Optimization of Oil Yield from Shea Kernels using Response Surface Methodology and Adaptive Neuro Fuzzy Inference System (ANFIS)

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***Abstract* - The present study applied response surface methodology (RSM) and the adaptive neuro fuzzy inference system (ANFIS) to optimize oil yield from shea kernels in an hydraulic press. A central composite design (CCD) was adopted to study the effects of five factors namely: moisture content, heating temperature, heating time, applied pressure and pressing time on oil yield. For ANFIS, subtractive clustering method was used in generating the FIS. The experimental data were divided into training and checking data. Cluster centers were evaluated for the training data by competitive learning. RSM suggested that the combination of moisture content and temperature has the most significant effect on the oil yield while ANFISplaced temperature and heating time as the most influential variables. RSM gave a better prediction performance having R^2 of 0.9998 while ANFIS has R^2 of 0.9865. Themodels developed are useful for the prediction of performance measure, optimization and training for operators.**

Keywords: ANFIS, Optimization, Response Surface Methodology, Variables

1. INTRODUCTION

Shea butter is extracted from the dried kernels of the shea tree (*Vitellariaparadoxa*). The shea tree grows naturally in the wild in the dry Savannah belt of West Africa with Nigeria inclusive. The shea fruit consists of a thin, tart, nutritious pulp that surrounds a relatively large, oil-rich seed from which shea butter is extracted. The kernel contains about 60% edible fat and the shea cake which is considered as a very good supplement for animal feed [1,2]. Shea products are considered to be of great economic significance as they have been found to have a very wide area of application ranging from food preparation to industrial applications [3,4]. It is therefore important to maximize the recovery of valuable components such as oil from this economic material.

Optimization of oil yield from oil seed using response surface methodology has been a subject of research in recent years [5,6,7,8]. Adaptive neuro- fuzzy inference system (ANFIS) has also be found to be an important optimization tool in the process industries [9,10]. Comparison of both methods could give insight into the selection of influential input variables and their levels that will give an appreciable product yield. The objective of this study is to optimize the recovery of oil from shea kernel using both response surface methodology (RSM) and adaptive neuro-fuzzy inference system (ANFIS). The information obtained on the optimum process conditions would give insight into the input variables combination that would favour the extraction of oil from shea kernel.

2. METHODOLOGY

2.1 Sample Collection and Preparation

Shea kernels were purchased from the local markets of Ogbomoso, Southwestern Nigeria. The moisture content was determined according to ASAE standard S410.1. The sample (100 g) were weighted into sample containers and oven dried at 130°C for 6hrs. The samples were cooled in a desiccator and weighed to determine moisture loss.

The moisture content of kernels in percent wet basis (D) is calculated as:

$$M = \frac{100(loss\ in\ mass\ of\ kernels\ )}{initial\ \ mass\ of\ kernels} \qquad 1$$

In determining the oil content, the direct gravimetric method of solvent extraction was used.The method involved using normal Hexane of boiling point 80°C. Grounded samples (50 g) were weighed into the thimble of the Soxhlet extractor. Reflux condenser was attached and the extraction was carried out for nine(9) hours after which the solvent was distilled off. The traces of solvent were removed by heating the flask containing the oil by using an air-oven method. The oil extracted was weighed while the defatted cake was kept.

The percentage of oil was calculated as follow

$$\%Oil = \frac{A-B}{W} * 100 \qquad 2$$

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 8, August - 2014

Where, A= Weight of flask +oil; B= Weight of flask only; W= Weight of sample taken.

2.2 EXPERIMENTAL DESIGN

2.2.1 Response Surface Methodology (RSM)

Response surface methodology (RSM) is a collection of mathematical and statistical technique useful for analyzing problems in which several independent variables influence a dependent variable or response and the goal is to optimize the response. In many experimental conditions, it is possible to represent independent factors in quantitative form as given inEquation 3.

$$Y = f(x_1, x_2, \ldots, x_n) + \varepsilon \qquad 3$$

Where f is the real response function, and its format is unknown, Y is the response, x_1, x_2,…,x_n are the input variables which can affect the response, n is the number of independent variables and ε is the residual error that represents other sources of variability not accounted for by f.

Previous studiesiindicated that the most important process parameters during oil expression are the moisture content of the feed materials, temperature, pressing time, applied pressure and the heating time [8,11,12,13].In this study, a central composite design (CCD) was adopted to study the interaction effects of five factors namely: moisture content, heating temperature, heating time, applied pressure and pressing time which are denoted as X_i(i=1, 2, 3, 4, 5), respectively. Response surface methodology (RSM) was used to determine the effect of these independent variables on product qualities as shown in Table 1.

