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Predictive Modeling of pH and Viscosity in Emulsion Paint Production Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

This study investigates the predictive capability of an Adaptive Neuro-Fuzzy Inference System (ANFIS) in modeling the pH and viscosity of emulsion paints. Eighteen paint samples were produced using standard formulation protocols, with three levels of mixer speed (200, 300, and 400 rpm), ambient temperatures (18°C, 23°C, and 27°C), and storage durations before use (12 and 24 hours). Analysis of Variance (ANOVA) was employed to assess the impact of these parameters on pH and viscosity. Results indicated an average pH of 8.0 and a mean viscosity of 3.22 poise, consistent with industry benchmarks. While the combination of variables significantly influenced viscosity, it had a limited effect on pH prediction. The ANFIS model demonstrated superior performance over linear regression, achieving root mean square errors (RMSE) of 7.47×10^{-6} for pH and 3.81×10^{-6} for viscosity. These findings underscore the model's effectiveness in capturing nonlinear relationships in paint production.

Keywords: Emulsion paint, pH, viscosity, ANFIS, predictive modeling, mixing parameters

INTRODUCTION

Emulsion paints, often used for both protective and ornamental applications, are intricate mixtures of pigments, resins, fillers, and other ingredients dissolved in water to form a durable emulsion when combined in the right amounts (Biegańska *et al.*, 1989*; Mohamed et al.*, 2020). Because of their adaptability, simplicity of use, and eco-friendliness, they are extensively used in both commercial and residential settings. They are frequently preferred over solvent-based paints due to their ease of use, low toxicity, fast drying time, and excellent environmental protection (Ifijen *et al*., 2022). Critical characteristics, such as pH and viscosity, which significantly impact paints' ultimate quality, stability, and performance, are precisely controlled throughout the production process (Weldon, 2009).

The pH value plays a significant role in guaranteeing the correct dispersion of the paint's components, inhibiting microbial growth, and preserving the product's long-term integrity (Koleske *at al*., 2011; Masurkar, 2024). The acidic or fundamental character of the materials employed in the formulation is the main factor influencing the pH of emulsion paints (Dillon *et al*., 2014). Mutschlechner *et al*. (2024) observed that it is crucial to comprehend and regulate the pH of emulsion paints throughout their lifecycle, from production to application and even during long-term storage. Also, additional components, such as surfactants, stabilizers, and pigments, can alter the formulation's overall pH, but the binder, typically an acrylic or vinyl resin, is usually neutral (Malshe, 2010). Additionally, pH affects how pigment particles disperse and how soluble some additives are, making it a crucial component of the paint's rheology and application qualities (Doroszkowski, 2020). High or low pH levels can result in unwanted effects, such as altered paint film appearance, shortened shelf life, or poor substrate adherence. pH is also significant beyond the formulation phase as paint compositions may become less stable over time due to chemical reactions, environmental factors, or container interactions, which can cause pH variations (Ariza *et al*., 2000). For example, paints exposed to moisture or high temperatures may undergo pH changes that impact their performance and uniformity (McGonigle and Ciullo,1996). Therefore, tracking and forecasting pH changes in emulsion paints is vital to guarantee that they retain their intended qualities over time and in satisfactory conditions.

However, one of the emulsion paints' most crucial rheological characteristics is its viscosity, which affects its application, functionality, and end quality (Larson, 2022; Pal, 1989). Viscosity directly affects the paint's flow, leveling, uniform surface coverage, application behavior, the final surface's quality, and the application process's effectiveness (Eley, 2019; Sutton, 2020). The kind and concentration of resins, pigments, fillers, and additives used in the formulation, as well as the temperature and shear conditions during application, all affect the viscosity of emulsion paints (Doroszkowski, 2020).

