator.

Pintos *et al*., (2000) also presented an ANN-based solution methodology for modeling atmospheric corrosion processes from observed experimental values.   The prediction of the corrosion rate of carbon steel in Iberoamerican Corrosion Map (MICAT) Project used seventy-two test sites in fourteen countries throughout Iberoamerica. The ANN model exhibited superior performance in terms of goodness of sum of square errors and residual distributions when compared against a classical regression model also developed in the context of the study. The methodology indicated that the tool can be used in the modeling of corrosion phenomenon from experimental data.

Duo *et al*., (2007), while studying the amount of ultimate strength reduction of locally corroded plates, used ANN method to derive a formula to predict behaviour. It was found out that the proposed formulae accurately predicted the ultimate strength of locally corroded plates under uniaxial in-plane compression. Transverse location of pit corrosion was also an important factor in determining the amount of strength reduction.

Birbils *et al.*, (2011) studied the corrosion rate and yield strength of magnesium-rare earth (Mg–RE) alloys using ANN. The dataset was provided by the additions of Ce, La and Nd to Mg in binary, ternary and quaternary combinations up to 6 wt. %. It was observed that the yield strength increased with RE additions, and the corrosion rates also systematically increased. The work permitted an understanding of Mg–RE alloy performance, which can be exploited in Mg alloy design for predictable combinations of strength and corrosion resistance.

The present study has been conducted to study and establish the inhibition potentials of *Eichhornia crassipes* for mild steel in acidic medium and to use neural network to simulate and predict the corrosion behavior of mild steel in this inhibited acidic medium. In the neural network simulation, specimen conditions, inhibitor conditions, and operation conditions, were used as the inputs of the network while corrosion rate was gained as the output. Finally, validity of the proposed model was tested using standard statistical parameters.

Materials and Methods
Preparation of water hyacinth extract

Water hyacinth leaves were obtained from the River Benue, shade-dried, crushed and ground into powder. Active ingredients were extracted using Soxhlet Extraction method. At each extraction cycle, sixty grams (60g) of the powdered water hyacinth were measured and extracted against 450 ml methanol for 2 hours. The resulting solution was then concentrated until the liquid was completely evaporated. This solid extract was used to study the corrosion inhibition properties and to prepare the required concentrations of the water hyacinth.

Specimen preparation

Mild steel specimens having nominal composition of 0.16% C, 0.30% Mn, 0.21% Si, 0.04% P, 0.03%S, and 99.257 Fe balance were used. Corrosion coupons were cut into 4 x 3 x 0.2cm dimensions for weight loss measurements. The coupons were mechanically abraded with 220, 400, 800 and 1000 grades of emery papers, degreased with acetone and rinsed with distilled water.

Weight loss measurements.

Experiments were performed at room temperature with different concentrations of the water hyacinth extract. The concentration range of the water hyacinth extract employed was varied from 0 - 15 g/l and the electrolyte used was 600 ml of 1M H_2SO_4 for each experiment. Immersion time for the weight loss experiment was 6 hours. The results of the weight loss experiments are the mean of three runs, each with a fresh specimen and 600 ml of fresh acid solution. Corrosion rate was calculated from weight loss of the coupons at room temperature at various concentration and immersion times, using the relation in Fontana (1998) givrn in equation (1)

$$Corrosion\ Rate\ (mm/yr) = \frac{87.6 \Delta W}{\rho AT} \quad (1)$$

Where, Δw is weight loss of mild steel Where, coupon in kg; ρ is density of mild steel in kg/cm^3; A is the Surface area of mild steel in cm^2; and T, the immersion time in hours

The inhibition efficiency (IE %) and surface coverage (θ) at each concentration for each coupon was calculated from the result obtained from the weight loss experiment as presented in equations 2 and 3 respectively.

$$IE\% = \frac{W_1 - W_2}{W_1} \times 100 \quad (2)$$

$$\theta = \frac{W_1 - W_2}{W_1} \quad (3)$$

Where, W_1 and W_2 are the weight loss of the mild steel in the presence and absence of inhibitor respectively.

