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COMPARATIVE STUDIES OF RESPONSE SURFACE METHODOLOGY (RSM) AND PREDICTIVE CAPACITY OF ARTIFICIAL NEURAL NETWORK (ANN) ON MILD STEEL CORROSION INHIBITION USING WATER HYACINTH AS AN INHIBITOR

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Abstract: Response surface methodology (RSM) and artificial neural network (ANN) on modeling and optimization of corrosion inhibition efficiencies of mild steel using water hyacinth as an inhibitor was carried out in this work. The optimization of the process was done using generic algorithm (GA) and RSM which were subsequently compared. The optimum inhibition efficiency predicted were 87.675924 and 82.89% by ANN and RSM, respectively. The value of R^2 obtained were 0.9695 and 0.85118 for ANN and RSM models, respectively while RMSE values of 3.90 and 4.3089 were gotten for RSM and ANN models, respectively. The model regression indicated that RSM best fit the experimental data thus perform better on mild steel corrosion inhibition.

Keywords: Optimization, artificial neural network, inhibition efficiency, water hyacinth

Introduction

Engineering structures and components service corrosion has been a huge source of concern to experts in corrosion engineering both in the academia and process industries. This is primarily to the adverse effect on both material reliability and mechanical properties that sometimes resulted in failure of equipment in critical cases.

Corrosion is referred to as the natural interface connecting the environment and metal which resulted in alterations of the properties of metal this might lead to substantial functional damage to the environment or the technical system, and metal which form a part. This type of reaction is frequently electrochemical in nature in which the metal is tarnished to create ferric rust, a red-brown compound this is an indication that electrochemical oxidation of the underlying metal can resulted in the damage, mortificationor corrosion of material and its environment. The corrosion process required the presence of a cathode, an anode, an electrolyte and electrical circuit (Ahmad *et al*., 2014)

Corrosion control is an important activity of technical, economical, and environmental importance to the process industries. Metals deterioration can be regulated by choosing suitable preventative methods such as electroplating, painting, use of alloys that is expensive, galvanizing, and use of corrosion inhibitors. Mild-steel is described as low carbon steel that is extensively used in Oil and Gas industries in the following fields; offshore environments for pipelines, flow lines, platforms, down-hole tubular equipments, well heads casing, and industrial vessels because of its inexpensive nature in manufacturing and due to good ductility, toughness, machinability, and weldability. Corrosion inhibitors are organic and inorganic constituents which when added in small amount to the corrosive media reduced or avert the reaction of the corrosive media with the metal (Abo El-Enin and Ashraf Amin, 2015).

Effectiveness of corrosion inhibitor depends on its ability to react with the metal surface to form a protective film; thereby militating or providing protection against corrosion. The current inhibitors are toxic and expensive this necessitated the development of non-toxic, ecofriendly and inexpensive materials to mitigate corrosion (Abo El-Enin and Ashraf Amin, 2015). The use of plant extracts as organic corrosion inhibitors for metals/alloys corrosion, has earned very wide awareness among researchers in recent time. The natural corrosion inhibitors are biodegradable and do not contain heavy metals or other poisonous constituents The use of naturally occurring plant extracts as corrosion inhibitors is particularly attractive and has economical gain because they are very cheap, non-toxic, and ecologically friendly and poses minor or no harm to the environment (Okafor *et al*., 2010).

Statistical modeling and optimization are very vital process in design of experiment this is because it enables improvement in the system and as well as increase in the process efficiency without increase in cost on the process. The classical method of experimentation where by one factor is considered at a time occasionally waste resources, very tiresome, and this do not present an overall complete effects of the process variables or constraints on the entire process studied. It does not give the combined interactions between the physicochemical variables and can also lead to misinterpretation of such results (Bas and Boyaci, 2007). These limitations of the classical method of experimentation can be surmounted by the use of methods that is empirical and statistically – based approach such as; the Artificial intelligence – based Neural Network Architecture approach and RSM. Artificial neural network (ANN) and Response Surface Methodology (RSM) is a very simplified model of the biological network structure (Mandal *et al*., 2009). The fundamental processing element of ANN is an artificial neuron (or simply a neuron). A biological neuron receives inputs from mother sources (inputs), combines them, performs generally a nonlinear operation on the result, and then outputs the final result (Bas and Boyaci, 2007). Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques that are useful for analysis and modeling of engineering problems in which a response of interest is influenced by several parameters (Montgomery, 2011). RSM is used for designing experiments, building numerical models, evaluating the effects of variables, and searching for optimum combinations of factors (Okewale *et al*., 2015). This method enable researcher to know the interactive effect of the parameters on the process.