Several works have been done on emulsion paint production and characterization, for instance, Surajudeen and Zebulu (2015) carried out a study on the production of emulsion house paint by supplementing imported synthetic binder (polyvinyl acetate, PVA) with a locally available binder (gum Arabic, GA) in six different proportions. They employed standard emulsion paint formulation. Results show that the samples gave high-quality emulsion paints regarding opacity, adhesion, ease of application, and coverage. Also, it was observed that paint brightness diminished with increased gum Arabic composition. Hence, gum Arabic (Acacia Senegal) can be used as a supplement to PVA in emulsion paint production. Ekeolisa *et al.* (2020) also produced water-based paint (emulsion, screeding, matt paint) and oil paint (gloss paint) using hydrosol formulated locally by adopting the steam method. Hibiscus flowers, mint leaves, rosemary, and lemongrass were used as raw materials. A soxhlet extractor was used to hydrosolate the crushed leaves using normal hexane as a solvent. A distillation process separated the hydrosol from the solvent in the hydrosol-solvent mixture obtained from the extraction process. The results showed that the hydrosol's physicochemical parameters were within the standard values and were used in producing emulsion, screeding, matt, and gloss paints, which showed reasonable agreement when compared with the standard. Abubakar and Gidigbi (2020) also explored using a modified polyvinyl acetate (PVAc) binder to produce emulsion paint. Hydroxylated Avocado seed oil (HASO) was extracted manually and copolymerized with conventional polyvinyl acetate. The physicochemical properties of HASO/PVAc copolymer resin conformed with the literature values and the standard, showing better water resistance, flexibility, and packaging density than the conventional PVAc binder. It exhibits better blistering, acidic, alkaline, and salt media resistance than conventional PVAc paint. The capacity to simulate intricate and nonlinear interactions between production factors and desired outcomes, including pH and viscosity, has drawn considerable interest in predictive modeling approaches, especially those based on machine learning and artificial intelligence. Despite the promising results from previous studies, applying the Adaptive Neuro-Fuzzy Inference System (ANFIS) to emulsion paint pH and viscosity prediction remains a relatively underexplored area, particularly in industrial-scale production environments. This study evaluates the potential of ANFIS for predicting the pH and viscosity of emulsion paints. Specifically, this study aims to develop an ANFIS model based on experimental data and assess its accuracy in predicting viscosity under varying production conditions.

MATERIALS AND METHODS

Procedure for Paint Production

The raw materials and their respective quantities are presented in Table 1. Zero point seven–two–five liters (0.725 L) of distilled water was measured into a mixer. Calgon (12.5 g) was added and stirred at a certain agitator speed (200 rpm). Titanium dioxide (250 g) was added and stirred at the same speed. 750 g of calcium carbonate was added bit by bit and stirred for 20 minutes. While the stirring persisted, 250 g PVA (acrylic), 25 g genipole, and 25 g de-foamer were introduced.

Table 1: Raw materials and their respective quantities

S/N	Ingredient	Amount
1.	Water	0.725 liters
2.	Calgon	12.5 g
3.	Titanium dioxide	250 g

4.	Calcium carbonate	720 g
5.	Binder (PVA, acrylic)	250 g
6.	Genipole	25 g
7.	Defoamer	25 g
8.	Nitrosol	21.8 g
9.	Texanol	27.5 g
10.	Ammonia	21.8 g
11.	Formalin	21.8 g
12.	Colourite	21.8 g

21.8 g of Nitrosol dissolved in 20 ml of distilled water was emptied into the processing vessel. Then, 27.5 g of Texanol, 21.8 g of ammonia, and formalin (21.8 g) were added while the stirring continued. The colourite (21.8g) was added and stirred as desired until the emulsion was formed. This sample was emptied into a clean container, corked, and kept to stabilize for P1 (12 hours) before use. The processing room temperature was set at T1 (18^0C).

Experimental design

Response surface methodology (RSM) was used to investigate the effect of independent variables, including Agitator speed (X_1), Temperature (X_2) and Stability period (X_3)on response variables, such as pH (Y_1), Viscosity (Y_2), drying time (Y_3), and the number of bubbles (Y_4) . RSM design and coded and uncoded levels are presented in Table 2.

Table 2: Independent variables and their corresponding levels

Independent variable	Symbol	Coded levels		
		−1	**0**	**+1**
Agitator speed	X_1	200	300	400
Temperature	X_2	18	22.5	27
Stability period	X_3	12	18	24

Actual levels of independent variables were coded according to Equation (1);

$$Z = \frac{Z_0 - Z_C}{\Delta Z} \qquad (1)$$

where Z and Z_0 indicate coded and actual levels of independent variables, respectively. ΔZ represents step change while Z_C indicates the actual value at the central point. The specific equations for each independent variable were derived from the above equation to code their actual values. Specific equations for Agitator speed (X_1), Temperature (X_2) and Stability period (X_3) are as presented in Equation (2) to Equation (4);

$$Z_1 = \frac{(AS - 300)}{100} \qquad (2)$$

$$Z_2 = \frac{(Temp - 22.5)}{4.5} \qquad (3)$$

and,

$$Z_3 = \frac{(Sp - 18)}{6} \qquad (4)$$

where,

$AS = Agitator\ speed$

$Temp = Temperature$

$Sp = Stability\ period$

Box Behnken Design of three levels and eighteen runs was used to design the experiment. The responses were sample pH, viscosity, drying time, and number of bubbles formation on application (nB), as shown in Table 3;

Table 3: Summary of 18 experimental runs.