Table 1: Factors and levels for Central Composite Design

Variable		Symbol			Coded levels		
			-2	-1	0	1	2
Moisture content(%wb)		A	7	9	11	13	15
Heating Temperature(oC)		B	90	100	110	120	130
Heating Time(Mins)		C	20	30	40	50	60
Applied Pressure(Mpa)		D	5	10	15	20	25
Pressing time(min)		E	3	4	5	6	7

A second degree polynomial equation was fitted in each response to study the effect of variables and to describe the process mathematically. The quality of the fit of the model was evaluated using analysis of variance (ANOVA). The fitted quadratic response model is as described in Equation 4
.

$$Y = b_0 + \sum_{i=1}^{k} b_i X_i + \sum_{i=1}^{k} b_{ij} X_i^2 + \sum_{i\;1<j}^{k} \sum_{j}^{k} b_i X_i X_j + e \qquad 4$$

where Y is response factor (% Oil yield), and i and j denote linear and quadratic coefficients,
respectively. b_o is the intercept, b_i is the first order model coefficient, k is the number of
factors, and e is a random number.

2.2.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS is an adaptive network that permits the application of neural network topology and fuzzy logic to predict the behaviour of variables and reduce optimization search space. It not only includes the characteristics of both methods but also eliminates some disadvantages of separate application. ANFIS uses the learningability of ANN to define the input–output relationship and construct the fuzzy rules by determining the inputs structure. The system results were obtained by thinking and reasoning capability of the fuzzy logic [14].

Figure 1 represents a typical ANFIS architecture consisting of five layers including the input layer (Layer 0). Layer 1 is the fuzzification layer in which each node represents a membership function, layer 2 provides the strength of the rule by means of multiplication operator in each node, layer 3 is the normalization layer which normalizes the firing strength of the rules, layer 4 has adaptive nodes and layer 5 has a single node which is fixed the summation of the inputs of the nodes in layer 4[14,15,16].

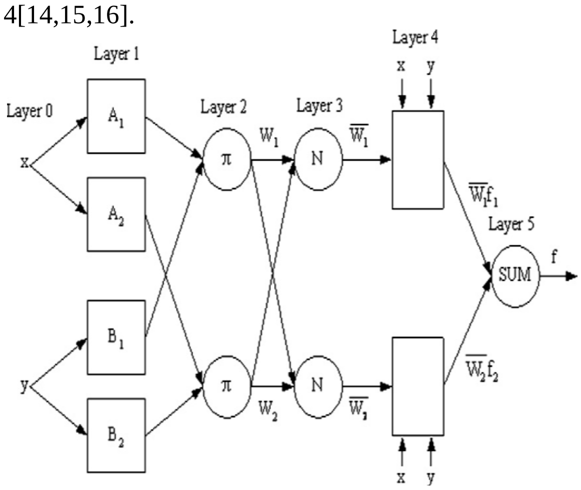


Figure 1: Basic ANFIS structure

Subtractive clustering is a very fast and efficient clustering method designed for a moderate number of input patterns, because its computation grows linearly with the data dimension and as the square of the number of data points. The subtractive clustering method is available in the fuzzy logic toolbox for MATLAB. In the subtractive clustering method, the training data are divided according to their respective class labels and then the subtractive clustering algorithm is applied on each group of data individually to extract the rules for identifying each class of data. A group of data points was specified for a particular class in the feature space. Subtractiveclustering was done to normalize the data in the feature space in the range [0, 1]. Each data point in the class was considered a potential cluster center while the data points outside this radius had little influence on the potential of the data points within this radius. Thus, the measure of the potential of a data point became a function of its distances to all other data points. A data point with many neighboring data points had a high potential value. After the potential of every data point had been computed, the data point with the highest potential as the first cluster center was selected as suggested by [15].

In this work, subtractive clustering method was used in generating the fuzzy inference system (FIS). The experimental data were divided into training and checking data. Cluster centers were evaluated for the training data by competitive learning. Antecedents and consequents were calculated using the initial fuzzy model and input parameter features were gotten with the neural fuzzy model. The training features were selected by applying subtractive clustering to obtain cluster centers, these cluster centers were then used to develop the fuzzy rule base and the membership function of the fuzzy rule was optimized using the back propagation algorithm. The model was developed, trained and evaluated.

2.3 Model Estimation

The performance of ANFIS model in training and testing sets is validated in terms of the common statistical measures; R (coefficient of determination which presents the degree of association between predicted and true values) and RMSE (which is preferred in many iterative prediction and optimization schemes).

$$R = \frac{\sum(Y_{obs} - Y_{obs}^{i})(Y_{pre} - Y_{pre}^{i})}{\sqrt{\sum(Y_{obs} - Y_{obs}^{i})^2 \sum(Y_{pre} - Y_{pre}^{i})^2}} \qquad 5$$

$$RMSE = \sqrt{\frac{1}{N}\sum\left(Y_{obs} - Y_{pre}\right)^2} \qquad 6$$

Where Y_{obs} = observed data, Y_{pre} = predicted data, Y_{obs}^{i} = average value of observed data and Y_{pre}^{i} =average value of predicted data.In the RSM model developed, the analysis of the variance including the sequential F-test and lack of fit test were used in the assessment of the performance of the model. Also residual analysis and diagnostics case statistics were checked to ensure adequacy of the model. The quality of fit
of the quadratic model was expressed by the coefficient of determination (R-squared).

$$R^2 = 1 - \frac{SS_{residual}}{SS_{model} + SS_{residual}} \qquad 7$$

Where SS = sum of square.