The basic merit of an ANN is that it does not need any model that is mathematical since it learns from examples and recognizes patterns in a series of input and output data deprived of any prior assumptions about their nature and interactions (Mandal *et al*., 2009). ANN removesthe limitations of the conventional methods in experimentation by extracting the information that is preferred using the input data. The application of ANN to a system needs sufficient input and output data instead of relevant mathematical equations (Ali Akcayol and Can Cinar, 2005). Employing these empirical approaches lead to time saving and decreased cost.

In this present study attempt is made to predict and optimized inhibition efficiency corrosion of water hyacinth because the phytochemical analysis carried out on the extract revealed that it is a complex mixture of many components like tannin, flavonoids, saponins, alkaloids, terpenoid, anthraquinone, cardiac and phlobatanin. This optimization can be done using ANN and RSM through proper selection of training algorithms and Central Composite Design of experiment, respectively. This is with a view to testing their efficacies on the rate of corrosion.

Materials and Methods

Materials

The water hyacinth was collected from Agbahro community located in Effurun, Delta State, Nigeria. Soxhlet extractor apparatus, pH – 211 (pH meter), oven (Genlab oven model Mino/75/f), BH – 600 weighing balance, and beakers, were used for the study. Distilled water was gotten from the Department of Chemistry Laboratory, Federal University of Petroleum Resources, Effurun Delta, State, Nigeria for solutions and sample preparation.Hydrochloric acid, acetic acid, ethanol and acetone that were used are analytical grades and were procured from a qualified chemical dealer in Effurun, Delta State, Nigeria.

Methods

Pre-treatment of sample and sample characterization

The particle size range of water hyacinth used for the mild steel corrosion study is 600 µm. The sample was shredded sun dried and subsequently dried in an oven for a period of 48 h at 60°C. This was subsequently stored in an air tight plastic bottle before use.

Analysis of the phytochemical constituents in water hyacinth leaf

Phytochemical constituents screening of water hyacinth leaf extract was carried out to identify the active constituents in the extract. The analyses were carried out using the methods described by Okwu (2001), Rahilla *et al*. (1994), Sofowora (1993), Odeja *et al*. (2015) and Herbone (1973).

Extraction of water hyacinth leaf extract

500 g of powdered water hyacinth samples were transferred on to a mushin cloth. This was then deposited inside the thimble of 500 ml soxhlet extractor. Ethanol of 200 ml quantity was poured into a round bottom flask that is fixed to the apparatus and the condenser was tightly fixed at the bottom end of the extractor. This experimental set up was heated on a heating mantle at 78°C temperature. The solvent (ethanol) was allowed to remain in contact with the sample for 12 hours while the solvent remaining in the oil was recovered through heating.

Procedure of the experiment

The mild steel corrosion investigation was carried out using Nwigbo *et al*. (2012) method. The mild steel coupons of dimension 2 x 3 x 0.12 cm were polished with rough paper, oiled to prevent corrosion, degreased with petroleum ether and subsequently washed with distilled water and dried. The mild steel specimen was suspended with the aid of a thread in 100 ml beaker that is made up of 100 ml of 0.1M HCl including various inhibitor (water hyacinth) concentrations. At time interval of 2 h, 0.1, 0.5, 1.0, 1.5 and 2.0 g/l of inhibitor concentrations of 0.1M HCl solution, and at 30, 40, 50, 60 and 70°C temperatures were studied. Each of the mild steel metal coupons after the corrosion process was dipped in both distilled water and methanol solutions. This was scrubbed to remove any remaining residual water hyacinth inhibitor concentration and acids. It was then washed thoroughly with washing liquor, rinsed with distilled water and later dried in acetone before been reweighed. The design experimental plan is seen in Table 2 using Design Expert (7.00) software.

Experimental design using (RSM)

The design expert software (Design – Expert 7.00) was used for the modeling of data and experimental runs. The process variables studied were water hyacinth concentration (X_1), time of exposure (X_2), and temperature (X_3) as shown in Table 1.