Runs	Independent Variables			Viscosity (cPs)
	Agitator Speed (rpm)	Temp. (ºC)	Period of Stability (hour)	
1	S1	T1	P1	

2	S1	T1	P2
3	S1	T2	P1
4	S1	T2	P2
5	S1	T3	P1
6	S1	T3	P2
7	S2	T1	P1
8	S2	T1	P2
9	S2	T2	P1
10	S2	T2	P2
11	S2	T3	P1
12	S2	T3	P2
13	S3	T1	P1
14	S3	T1	P2
15	S3	T2	P1
16	S3	T2	P2
17	S3	T3	P1
18	S3	T3	P2

Determination of pH

The pH of the samples was determined. 10 ml of the sample was measured into a measuring cylinder; a pH meter (pH meter—signified medical England SM-6029A) probe was used to determine the pH value of the paint, which was standardized using buffer solution. After shaking, the probe was inserted into the paint sample and allowed to stand for 10 minutes. The reading was recorded (HACH, 2022).

Determination of Viscosity (V) of the Samples

The viscosity of the prepared samples was determined using a Brookfield viscometer (Type LV-8 viscometers UK LTD) according to the method of Martínez (2015). A 25ml paint sample was measured in the viscometer up to the mark. The viscosity (in cPs) was determined using spindle No. 2 at a speed of 12 rpm. Readings were taken after 120 sec of rotation.

3.3 DEVELOPMENT OF AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM PREDICTIVE MODELING

Matlab software was used to compute the data for an adaptive neuro-fuzzy inference system (ANFIS). The observed dataset was divided into three stages: training, testing, and validation. Gaussian membership function (gaussmf) was considered for input parameters, and linear membership function was considered for output parameters. The hybrid algorithm defined the optimum number of parameters to describe the FIS. 75% of the dataset was used for training, 25% was assigned for testing in ANFIS, and 25% was used for validation. The structure and the Layout of the developed ANFIS predictor are presented in Figures 1 and 2, respectively. The input data is mapped several times during the model's training process to minimize the prediction error. The number of iterations required for mapping is known as epochs. The results were compared with the ordinary