3. RESULTS AND DISCUSSION

3.1 RSM Modeling Analysis

The experimental results, the predicted values and the residuals were shown in Table 2. The residual measured the experimental errors. From table 2, the residuals having less value indicated that the actual and predicted values were relatively close. The quadratic model equation in terms of the coded factors was presented in Equation 8.

The adequacy of the developed model was tested using the analysis of variance(ANOVA) technique and the results of second order response surface model fitting in the form of analysis of variance (ANOVA) are given in Table 3. The determination coefficient (R^2) indicates the goodness of fit for the model. In this case, the value of the determination coefficient (R^2=0.9998) indicates that only less than 1% of the total variations are not explained by the model. The value of adjusted determination coefficient (adjusted R^2=0.9995) is also high, which indicates a high significance of the model. Predicted R^2 is also in a good agreement with the adjusted R^2. Adequate precision compares the range of predicted values at the design points to the average prediction error.

Table 2: Experimental Design for Variables and the Response

Run	Variables					Oil Yield(%)		
	A(%wb)	B(deg C)	C(mins)	D(Mpa)	E(min)	Actual	Predicted	Residual
1	9	100	30	10	6	22.27	22.273	-0.0034
2	13	100	30	10	4	30.81	30.811	-0.0009
3	9	120	30	10	4	25.22	25.223	-0.0034
4	13	120	30	10	6	36.89	36.890	-0.0001
5	9	100	50	10	4	25.61	25.615	-0.0051
6	13	100	50	10	6	29.18	29.182	-0.0018
7	9	120	50	10	6	29.11	29.114	-0.0043

8	13	120	50	10	4	39.42	39.422	-0.0018
9	9	100	30	20	4	28.44	28.443	-0.0026
10	13	100	30	20	6	37.14	37.139	0.0007
11	9	120	30	20	6	28.15	28.152	-0.0018
12	13	120	30	20	4	41.88	41.879	0.0007
13	9	100	50	20	6	30.64	30.643	-0.0034
14	13	100	50	20	4	38.27	38.271	-0.0009
15	9	120	50	20	4	33.87	33.873	-0.0034
16	13	120	50	20	6	44.31	44.310	-0.0001
17	7	110	40	15	5	17.71	17.700	0.0098
18	15	110	40	15	5	36.34	36.342	-0.0019
19	11	90	40	15	5	32.2	32.195	0.0048
20	11	130	40	15	5	41.32	41.317	0.0031
21	11	110	20	15	5	29.84	29.839	0.0015
22	11	110	60	15	5	34.75	34.744	0.0065
23	11	110	40	5	5	26.09	26.084	0.0065
24	11	110	40	25	5	37.13	37.129	0.0015
25	11	110	40	15	3	41.01	41.005	0.0048
26	11	110	40	15	7	39.55	39.547	0.0031
27	11	110	40	15	5	37.68	37.640	0.0403
28	11	110	40	15	5	37.63	37.640	-0.0097
29	11	110	40	15	5	38.01	37.640	0.3703
30	11	110	40	15	5	37.45	37.640	-0.1897
31	11	110	40	15	5	37.41	37.640	-0.2297
32	11	110	40	15	5	37.65	37.640	0.0103

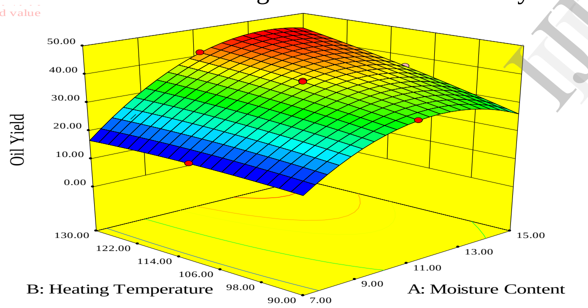
$$Oil\,Yield = 37.63 + 9.32A + 4.56B + 2.45C + 5.52D - 0.73E + 4.44AB - 2.67AC + 1.60AD + 0.028AE + 2.38BC - 2.26BD + 0.49BE + 0.84CD - 0.51CE + 0.35DE - 10.62A^2 - 0.88B^2 - 5.35C^2 - 6.03D^2 + 2.63E^2 \quad 8$$