Neural Network Modeling

The input data captured in the artificial neural network was broadly grouped into three namely, specimen dimensions, inhibitor condition, and operating conditions. This resulted in a total number of nine inputs parameters as shown in Table 1. Input data F_{T1}-F_{T9} were used for training the network while F_{P1}-F_{P6} was employed for testing the prediction capabilities. The working together of the influence of these nine inputs parameters on corrosion rate are illustrated in Fig.2. Corrosion rate of the mild steel in H_2SO_4 inhibited by *Eichhornia crassipes* leaves extract at various concentrations was taken as the output. Corrosion rate was computed using equation (1).

Since the best neural network's architecture and learning algorithm are not known in advance, a trial and error approach was used to find the best network characteristics for matching the particular input/output relationship. These were investigated, using MATLAB 7.9.0 (r20096), for one layered network 9 [1]$_1$ **1**, 10 [5]$_1$ **1**, two layered network 9 [4-3]$_2$ **1**, 9 [5-5]$_2$ **1**, and three layered network 9 [5-5-3]$_3$ **1**, 9 [6-5-4]$_3$ **1,** respectively. The above networks architecture was trained using three different algorithms i.e. Levenberg-Marquardt (LM), Bayesian Regulation (BR), and Resilient Back-propagation (RB). The sigmoid function (equation 4) was used between the input and the hidden layers (Dragen, 2010).

$$f(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

The linear function f(x) = x) was used between the hidden and output layer. Pre-processing of the input parameters was carried out before training of the neural network. Inhibitors concentration and specimen dimensions were pre-determined and presented to the network, while exposure time and temperature were scaled using equation (5) (Dragen, 2010)

$$I_{Skal} = 1 + \frac{(I_{Curr} - I_{Max})}{(I_{Max} - I_{Min})} \quad (5)$$

Where; I_{Curr} -current input value. I_{Max} maximum input value and I_{Min} -minimum input value.

Results and Discussion

After a series of repeated trials using different neural network architectures namely; one layered network 9 [1]$_1$ **1**, 9 [5]$_1$ **1**, two layered network 9 [4-3]$_2$ **1**, 9 [5-5]$_2$ **1**, and three layered network, 9 [5-5-3]$_3$ **1**, 9 [6-5-4]$_3$ **1**; it was discovered that the LM 9 [5]$_1$ **1** gave the best trade off error and cost. It was therefore, selected for the prediction. It also showed very good correlation for both the training and testing compared with the other architecture models. Training performance indicted values of regression R= 0.99994 at epoch 8 and the overall performance of regression R= 0.999864 for training validation and testing. The established ANN model has been used to study the corrosion behaviour of mild steel in H_2SO_4 inhibited by *Eichhornia crassipe* leaves extract. Fig.3 shows the effect of inhibitor concentration on corrosion rate of mild steel in H_2SO_4 inhibited by *Eichhornia crassipe* leaves extract. It can also be observed from the figure that the higher the concentration of inhibitor, the lower the corrosion rate. As is observed, the ANN model may well predict the effect of inhibitor concentration on the corrosion rate of mild steel in H_2SO_4. The ANN model was also applied to simulate the effect of inhibitor efficiency on the corrosion rate. The results of variation of corrosion rate with inhibitor efficiency are presented in Fig. 4 while those of effect of weight loss on corrosion rate are presented in Fig. 5. These figures argue that corrosion rate decreases with increase in both inhibitor efficiency and weight loss. As is also observed, the simulated corrosion rates may well tract their corresponding measured values. It also indicates that the neural model has performed well as reported by other researchers, Dragen (2010), Cottis *et al.*, (1999), Kamrunnahar and Urquidi-Macdonald (2010).

Assessment of the proposed model

To have a more detailed quantitative view regarding the predictability of the model the root mean square error (RMSE) and Nash-scurtclisse efficiency (NSE) were used to evaluate the model (Mohanty, et al., 2013).

These are presented in equations 6&7 respectively:

$$RMSE = \sqrt{\frac{\sum_{p=1}^{n}(d_p - o_p)^2}{n}} \quad (6)$$

Where; d_p is the desired output for performance and O_p is the network output.

$$NSE = 1 - \frac{\sum_{i=1}^{N}(E_i - P_i)^2}{\sum_{i=1}^{N}(E_i - \bar{E}_i)^2} \quad (7)$$

Where; E_i is the experimental value, P_i, the predicted while $\bar{E}_i$ is the mean of experimental values.