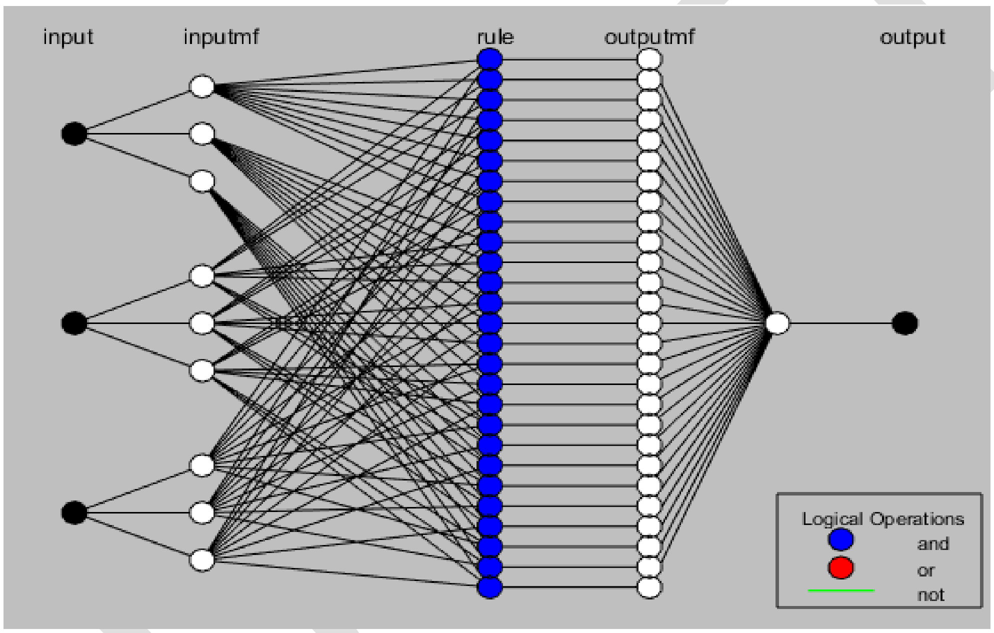


Figure 1: Structure of the developed ANFIS modelling

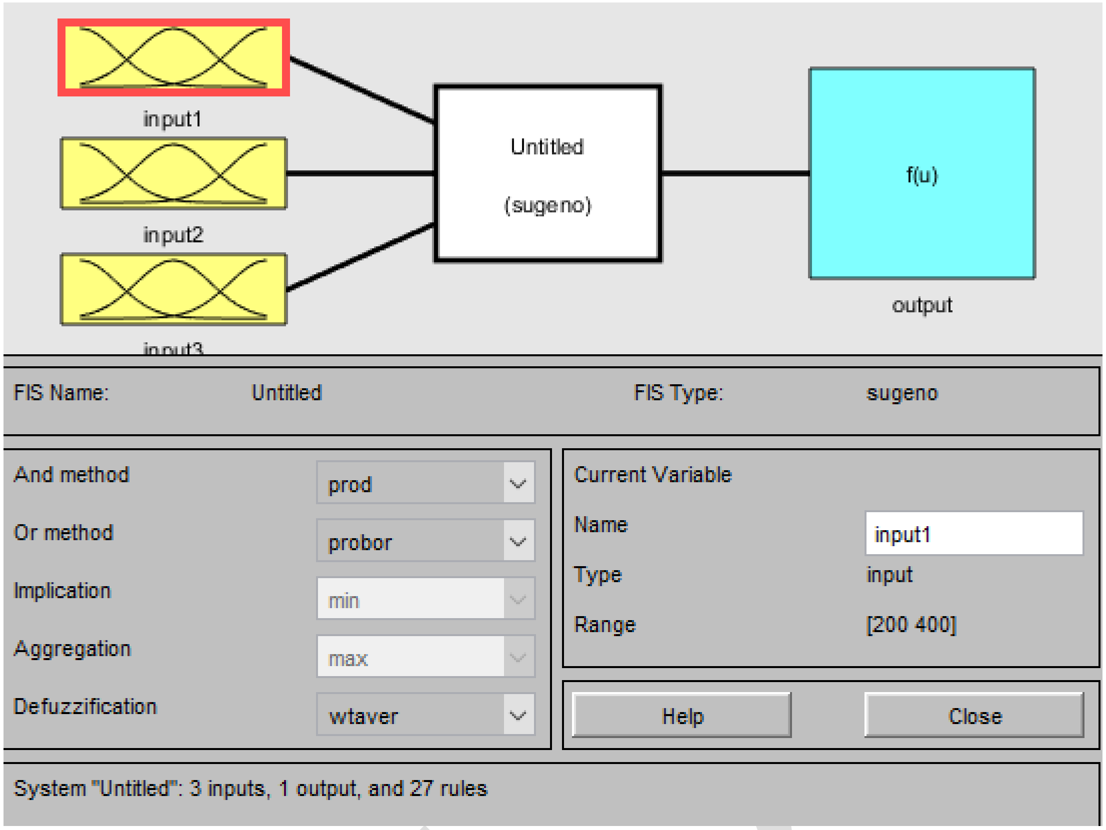


Figure 2: Layout of developed ANFIS predictor

Least square regression method using Design Expert Software (version 13). The performance of both the models was compared by the mean absolute error (MAE) and the root mean squared error (RMSE). The MAE indicates how close the predictions are to the eventual outcomes, given by Equation 5.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |f_i - y_i| \quad (5)$$

That is, the mean absolute error can be defined as the average of absolute errors; However, the absolute error is given by Equation 6.

$$|e_i| = |f_i - y_i| \quad (6)$$

Where f_i is the prediction and y_i the actual value. It should be noted that in MAE, all the individual errors have equal weight in the average, making it a linear score. To have a reliable statistical comparison between the mathematical models, the MAE and RMSE can be used together to ascertain the variation in errors in a given set of predictions. Calculating RMSE involves squaring the difference between the predicted and corresponding observed values, averaging it over the sample, and finally taking its average. This can be written as shown in Equation 7.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {e_i}^2} \qquad (7)$$

RMSE has a quadratic error rule, where the errors are squared before being averaged.