Table 3: ANOVA for Response Surface Methodology

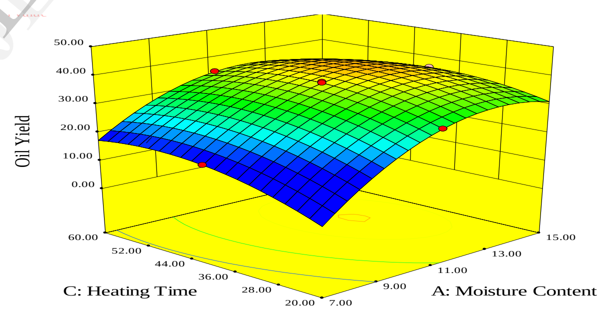
Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F	
Model	1229.52	20	61.48	2965.19	<0.0001	significant
A	521.27	1	521.27	25142.36	<0.0001	
B	124.81	1	124.81	6019.84	<0.0001	
C	36.09	1	36.09	1740.66	<0.0001	
D	182.99	1	182.99	8826.08	<0.0001	
E	3.19	1	3.19	153.87	<0.0001	
AB	19.60	1	19.60	945.50	<0.0001	
AC	7.14	1	7.14	344.49	<0.0001	
AD	2.57	1	2.57	123.86	<0.0001	
AE	0.00	1	0.00	0.04	0.8520	
BC	5.68	1	5.68	273.79	<0.0001	
BD	5.12	1	5.12	246.90	<0.0001	

BE	0.24	1	0.24	11.70	0.0057	
CD	0.70	1	0.70	33.83	0.0001	
CE	0.26	1	0.26	12.42	0.0048	
DE	0.12	1	0.12	5.82	0.0344	
A^2	206.72	1	206.72	9970.67	<0.0001	
B^2	1.43	1	1.43	69.05	<0.0001	
C^2	52.45	1	52.45	2529.72	<0.0001	
D^2	66.74	1	66.74	3219.18	<0.0001	
E^2	12.74	1	12.74	614.61	<0.0001	
Residual	0.23	11	0.02			
Lack of Fit	0.00	6	0.00	0.00	1.0000	not significant
Pure Error	0.23	5	0.05			
Cor Total	1229.75	31				
Std. Dev.	0.144		R^2	0.9998		
Mean	33.843		AdjR^2	0.9995		
C.V. %	0.425		PredR^2	0.9997		
PRESS	0.331		Adeq Precision	228.1296		

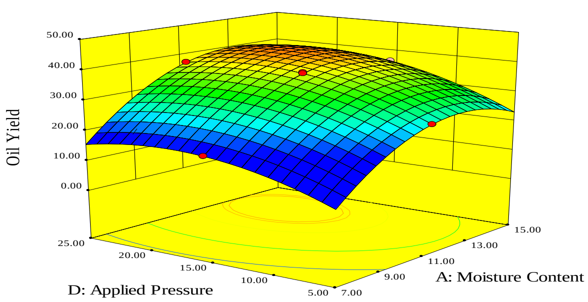
The model value of 2965.19 indicates that the model is significant. Values of prob>F less than 0.05 indicate the model terms are significant. From this table 3, A, B, C, D, E, AB, AC, AD, BC, BD, BE, CD, CE, DE, A^2, B^2, C^2, D^2, E^2 are significant model terms. The parameter with highest F-value of 25142.36 is moisture content (A), therefore it is the most significant for the oil yield percentage. In terms of two factors interaction, the combination of moisture content and heating temperature (AB) has the highest effect on the oil yield while the factors that had least effect on oil yield are the moisture content and pressing time.



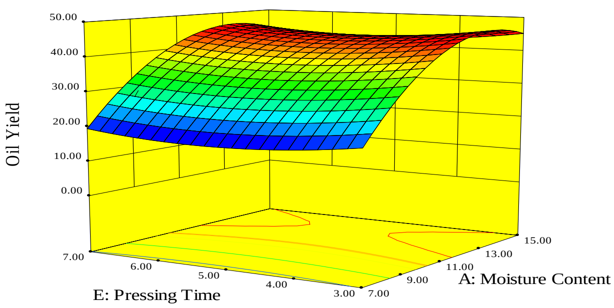
2a. Heating Temperature and Moisture Content