Table 2 shows the values of the predicted and computed (targeted) corrosion rates together with their respective relative errors. It can be observed that values of corrosion rate predicted using the ANN model deviated by amounts less than half a percent from their measured values and NSE values of close to unity indicating that they are, indeed in good agreement with the targeted values. Accuracy of the prediction was also determined by considering scatter of predicted and measured values around regression lines as shown in Fig. 6. The distributions of real data around regression lines demonstrate good conformability of the developed model to the real process. In other words, there was high correlation between the predicted values by the ANN model and the measured values. The correlation coefficients was over 95% which implied that the model succeeded in the prediction of the corrosion behavior of mild steel in H_2SO_4 inhibited by *Eichhornia crassipe* leaves extract.

Conclusion

In this study, potentials of *Eichhornia crassipe* (water hyacinth) as corrosion inhibitor for mild steel in acidic media was established while procedure for modeling the influence of relevant factors such as specimen dimension, inhibitor conditions, and operating conditions using artificial neural network has been suggested. It is shown that *Eichhornia crassipe* gave 98% inhibition efficiency and that the computer-based model provided may help in predicting corrosion behavior. The best results in prediction of the corrosion

behaviour of mild steel in H_2SO_4 inhibited by *Eichhornia crassipe* (water hyacinth) leaves extract was obtained with simple neural model LM 9 5 **1**. The developed neural model was able to predict the corrosion rate of different types of samples F_{P1}-F_{P6}. The obtained results show that the ANN model is statistically accurate and is a robust tool to describe and predict corrosion behavior of mild steel in inhibited acidic media..

Table 1: Set of Input Parameters used for Training and Testing the ANN

Parameters	Training data set			Test	data	Set	
	F_{T1}-F_{T9}	F_{P1}	F_{P2}	F_{P3}	F_{P4}	F_{P5}	F_{P6}
(1)Specimen dimensions							
Length of sample (cm)	3-8	4.00	4.00	4.00	4.00	4.00	4.00
Width of sample (cm)	2.0-8.0	3.00	3.00	3.00	3.00	3.00	3.00
Area of sample (cm^2)	10-14	12.00	12.00	12.00	12.00	12.00	12.00
(2)Inhibitor condition							
Concentration (ml)	0.00-20	0.00	3.00	6.00	9.00	12.00	15.00
(3)Operating conditions							
Exposure time (hrs)	90-220	216	216	216	216	216	216
Temperature (^{O}C)	0-25	25	25	25	25	25	25