RESULTS AND DISCUSSION

pH values and viscosity as physicochemical properties of emulsion paint samples

The pH values and the viscosity of the samples of the emulsion paints are presented in Figures 3 and 4, respectively. The average value of the pH was found to be 8.0, which fell within the

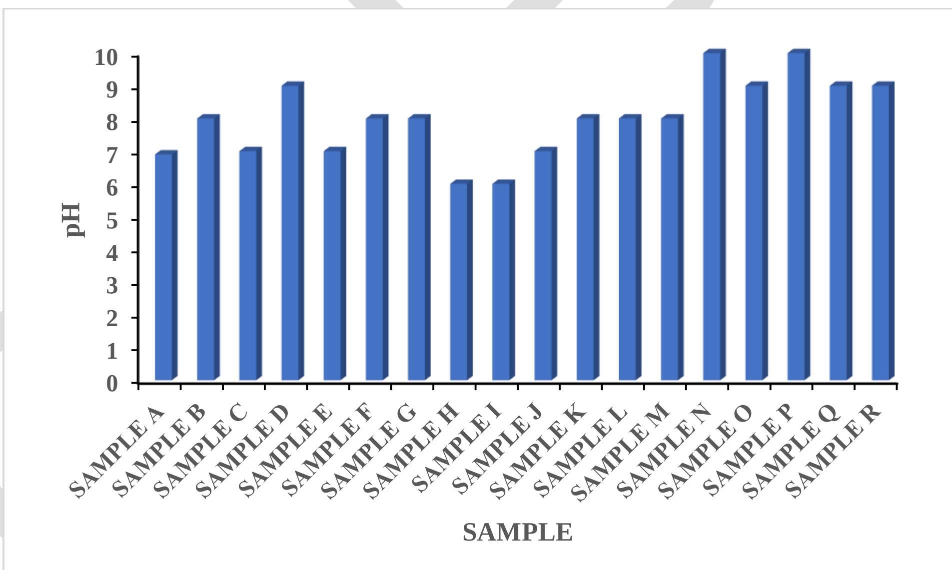


Figure 3: pH values for the different emulsion paint samples

specified range by the Standard Organization of Nigeria (SON, 2008). From these results obtained, sample N and sample P had the highest pH value (10), while samples H and sample I had the lowest value (6). These differences in pH values could be attributed to differences in the proportion of PVA (acrylic) used. PVA has a pH value of 5-6.5 (Nigerian Industrial Standard, 1989). This shows the binder's alkalinity nature, which could also be responsible for the alkalinity nature of the different samples.

Samples C, E, and J had pH values between 7.27 and 7.62, which is within the pH range where bacteria thrive (Jumbo,1996) and, therefore, susceptible to bacterial attack because of the favorable environment to thrive. To address this problem, the pH value for all the affected samples must be adjusted to 9.0 using an ammonia solution.