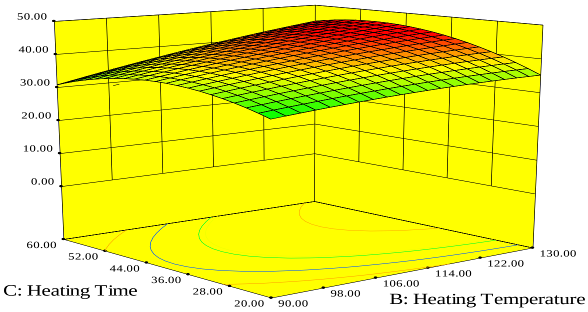
2b.Heating Time and Moisture Content



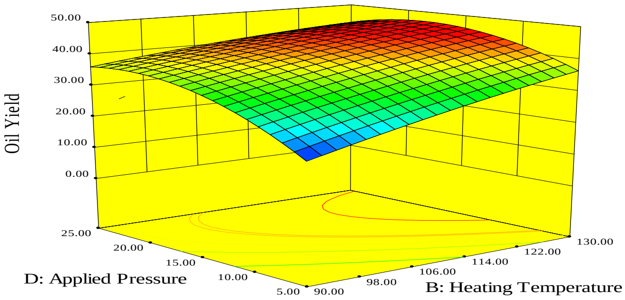
2c.Applied Pressure and Moisture Content



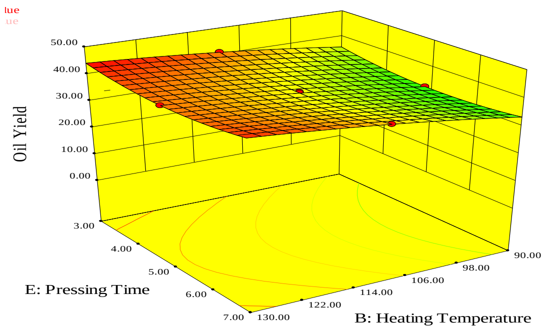
2d.Pressing time and Moisture content



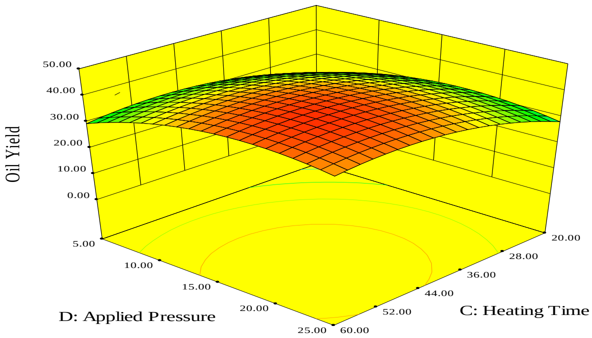
2e.Heating Time and Heating temperature



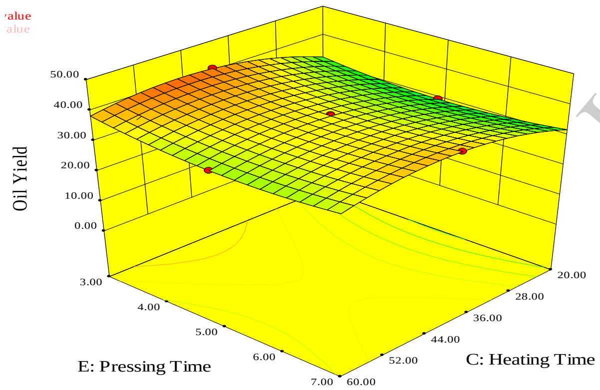
2f.Applied Pressure and Heating temperature



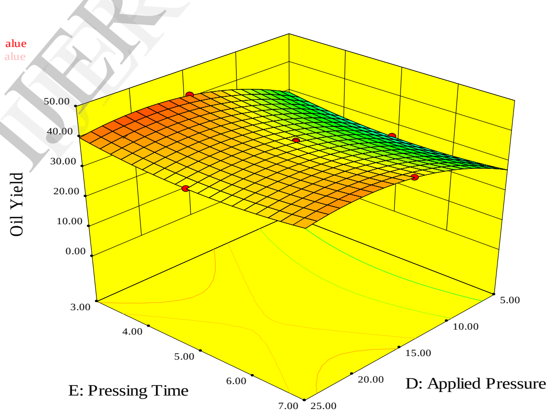
2g.Pressing Time and Heating Temperature



2h.Applied Pressure and Heating Time



2i.Pressing Time and Heating time



2j.Pressing Time and Applied Pressure.

Figure 2: Response surface plots for the effect of input variables on the Oil Yield.

The interactive effect of the process parameters on the response was reported in Figure 2a-j. Figure 2a shows the effect of moisture content and heating temperature on the oil yield keeping all other variables constant. At low heating temperature 90^{o}C, oil yield was minimal and as temperature increases to 130^{o}C, the oil yield was increased to 44.45%. This therefore indicates that oil extraction depends on heating temperature. Also, at temperature of 110^{o}C, oil yield increased with increase in moisture content.