Table 2: Predicted and Real (Target) Corrosion Rates with Network Errors

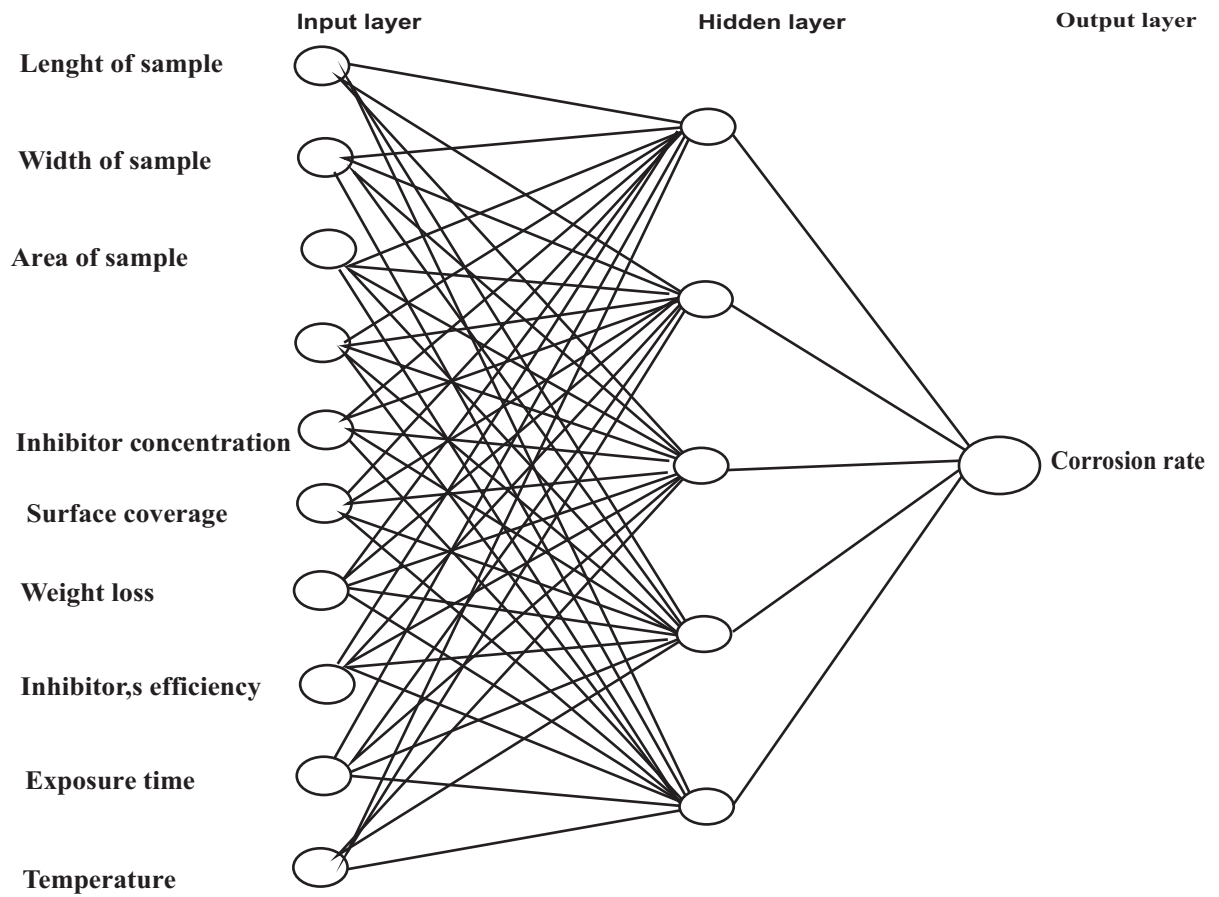| Corrosion rate	(gmmy^{-1})	RSME	NSE
Predicted	**Real(Target)**		
2.012	2.274	0.0001390	0.9606
0.203	0.208	0.0000043	0.9998
0.187	0.199	0.0000926	0.9999
0.161	0.175	0.0000583	0.9985
0.100	0.113	0.0000892	0.9990
0.121	0.110	0.00022800	0.9993

Fig. 2: Neural model for corrosion behavior of mild steel in 1M H_2SO_4 inhibited by Eichhornia Crassipes.
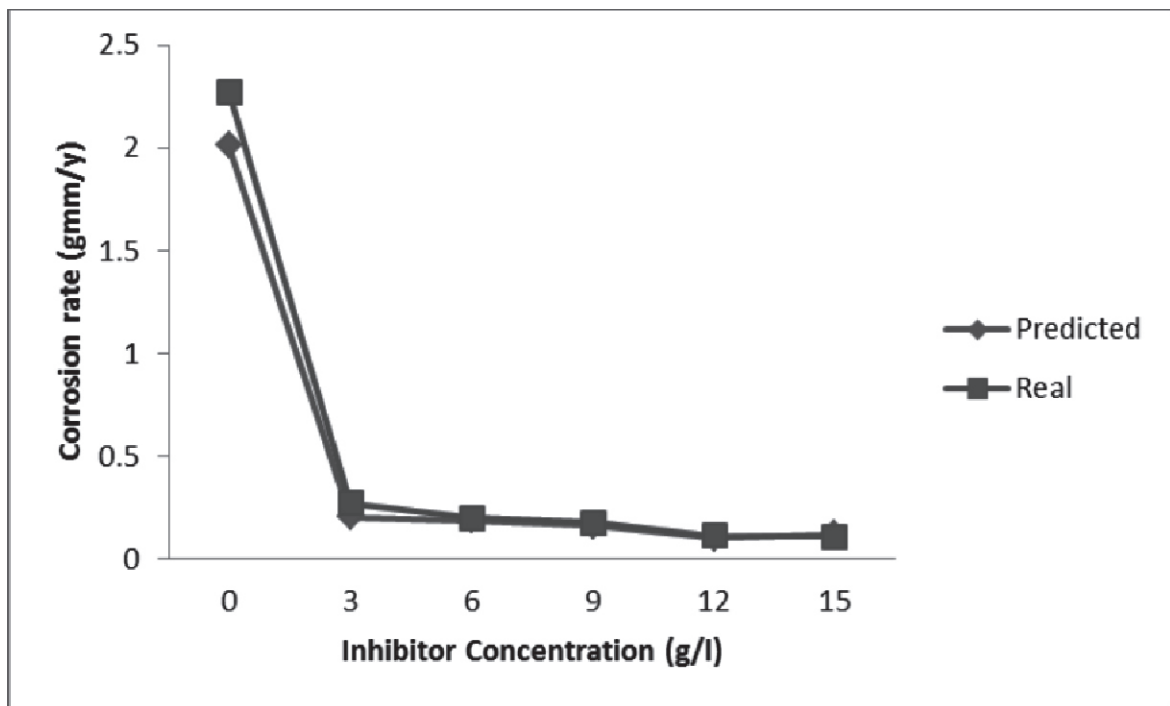