Table 1: Central-composite design factor levels of independent variables

Independent Variables	-α (-2)	Low factor level (-1)	Mid-point factor level (0)	High factor level (+1)	+α (+2)
Concentration of Inhibitor (g/l)	0.1	0.5	1.0	1.5	2.0
Exposure Time, (Hr)	2.0	4.0	6.0	8.0	10
Temperature, (°C)	30	40	50	60	70

These three variables were considered at five levels. Twenty (20) experimental runs were generated with CCD (Central – Composite Design) as shown in Table 2.

Table 2: Experimental design plan for CCD in terms of coded variables

Run Order	Inhibitor Concentration (g/l)	Exposure Time (Hr)	Temperature (°C)
1	0	0	+2
2	0	0	0
3	+1	-1	+1
4	0	0	0
5	+1	+1	+1
6	-2	0	0
7	0	0	0
8	0	+2	0
9	0	0	0
10	0	0	-2
11	+1	-1	-1
12	0	0	0
13	-1	+1	+1
14	-1	-1	+1
15	0	0	0
16	+1	+1	-1
17	0	+2	0
18	+2	0	0
19	-1	-1	-1
20	-1	+1	-1

Determination of water hyacinth inhibition efficiency

The efficiency of corrosion inhibition was obtained using the equation below

$$E(\%) = \frac{W_a - W_b}{W_a} \times 100 \qquad (1)$$

Where, W_a is the loss in weight in uninhibited medium (blank), and W_b is the loss in weight in inhibited medium

Artificial neural network analysis

The commercial ANN software, Neural Power version 2.5 (CPC – X Software) was used in the study. The data were tested with multilayer normal feed forward and multilayer full feed forward neural networks (Adesina *et al*., 2014; Okewale *et al*., 2017).

The networks were trained with different learning algorithms (incremental back propagation, IBP; batch back propagation, BBP, quick prop, QP, Levenberg – Marquardt algorithm, LM and Generic algorithm GA). The architecture of the network consisted of an input layer with three neurons, an output layer with one neuron, and two hidden layers. The network inputs are water hyacinth concentration, time of exposure, and temperature, while the output was the inhibition efficiency of the water hyacinth in (%). The optimum nodes number for the artificial neural network was gotten for water hyacinth ANN corrosion inhibition efficiency network, series of topologies were used, and in turn the nodes were varied (Mansour and Mostafa, 2011). An ending criterion of 100000 was used in training the ANN networks. Numerous networks were iteratively established to establish the transfer functions of unseen and output layers (sigmoid, linear, threshold linear, Gaussian and bipolar linear hyperbolic, tangent function). The experimental data was divided into testing and training sets of data. Four experimental data were used for testing the inhibition efficiency of water hyacinth as a corrosion inhibitor on mild steel while sixteen data were used for training purposes.

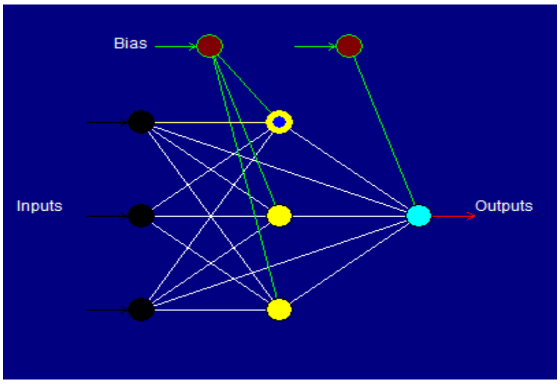


Fig. 1: The ANN architecture

RSM regression model optimization

Response surface methodology quadratic model generated was optimized using the global response surface equation below;

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i<j} \beta_{ij} X_i X_j + e \qquad (2)$$

For three factor inputs of x_1, x_2 and x_3, the equation of the quadratic response is given as;

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_{12}X_1X_2 + b_{13}X_1X_3 + b_{23}X_2X_3 + b_{11}X_1^2 + b_{22}X_2^2 + b_{33}X_3^2 \qquad (3)$$

Y is the response predicted by the Response Surface Methodology, the linear coefficient is i and j is the quadratic coefficients, regression coefficient is β, while parameters studied is k, and optimized in the experiment, and the random error is e (Ghorbana *et al*., 2008).

Verification of experimental data

The minimum error for the testing and coefficient of determination (R^2) that is greatest was used in making decision for the optimum topology with the repetition of each topology ten times. To determine the optimum conditions, the networks were trained until the root mean square error of each network is close to zero and R^2 value very close to unity.

The value of software was used for other parameters in default form. In order to minimize error in network analysis, weights were initialized with random values and adjusted through a training process (Ahmad *et al*., 2014).