Figure 2b shows the effect of moisture content and heating time on the percentage oil yield, keeping all other variables constant. At low heating time of 20minutes and moisture content of 7%wb, the oil yield was 7.23%, as moisture content increases to 15%wb and time 20minutes, oil yield gave 31.2%. Generally, oil yield increases with increase in moisture content. Also, at high moisture content 15% wb and time 60minutes, oil yield decreases to 30.7%. This indicates that higher oil yield will be obtained at high heating time and low moisture content 11%wb. The interaction of moisture content and applied pressure on the oil yield was seen in Figure 2c. At pressure of 5MPa and moisture content of 11%wb, oil yield was found to be 26.1% and at high pressure of 25MPa and 15%wb, high oil yield was obtained. This indicates that oil yield increases with increase in moisture content and applied pressure.

The effect of moisture content and pressing time was observed on the response as shown in Figure 2d, keeping all other variables constant. High oil yield was obtained at low pressing time 3minutes and high moisture content. But as pressing time increases to 7minutes and high moisture content 15%wb, the oil yield was reduced. This therefore indicates that high oil yield will be achieved at high moisture content and short pressing time. Figure 2e shows the effect of heating temperature and heating time on percentage oil yield. When the heating time was 20minutes and the heating temperature increased within the range (90-130^{o}C), the oil extracted was 31.1%. High oil yield was favoured at high heating time 60minutes and high heating temperature. From Figure 2f, it was observed that oil extracted from sheabutter is favoured with increase in applied pressure 25MPa and heating temperature of 130^{o}C giving oil yield of 38.54%. At low pressure 5MPa and high temperature, oil yield was 32%.

Interaction effect of heating temperature and pressing time on the oil yield was shown in Figure 2g. Low pressing time favoured the yield of oil at temperature of 90^{o}C than high pressing time of 7minutes at the same temperature. At 3minutes and 110^{o}C, oil yield was 41% while it is 39% at 110^{o}C and 7minutes. This indicated that high oil yield was obtained at low pressing time and high temperature. Figure 2h shows the interaction effect of heating time and applied pressure on the oil yield. At low pressure of 5MPa, low amount of oil was extracted with increase in heating time. At 60minutes heating time and high applied pressure of 25MPa, high oil yield of 35% was obtained. The interaction of heating time and pressing time on percentage oil yield was shown in Figure 2i. High oil yield was obtained at low pressing time of 3minutes in the range of heating time 20-60minutes while the oil yield was minimal at increase in pressing time to 7minutes. At heating time of 40minutes and pressing time 3minutes, oil yield was found to be 41%. From Figure 2j, the effect of applied pressure and pressing time was seen on the oil yield percentage. At low pressing time 3minutes, oil yield increases from 29.8% to 40.1% with increase in the range of applied pressure (5-25MPa) while at 7minutes and 15MPa, oil yield was 39.5%. This indicated that oil yield increases with increase in applied pressure and decrease in pressing time.

3.2 ANFIS MODELLING ANALYSIS

From the clusters formed from the data, exhaustive search was performed to determine the single parameter which is most influential in predicting the oil yield.

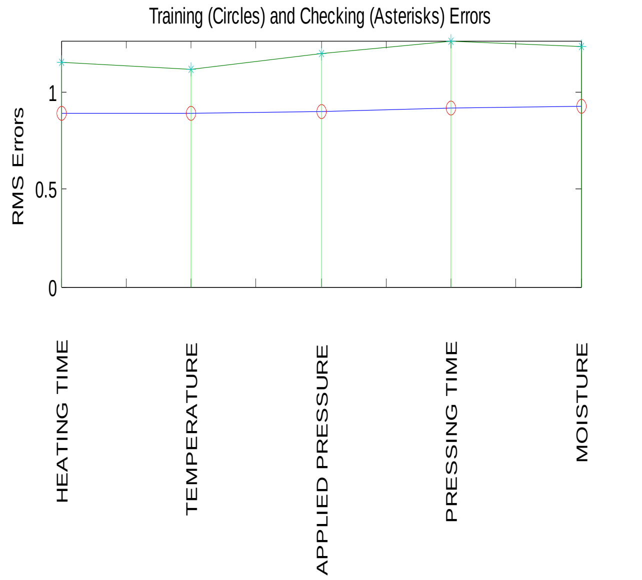


Figure 3: Plot of RMS errors of the input parameters

The effect of each input parameter in predicting the oil yield extraction was shown in Figure 3 with their corresponding RMS errors. Heating time, which is the left-most parameter, has the least training error value of 0.8871 and checking value of 1.1570. Therefore, it is the most influential parameter followed by temperature with training error of 0.8892 and 1.1175 as the checking error value. The variable with least influence on oil yield was moisture content with training and checking error of 0.9274 and 1.2362, respectively.

The effect of two input combination on the oil yield was reported in Table 4. The combination of temperature and heating time has the least training error of 0.7062 and checking error of 1.0379, thereby, the most significant in predicting the oil yield percentage. The least significant effect was observed when combining applied pressure with pressing time having the highest training error of 0.8708 and 1.2270 as the checking error.