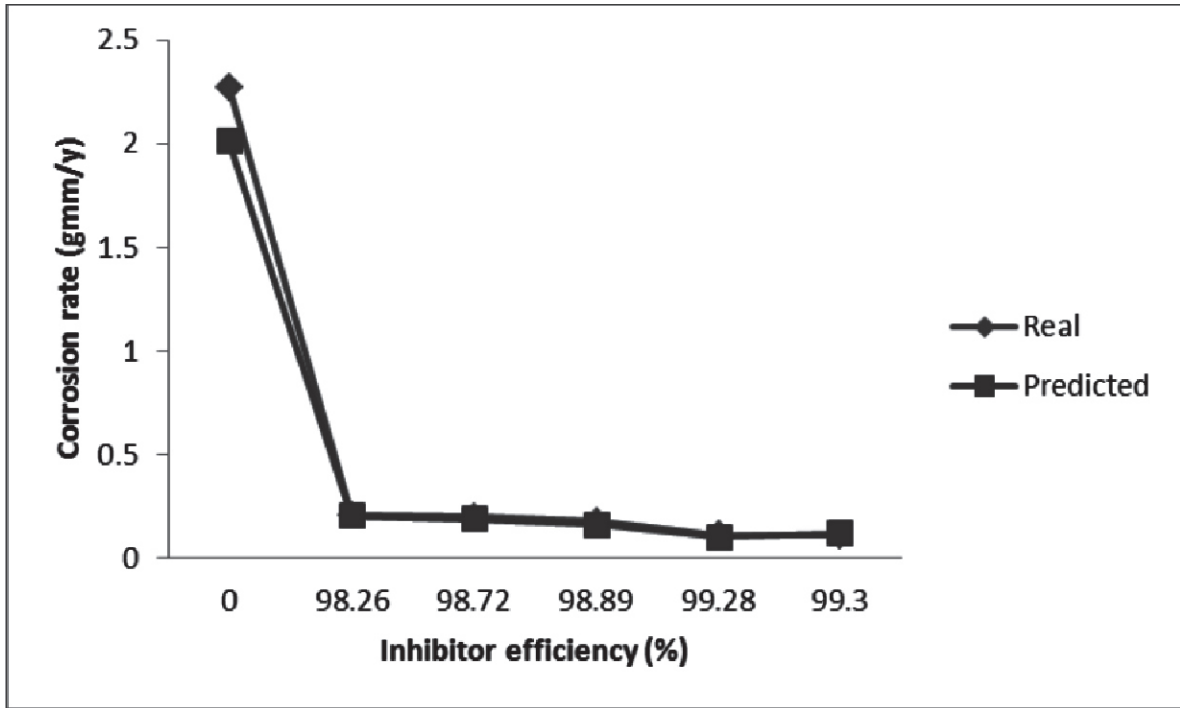**Fig. 3:** Effect of inhibitor concentration on corrosion rate