Results and Discussion

The presence of alkaloids, saponins, terpenoids and aromatic carbon in the water hyacinth chemical structure as shown in Table 3 enhanced the process of inhibiting corrosion on mild steel surface. This finding was corroborated by the report of (Nwigbo *et al*., 2012; Prithiba *et al*., 2014; Owate *et al*., 2014). Nitrogen and acetylenic alcohols molecules as contained in water hyacinth are adduced by forming a film on metal surface and thus prevent the dissolution process of the mild steel (Anodic reaction) as well as evolution of hydrogen (cathodic reaction) (Barmatov *et al*., 2012).

Table 3: Phytochemical analysis of water hyacinth leaf extract

Chemical constituents	Percentage composition (%)
Alkaloid	10.40
Terpenoid	5.60
Phenol	Nil
Sterols	Nil
Flavonoid	Nil
Cardiac glycoside	1.80
Glygoside	Nil
Tannin	Nil
Phytosterol	3.40
Saponins	3.20
Anthraquinones	2.60
Reducing sugar	Nil
Phlobatannis	Nil

ANN modeling

The network architecture and topologies of the ANN were chosen and established for the prediction and estimation of inhibition efficiency of the inhibitor on mild steel corrosion. The algorithm learning effect and transfer functions were analyzed by effective training of the model neural network by using diverse learning transfer functions and algorithms of Artificial Neural Network (Ebrahimpour *et al*., 2008). Subsequently, series of testing was performed and it was seen that the best algorithm was the one with hyperbolic tangent as hidden neuron which is quick propagation (QP) and output transfer functions for inhibition of mild steel corrosion in aggressive medium. The diverse topologies varying from 1 to 20 neurons that were hidden were studied as well, using (QP) algorithm of the ANN.

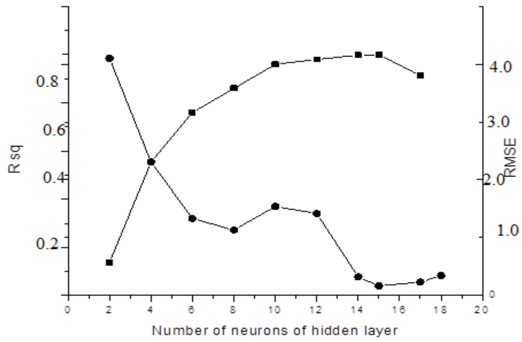


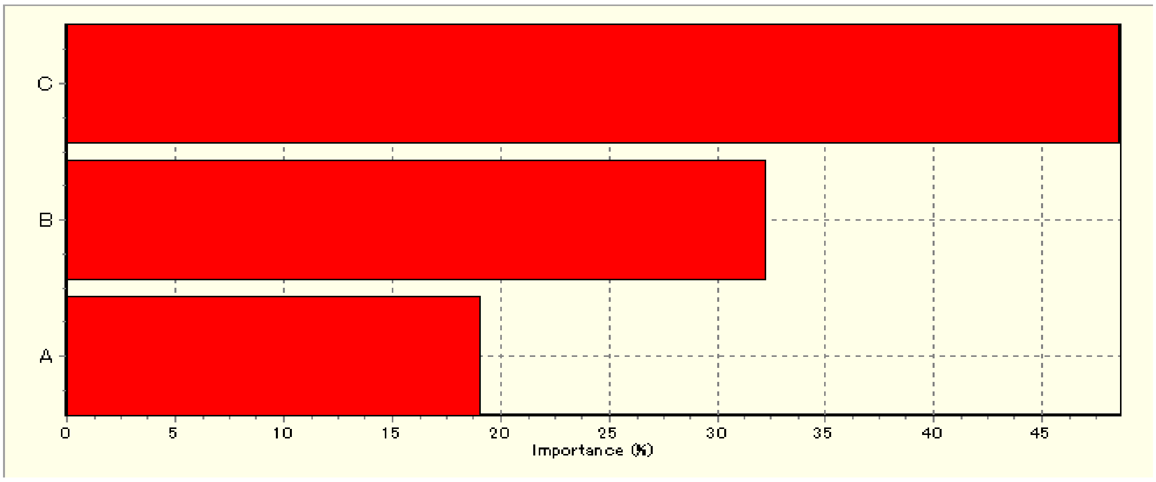
Fig. 1: The number of neurons in the hidden layer against network performance for the testing data