Table 4: Input parameter combination with RMS errors.

S/N	Input Combination		Training Error	Checking Error
1	Moisture content and Temperature		0.8137	1.4262
2	Moisture content and Heating time		0.7693	1.1896
3	Moisture content and Applied pressure		0.8069	1.1281
4	Moisture content and Pressing time		0.8666	1.2855
5	Temperature and Heating time		0.7062	1.0379
6	Temperature and Applied pressure		0.7498	0.966
7	Temperature and Pressing time		0.8055	1.1806

8	Heating time and Applied pressure		0.7661	1.1341
9	Heating time and Pressing time		0.7366	1.1393
10	Applied pressure and Pressing time		0.8708	1.227

Subtractive clustering algorithm was simulated for various values of radius in the range 0.2 to 1.4. The results so obtained in terms of efficiency of the algorithm on the data are plotted in Figure 4. The radius determines the number of clusters formed which is the corresponding membership function. As the radius increases, the number of clusters formed decreases, thereby increasing the degree of accuracy (R) value and decreasing the RMSE. An Epoch number 500 was used as benchmark. Radius 1.4 has MF of 2, 1.2 radius has MF of 3, 7 MF for radius. The lower the MF number, the better the performance of the model. The plot of accuracy showing the correlation coefficient (R-value) of 0.9865 was shown in Figure 5. The predicted data values cluster round the straight line indicating nearness of predicted value with experimental value of the oil yield extraction with less disparity.

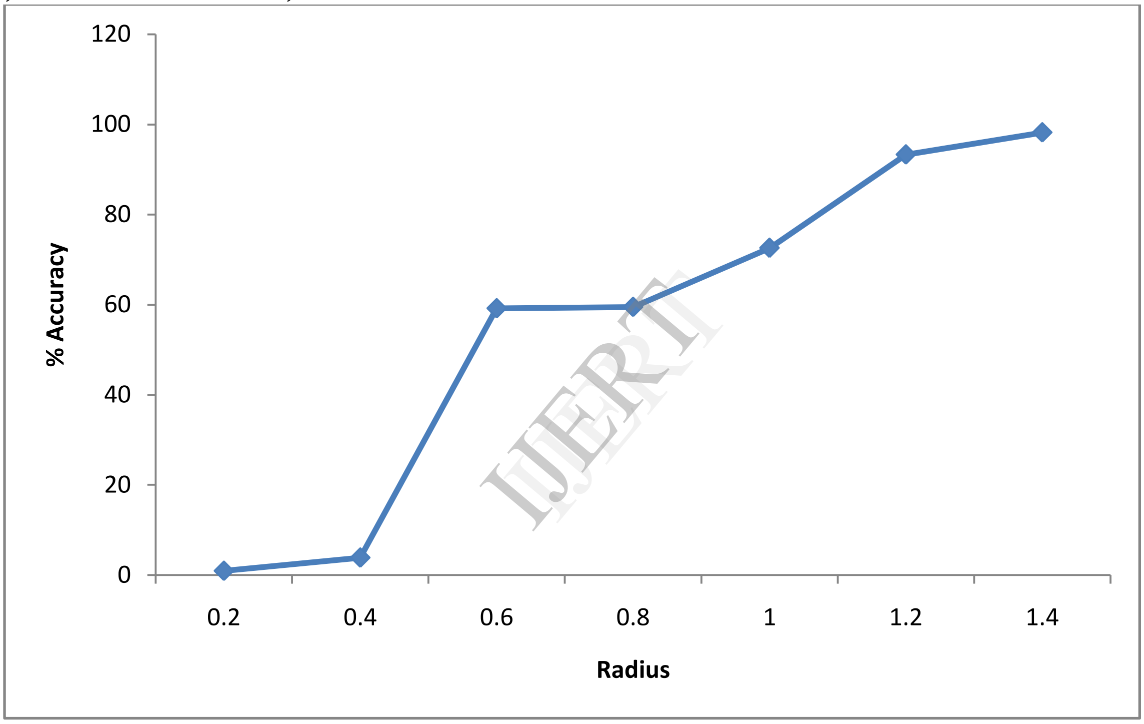


Figure 4: Percentage accuracy of the developed model for different radii values.