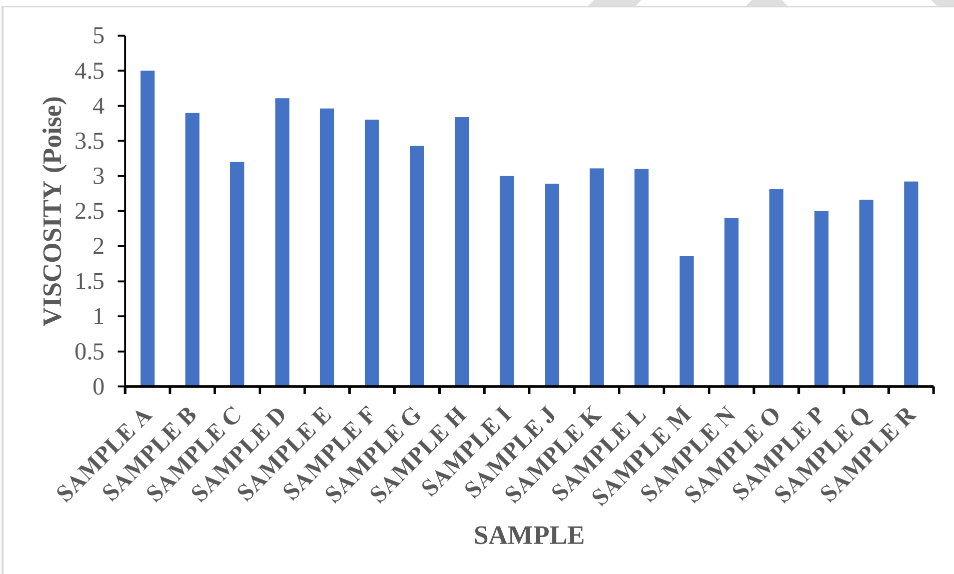


Figure 4: Viscosity of the different emulsion paint samples

Also, the mean value of the viscosity of the samples (Figure 4) was computed as 3.22 poise. This is within the average standard value, as presented by Ekeolisa *at al*.(2020). It could be seen that the binder (PVA) affects their viscosities; the higher the proportion of PVA in the paint, the higher its viscosity (Abdulsalam and Yahaya, 2010). The highest viscosity is attributed to sample A (4.5 Poise), while sample M has the lowest viscosity (1.86 Poise). Proper paint viscosity is critical for obtaining a quality finish; excessive viscosity can cause orange peel, while a low viscosity can create a too-wet film and run (Bailey and Ollis, 1986). The paint samples displayed good flow and ease of application, which can be attributed to their viscosities.

Contributions of independent variables on the response variables

Table 4 shows the analysis of variance for the pH distribution, while Table 5 presents the contribution of the explanatory variables about the pH value. The regression is statistically not significant at $\alpha = 0.05$ since the F statistic is not significant at $p - value > 0.05$, that is, the

Table 4: Analysis of variance for the pH value

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	9.335	3	3.112	2.929	.070
Residual	14.874	14	1.062		
Total	24.209	17			

combination of variables does not significantly predict the pH value, $F(3,17) = 2.929, p > 0.05$. From Table 5, both the temperature, $t(3,17) = 0.588, p > 0.05$, and the stability period, $t(3,17) = 1.395, p > 0.05$, does not contribute to the prediction of the pH value. Also, the agitator speed, which is statistically significant ($t(3,17) = 2.549, p < 0.05$) does not contribute

Table 5: Relationship between the explanatory variables and the pH value

*Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	3.823	1.904		2.008	.064
Agitator Speed	.008	.003	.534	2.549	.023
Temperature	.039	.066	.123	.588	.566
Stability Period	.056	.040	.292	1.395	.185

***Dependent Variable: pH; R^2: .386; Adjusted R Square: .254**

to the pH value for every 1 rpm increase in the agitator speed at constant temperature and stability period. The coefficient of determination (R^2) was 0.386, indicating that the model explains only

38.6% of the variance in the pH value. Tables 6 and Table 7 show the analysis of variance for the viscosity distribution and the contribution of the explanatory variables about the viscosity. The regression is statistically significant at $\alpha = 0.05$ since the F statistic is not significant, that is, the combination of variables does significantly predict the viscosity, $F(3,17) = 12.568,\ p < 0.05.$

Table 6: Analysis of variance for the viscosity

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	5.835	3	1.945	12.568	.000
Residual	2.167	14	.155		
Total	8.002	17			

From Table 6, both the temperature, $t(3,17) = -0.345, p > 0.05$, and the stability period, $t(3,17) = 0.557, p > 0.05$, does not contribute to the prediction of the viscosity. Also, the agitator speed, which is statistically significant ($t(3,17) = -6.105, p < 0.05$) (Table 7) does not

Table 7: Relationship between the explanatory variables and the viscosity

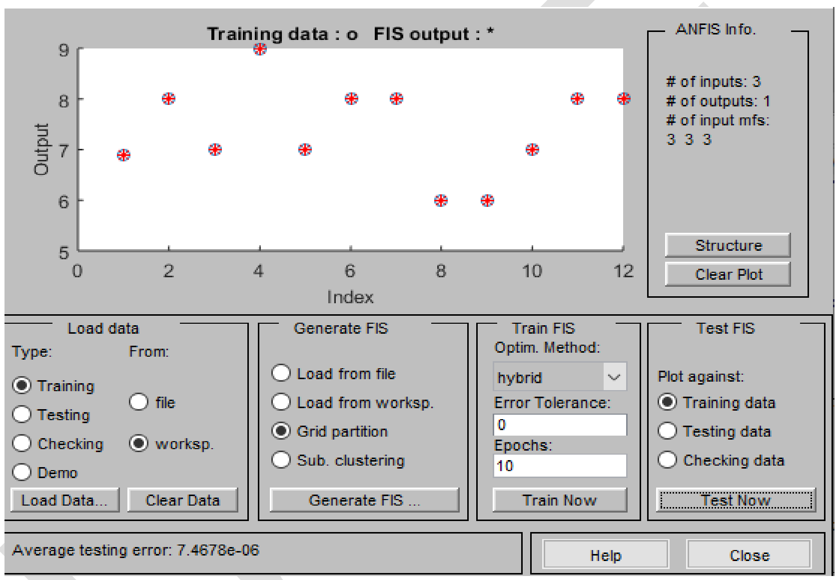
*Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	5.344	.727		7.354	.000
Agitator Speed	-.007	.001	-.849	-6.105	.000
Temperature	-.009	.025	-.048	-.345	.735
Stability Period	.009	.015	.077	.557	.586