After series of trials, it was noted that a network with 15 hidden neurons produced the best performance for water hyacinth inhibition efficiency as depicted in Fig. 1 which showed the network data testing and performance of experimental data against the number of neurons that are hidden in the architecture layer. The optimum configuration of ANN is realized using normal feed forward quick prop network that is multilayer, the structure of model is 3-15-1. Likewise the greatest of the ANN model is seen to be Multilayer Normal Feed Forward (MNNF) with correlation coefficient (R^2) and RSME for set of training to be 0.85118 and 4.3089, respectively. The testing set values of R^2 and RSME for corrosion inhibition on mild steel are 0.8423 and 4.1924 respectively as shown in Table 4. Fig. 2 depicted the importance of the level of the variables studied on the inhibition efficiency on mild steel. It can be seen that temperature is the most important variable followed by time of exposure while inhibitor concentration is the least.

Table 4: Effect of ANN architecture and topologies on R^2 and RSME obtained in training and data set for corrosion

inhibition of water hyacinth

Configuration	Algorithm	Model	Output Transfer function	Input Transfer function	Training Set R^2	Testing Set R^2	Training set RSME	Testing Set RSME
3-15-1	QP	MNFF	Tanh	Tanh	0.85118	0.8423	4.3089	4.1924
3-15-1	QP	MNFF	Tanh	Linear	0.8274	0.8377	4.4307	4.5231
3-15-1	BBP	MNFF	Linear	Sigmoid	0.8055	0.8377	4.4988	5.2998
3-15-1	IBP	MNFF	Tanh	Linear	0.83841	0.8284	4.8765	4.8990
3-15-1	QP	MNFF	Tanh	Gaussian	0.83220	0.8211	4.9078	4.4988



A: Concentration of inhibitor, (g/L); **B:** Exposure time, (hours); **C:** Temperature, (°C)

Fig. 2: Level of performance of process variable on the inhibition efficiency of water hyacinth on mild steel

Plots of Response Surface model using ANN

Figures 3 – 5 depicted the surface response plots for the inhibition of mild steel corrosion. The curvature nature of the curves indicated that there is an interaction between between the response and the different variables studied. It showed that as temperature increases with inhibitor concentration the inhibition efficiency of corrosion decreases. Likewise, as exposure time is increase with with temperature the inhibition efficiency of water hyacinth decreases. However, increase in inhibitor concentration reduce the rate of corrosion this can be attributed to the fact that the level of permeation of corrosion is reduced as inhibitor concentration is increased (Okewale and Omoruwuo, 2018). The inhibitor molecules acts as physical impediment that prevent the diffusion of inhibitor ions intraparticle to and fro the surface of mild steel metal that subsequently inhibit the atom of mild steel metal from taking part in the cathodic or anodic reactions, thereby causing reduction in rate of corrosion. Inhibitor concentration was the most significant of all the process variables considered.

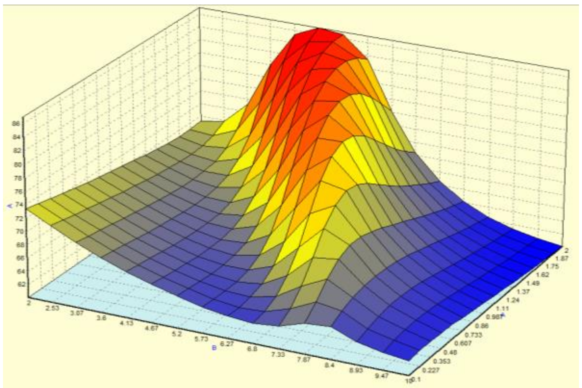


Fig. 3: Surface plot for the effect of concentration of water hyacinth inhibitor (g/L), and time of exposure (hrs) on corrosion inhibition efficiency of water hyacinth

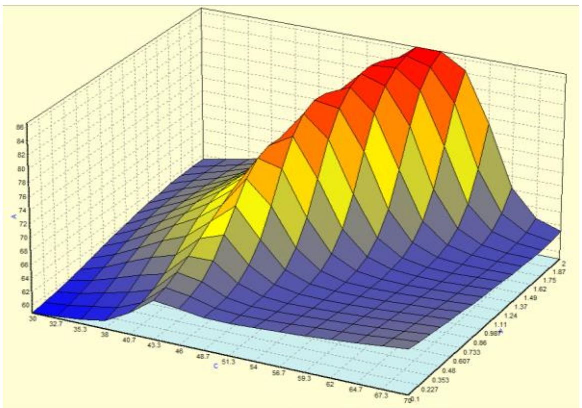


Fig. 4: Surface plot for effect of water hyacinth inhibitor concentration (g/L), and temperature (°C) on inhibition efficiency of water hyacinth on mild steel corrosion