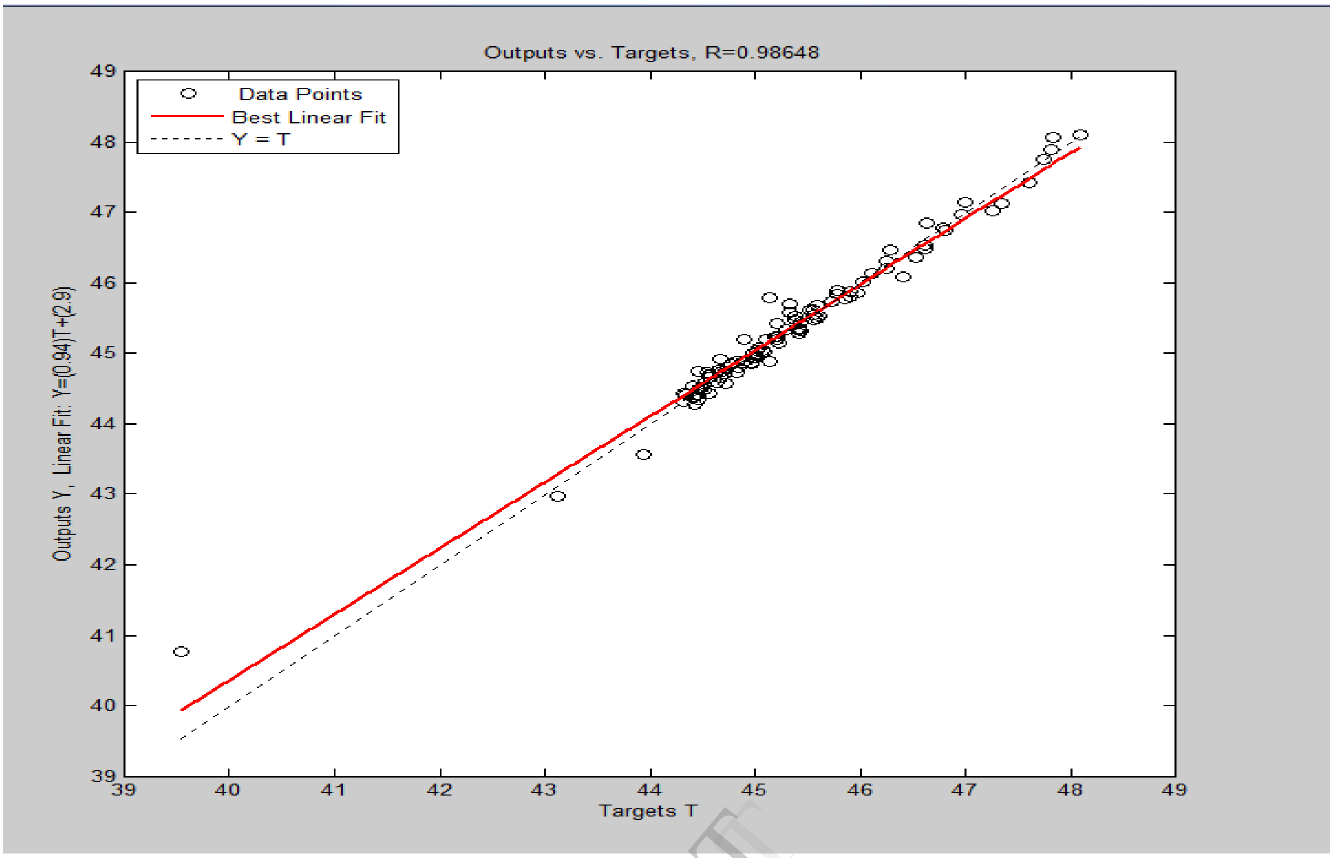


Figure 5: Experimental data value against the predicted value for the oil yield.

3.3 Comparison of RSM and ANFIS

RSM and ANFIS are both data driven model used in predicting the outcome of an experimental work. In this study, both models were used to predict the extraction of oil yield from shearbutter. The ability of RSM is powerful in identifying the insignificant main factors and interaction factors or insignificant quadratic terms in the model and thereby can reduce the complexity of the problem. On the other hand, ANFIS is a black box model approach which requires large and sufficient data for better performance. In this study, RSM gave a better prediction performance having R^2 of 0.9998 while ANFIS has R-value of 0.9865. RSM is more statistical in analyzing and optimizing process variables.

4. CONCLUSION

This study looked into the optimization of process parameters involved in oil yield extraction from shea kernel using RSM and ANFIS (sub-clustering) as predictive tools. From the input parameters, RSM suggested the combination of Moisture content and Temperature has the most significant effect on the oil yield percentage with the highest F-value of 945.50 and R^2 value of 0.9998. On the other hand, the best combination of two input parameter suggested by ANFIS is Temperature and Heating time having less RMSE of 0.1876 and R-value of 0.9865. Optimum oil yield of 47.13% was obtained when the moisture content, heating temperature, heating time, applied pressure and pressing time were 14.09%wb, 128.70^{o}C, 35.93minutes, 19.21MPa and 6.69minutes, respectively. The two models proved effective at predicting the percentage oil yield on 99% accuracy. RSM gave a better prediction than ANFIS with reference to the obtained R^2 values for both models. The model developed can be used for process behaviour prediction, performance measure, optimization and as training tools for operators.

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