***Dependent Variable: Viscosity; R^2: .729; Adjusted R Square: .671**

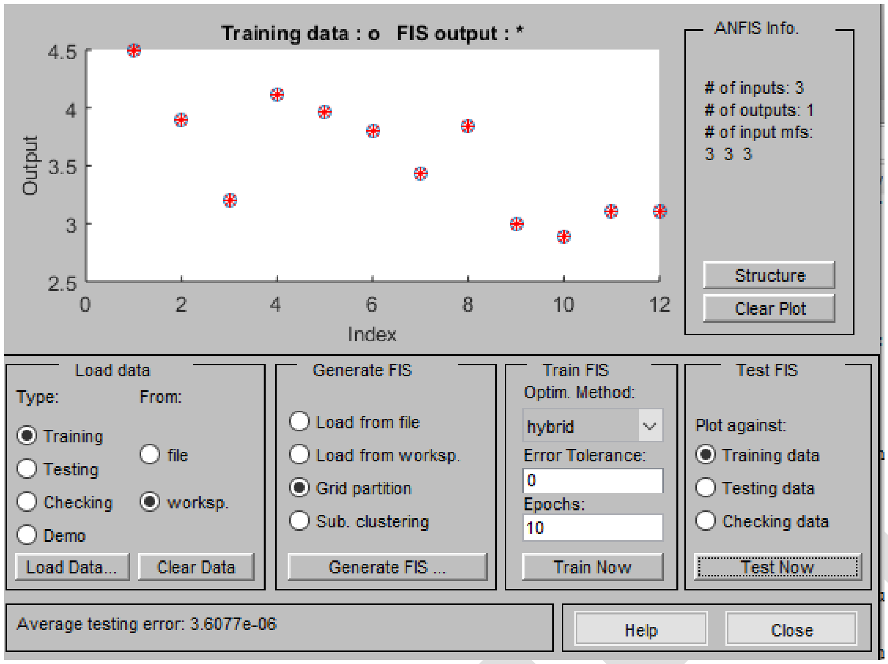
contribute to the viscosity for every 1 rpm increase in the agitator speed at constant temperature and stability period. The coefficient of determination (R^2) was 0.729, indicating that the model explains only 72.9% of the variance in the viscosity.

Predictive modelling of the response variables using adaptive neuro-fuzzy inference system

The training processes of the proposed ANFIS pH and viscosity are presented in Figures 5 and 6, respectively. It is observed that 10 iterations (epochs) are required to train the model. The root mean square error for the pH value and the viscosity is 7.467e-06 and 3.6077e-06, respectively.



Figures 5: Training process for proposed ANFIS predictor for the pH value



Figures 6: Training process for proposed ANFIS predictor for the viscosity

Comparative analysis of the experimental data, linear regression modelling and ANFIS

Table 8 and Table 9 present the percentage prediction error when the experimental data was compared with the Adaptive neuro-fuzzy inference system (ANFIS) and the linear regression-based prediction system, for the pH value, and the viscosity respectively. The Table shows that ANFIS