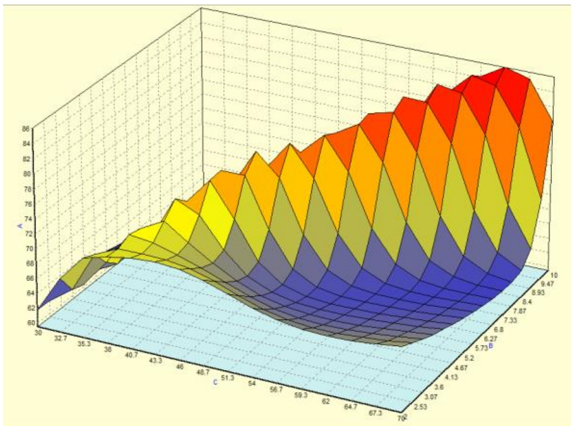


Fig. 5: Surface plot for effect of time of exposure (hr), and temperature (°C) on corrosion inhibition efficiency of water hyacinth

Response surface methodology (RSM) modeling and optimization

Equation 1 was used in calculating the inhibition efficiency of the inhibitor on mild steel surface. Regression equation from a quadratic model was used to describe the water hyacinth as a corrosion inhibitor on mild steel. The analysis of variance (ANOVA) results depicted in Table 4 show that the F – value of 35.5 and p – value < 0.0001 of the model gotten from mild steel corrosion inhibition using water hyacinth is significant. The experimental data obtained was well represented with the quadratic model obtained and 1.98 value of standard deviation was achieved. R^2 value of 0.9695 which was considered high was achieved for the model indicating that the predicted value was close to the actual value which suggests it to be accurate (Mohd and Rasyidah, 2010). The result from this study indicates that the selected factors was adequately represented by the obtained model and also depict an actual relationship among selected factors. It is seen that 96.95% of the total variation in the inhibitor efficiency of water hyacinth can be linked to the experimental variables studied. The significance of each coefficient in the model was checked using the p – values which in turn were useful variables pattern (Ebrahimpour *et al*., 2008). An adequate precision ratio of 17.132 was obtained in this study which showed that there was an adequate signal in the model design space. Results affirmed that there was signal adequate for the obtained model as shown by the value obtained. As depicted in Table 5, the predicted coefficient of determination, R – squared value of 0.7427 is in agreement with the Adjusted R – squared value of 0.9421. The coefficient of variation, the standard deviation of the mean and experimental data expressed in percentage which is 2.83%, that is lesser than 10% specify that the data from the experiment is reproducible. The significant model terms at 95% confidence level i.e. $p<0.05$ were (X_1, and X_3) linear terms, (X_1X_2, X_1X_3, and X_2X_3) the interaction terms and (X_1^2, and X_3^2) the quadratic terms. This suggested an interaction between the process variables studied which were adjudged to be the core factors that affect the corrosion rate and inhibitors efficiency of a corrosion inhibitor.

The final equation in terms of coded factors for the CCD response surface quadratic model obtained in this corrosion study is represented by equation 4.

$$Y = 63.82 - 2.75X_1 + 1.06X_2 + 1.26X_3 + 2.94X_1X_2 + 3.86X_1X_3 + 4.92X_2X_3 + 4.36X_1^2 - 0.47X_2^2 + 3.90X_3^2 \quad \ldots\ldots (4)$$

The desirability function of the RSM model for the corrosion inhibition of mild steel using water hyacinth was used in optimizing the process variables. The optimum conditions predicted from the quadratic model were inhibitor's concentratrion (1.50 g/l), exposure time (8 h), and temperature (60°C) corresponding to the inhibitor's efficiency of 82.89%. These were validated with an average inhibitor's efficiency of 81.5% from three replicates. This was closely approximated by the obtained optimum result predicted by the model. The experimentally obtained inhibitor's efficiency is very close to that predicted by the RSM model as seen in Table 5.