Fig. 4: Effect of inhibitor efficiency on corrosion rate
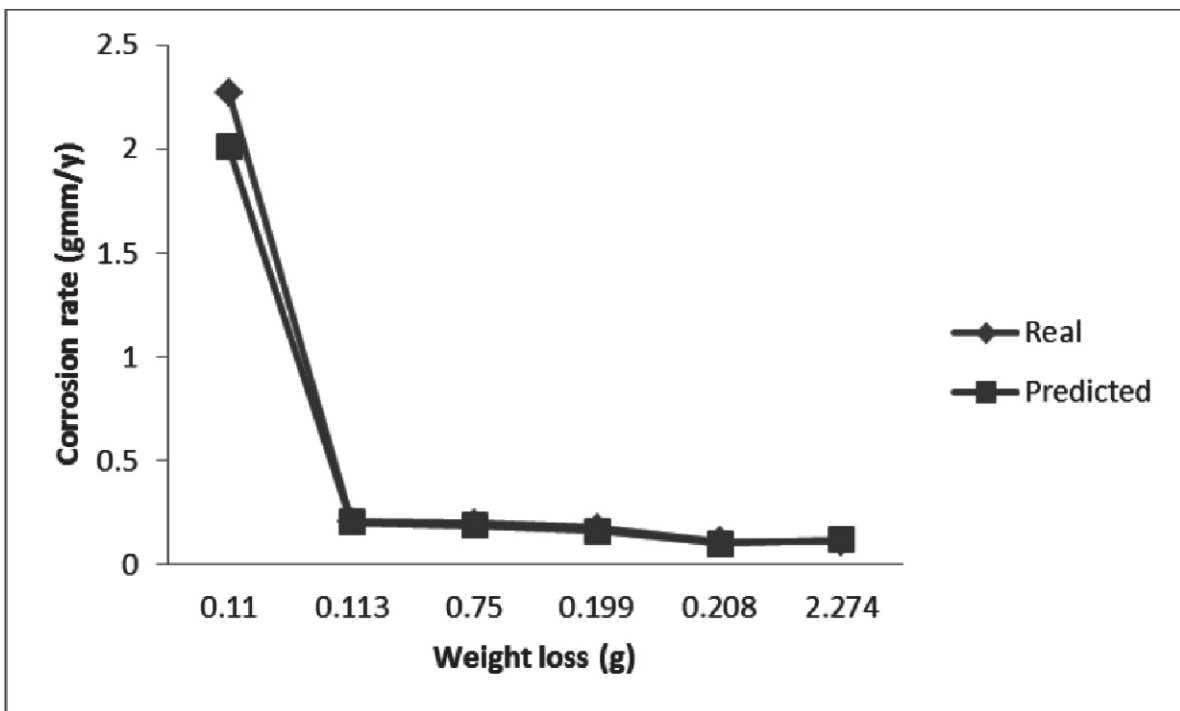

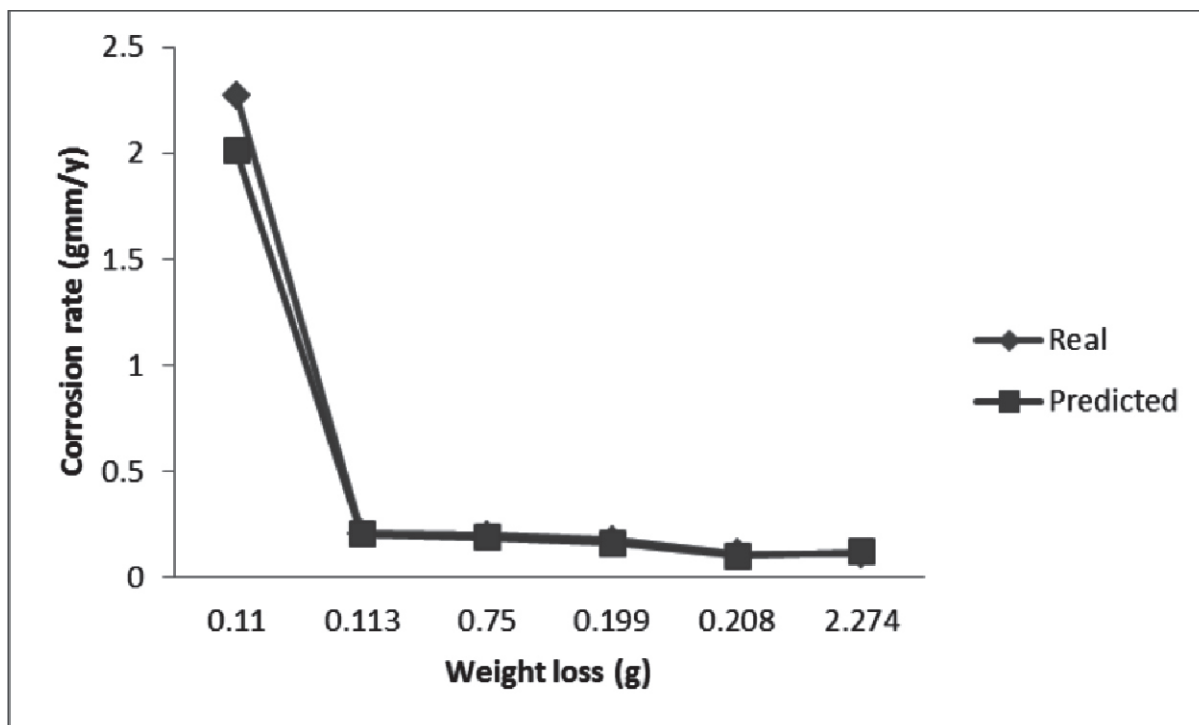**Fig. 4:** Effect of inhibitor efficiency on corrosion rate