Table 8: pH prediction using ANFIS and comparison with Linear regression

S/N	Experimental Data	ANFIS	Difference	Percentage prediction error	Linear regression	Difference	Percentage prediction error
1.	6.9	6.899993	7.00312E-06	0.000101494	6.72	0.18	2.608695652
2.	8	8.000119	-0.000118539	-0.001481741	7.39	0.61	7.625
3.	7	6.999884	0.000116441	0.001663437	6.91	0.09	1.285714286
4.	9	8.999936	6.43621E-05	0.000715134	7.59	1.41	15.66666667
5.	7	6.999969	3.06161E-05	0.000437373	7.07	-0.07	-1
6.	8	7.999949	5.05813E-05	0.000632267	7.74	0.26	3.25
7.	8	7.999925	7.47036E-05	0.000933795	7.47	0.53	6.625
8.	6	5.99994	6.00457E-05	0.001000762	8.15	-2.15	-35.83333333
9.	6	6.000039	-3.87456E-05	-0.00064576	7.67	-1.67	-27.83333333
10.	7	7.000154	-0.000153716	-0.00219595	8.35	-1.35	-19.28571429
11.	8	8.000269	-0.00026868	-0.003358503	7.82	0.18	2.25
12.	8	8.000134	-0.000133777	-0.001672218	8.5	-0.5	-6.25
13.	8	8.000279	-0.000278887	-0.003486093	8.23	-0.23	-2.875

14.	10	9.999793	0.000206906	0.002069065	8.91	1.09	10.9
15.	9	8.999971	2.88114E-05	0.000320127	8.43	0.57	6.333333333
16.	10	10.00003	-3.1518E-05	-0.00031518	9.1	0.9	9
17.	9	8.999603	0.000397127	0.004412524	8.58	0.42	4.666666667
18.	9	9.000222	-0.000222331	-0.00247034	9.26	-0.26	-2.888888889
	Average Percentage Prediction error			**-0.000806324**			**-0.000185545**

Table 9: Viscosity prediction using ANFIS and comparison with Linear regression

S/N	Experimental Data	ANFIS	Difference	Percentage prediction error	Linear regression	Difference	Percentage prediction error
1.	4.5	4.499996	4.28412E-06	9.52026E-05	3.9	0.6	13.33333333
2.	3.9	3.900041	-4.14208E-05	-0.001062071	4.01	-0.11	-2.820512821
3.	3.2	3.200003	-2.82697E-06	-8.83429E-05	3.86	-0.66	-20.625
4.	4.11	4.109935	6.45959E-05	0.001571677	3.96	0.15	3.649635036
5.	3.96	3.960042	-4.21473E-05	-0.001064326	3.83	0.13	3.282828283
6.	3.8	3.800006	-6.04643E-06	-0.000159117	3.93	-0.13	-3.421052632
7.	3.43	3.430004	-3.6936E-06	-0.000107685	3.21	0.22	6.413994169
8.	3.84	3.839962	3.81915E-05	0.00099457	3.31	0.53	13.80208333
9.	3	3.000111	-0.000111017	-0.003700571	3.17	-0.17	-5.666666667
10.	2.89	2.890063	-6.34746E-05	-0.002196354	3.27	-0.38	-13.14878893
11.	3.11	3.110029	-2.89734E-05	-0.00093162	3.13	-0.02	-0.643086817
12.	3.1	3.100051	-5.1178E-05	-0.001650902	3.24	-0.14	-4.516129032
13.	1.86	1.860061	-6.12204E-05	-0.003291418	2.52	-0.66	-35.48387097
14.	2.4	2.399953	4.71326E-05	0.00196386	2.62	-0.22	-9.166666667
15.	2.81	2.809949	5.09067E-05	0.001811626	2.47	0.34	12.09964413
16.	2.5	2.500009	-8.54203E-06	-0.000341681	2.58	-0.08	-3.2
17.	2.66	2.659884	0.00011554	0.004343628	2.44	0.22	8.270676692
18.	2.92	2.920072	-7.22796E-05	-0.002475327	2.54	0.38	13.01369863
Average Percentage Prediction error				**-0.000349381**			**-1.379215607**

predicts the pH and viscosity better than the linear regression approach. The average percentage prediction error due to the adaptive neuro-fuzzy inference system and linear regression to the experimental data are -0.000806324 and -0.000185545 respectively for the pH value while those of viscosity are respectively -0.000349381 and -1.379215607 (Table 9).

CONCLUSION

The evaluation and potential of ANFIS for predicting the pH and viscosity values of emulsion paints were investigated. This study aimed at developing an ANFIS model based on experimental data to assess its accuracy in predicting the pH value and viscosity under varying production conditions. Eighteen samples of emulsion paint were produced using standard ingredients and experimental design techniques. The following conclusions were made:

1.) The average pH value was 8.0, while the mean viscosity of the samples was computed as 3.22 poise.
2.) The combination of variables significantly predicts the viscosity but does not significantly predict the pH value.
3.) The adaptive neuro-fuzzy inference system (ANFIS) predicts the responses better than linear regression formulation.

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