ANN Optimization

The input vector comprising of input variables (inhibitor concentration, time of exposure, and temperature) was optimized using generic algorithm (GA) as seen in Table 7. The predicted inhibition efficiency of 87.675924% at optimum conditions of temperature 69.997148°C, exposure time 9.1990889 h, and inhibitor concentration of 1.9996162 g/l, the predicted inhibition efficiency was validate in triplicate as 86.657%.

Table 5: RSM ANOVA of regression equation results for quadratic model of corrosion inhibition study

Sources	Sum of Squares	Df	Mean Square	F - Values	Prob>F, P – Value
RSM Model	1241.57	9	137.95	35.35	< 0.0001 significant
X_1	113.55	1	113.55	29.10	0.0003
X_2	18.02	1	18.02	4.62	0.0572
X_3	25.25	1	25.25	6.47	0.0292
X_1X_2	69.03	1	69.03	17.69	0.0018
X_1X_3	118.89	1	118.89	30.46	0.0003
X_2X_3	193.65	1	193.65	49.62	< 0.0001
X_1^2	400.17	1	400.17	102.54	< 0.0001
X_2^2	5.55	1	5.55	1.42	0.2605
X_3^2	384.60	1	384.60	98.55	< 0.0001
Residual	39.03	10	3.90	39.03	
Lack of fit	39.03	5	7.81	39.03	
Pure error	0.000	5	0.000	0.000	
Cor Total	1280.60	19			

Table 6: Results of the RSM model optimization

	X_1 (Inhibitor's Concentration, g/l)	X_2 (Exposure Time, Hr)	X_3 (Temperature, °C)	Inhibitor's Efficiency (%)
Actual Variables	**1.5**	**8.0**	**60**	**82.89**

Table 7: Results of the ANN Model Optimization

	A (Inhibitor's Conc. g/l)	B (Exposure Time, Hr)	B (Temperature, °C)	Inhibitor's Efficiency (%)
Actual Variables	1.9996162	9.1990889	69.997148	87.675924

Table 8: Experimental design plan for CCD in terms of coded variables

Run Order	Inhibitor Concentration X_1 (g/l)	Exposure Time X_2 (Hr)	Temperature X_3, (°C)	Experimental Value	RSM Predicted	ANN Predicted
1	0	0	+2	63.64	63.82	63.64
2	0	0	0	76	74.8	73.922
3	+1	-1	+1	63.64	63.82	63.64
4	0	0	0	74	75.76	73.922
5	+1	+1	+1	86.2	82.89	86.2
6	-2	0	0	63.64	63.82	63.64
7	0	0	0	63.9	62.83	73.922
8	0	+2	0	61.5	64.06	61.5
9	0	0	0	64.33	64.67	73.922
10	0	0	-2	61.53	59.82	61.53
11	+1	-1	-1	78	76.91	78
12	0	0	0	84	82.88	73.922
13	-1	+1	+1	63.64	63.82	63.64
14	-1	-1	+1	65.5	65.06	65.5
15	0	0	0	81.3	83.75	73.922
16	+1	+1	-1	63.64	63.82	63.64
17	0	+2	0	70.57	70.16	70.57
18	+2	0	0	80	81.94	80
19	-1	-1	-1	68.5	68.71	68.5
20	-1	+1	-1	63.64	63.82	63.64

RSM and ANN predictive capability evaluation

Table 8 revealed Central Composite Design (CCD) of the studied process variables and experimental values, predicted responses for RSM model and ANN for water hyacinth as a corrosion inhibitor on mild steel. In contrasting the values predicted by both ANN and RSM models, it was seen that the ANN model estimates are more accurate to the experimental data than the RSM model. This substantiates the dominance of ANN in prediction capacity over RSM. In evaluating the R^2 and RMSE for the two models used, R^2 and RMSE for RSM model were 0.9695 and 3.90, respectively while R^2 and RMSE values for ANN model were 0.85118 and 4.3089, respectively. In relations to the coefficient of determination and root mean square error the RSM is more superior to ANN for the inhibition of mild steel corrosion. The ANN predicted a higher value for efficiency of inhibition likened to RSM.

Conclusion

This work focused on comparison off RSM and ANN models for their predictive ability and optimization efficiency in corrosion study on mild steel. CCD was used to design the experiment, ANN showed higher value in term of optimum inhibition efficiency compared to RSM.

RSM better fits the experimental data in contrast to the model of ANN. Thus, Response Surface Methodology model performed better in corrosion study compared to ANN model that has been established to achieved better performance in biological systems.

Conflict of Interest

Authors declare that there is no conflict of interest reported on this work.

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