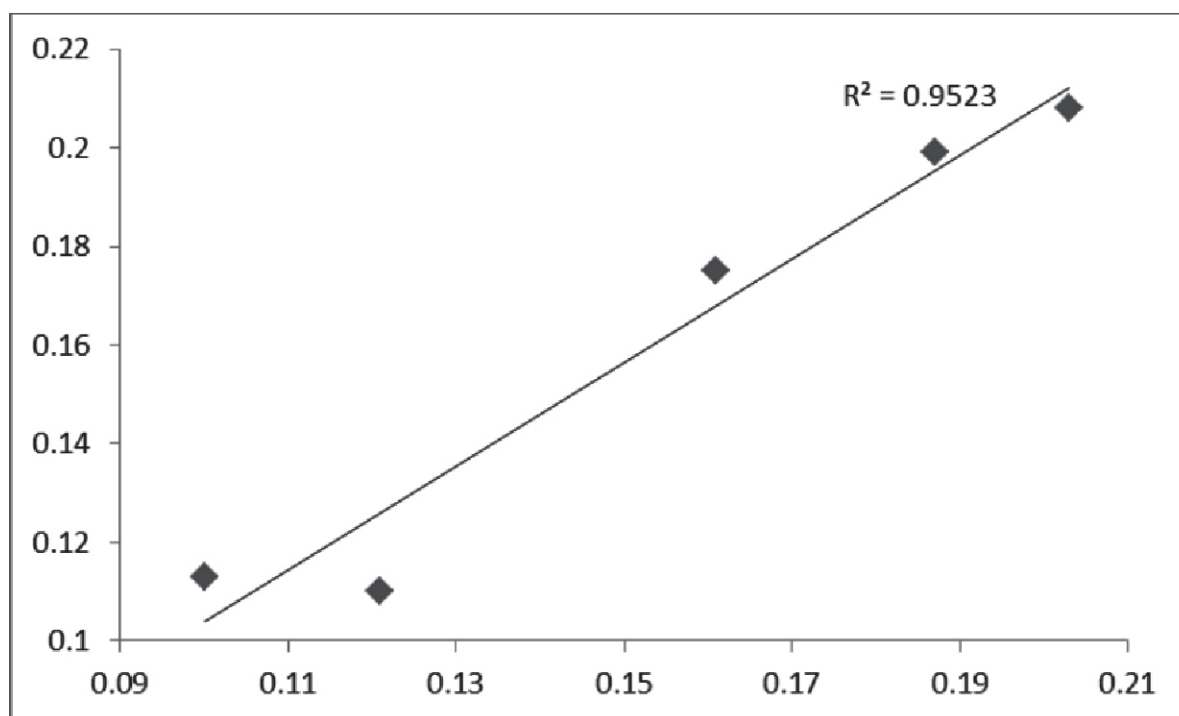**Fig. 5:** Variation of Corrosion rate with weight loss.

Fig. 6: Measured vs predicted corrosion rates

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