NEURAL NETWORK MODELING OF OIL YIELD FROM SHEAKERNELS IN AN HYDRAULIC PRESS

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Abstract

An investigation on prediction of oil from shea kernels in an hydraulic press subject to process variables such as moisture content, pressing time, applied pressure, heating time and heating temperature was carried out. Artificial neural network (ANN) technique was applied using experimental data from a previous study. These data were then used for network training and testing. The back propagation technique was then used for establishing the network. The prediction accuracy of the neural network model was significantly improved compared to statistical model. (R=0.96)

Keywords: Oil expression, yield, neural network, prediction.

Introduction

The shea tree (Butyrospermum parkii) produces second most important oil crop in Africa after oilpalm (Poulsen, 1981).

It is an indigenous tree in Africa found in large quantities in the savannah zone of Nigeria (Ezebor et al., 2005). The fleshy, edible pulp of the shea fruit is removed to expose the shea nuts which are parboiled and sundried. The nuts are crushed to expose the shea kernels which contain 55% by weight of fat (Casten and Synder, 1985).

Sherkernels are processed to obtain shea oil which solidifies to form a solid fat, butter-like substance, called shea butter. Shea butter is a luxury product used as raw material by the Cosmetic, Food and Pharmaceutical industries in developing and developed countries. In European countries, it is often used as a substitute for cocoa butter in the chocolate and confectionary industry because it is sweat and oily. It is used in the cosmetic industry for its high cleansing power (FAO, 1991). The production of shea butter is an important source of income for women in African countries.

It is estimated that over 2 million women in Africa countries produce sheabutter for both cash and food (Boateng, 1992).

Mechanical expression using hydraulic presses is one of the ways by which oil is removed from oilseeds (Khan and Hanna, 1994). This method is generally preferred because of its lower initial and operational costs. It produces relatively uncontaminated oil as compared to the solvent extraction process and it allows the use of the cake residue. Investigation by previous researchers have shown that oil yield during this process is dependent primarily on process variables such as moisture content, particle size, heating temperature, heating time, applied pressure and pressing time (Khan & Hanna, 1981, 1984, and Mrema and Mc-Nulty 1985)

In recent times, sheabutter has attached export potential for use mostly in Foods, Cosmetics, Pharmaceuticals and as cocoa butter substitute in the chocolate and confectionery industry. There is a renewed effort to promote sheabutter production by the Federal government of Nigeria through the distribution of improved seedlings of sheatrees by raw materials research council.(Elemo et al., 2002)

Many researches have been carried out to predict oil yield in terms of process parameters using empirical equations/ models developed by statistical methods. The oil yield from sun flower, conorphor nuts, peanut, rice bran and shea nut have been predicted using such empirical equations (Singh et al., 1984; Adeeko and Ajibola, 1990; Fasina and Ajibola, 1990; Sivakumaran et al., 1985; Sivala et al., 1991; Olajide, 2000). Hamzat and Clarke (1993) also used the concept of Quasi Equilibrium oil yield to predict the oil yield from groundnuts. The empirical equations gave an insight into the influence of some of the parameters on the oil yield from these seeds. However, the prediction power of these models is limited.

Neural network is a new class of information processing techniques. The most basic components of neural networks are modeled after the structure of the human brain like human information processing systems artificial neural systems or networks acquire, store and utilize knowledge. It has been applied in solving wide varieties of problems. The most common is the use of neural network to forecast what will most likely happen. It has a unique ability to recognize relationship before input and output events.

Numerous researches have applied neural networks in the modeling and predicting of various systems in which no explicit scientific solutions were available. Zhang et al (1992) used a neural network model for prediction of the secondary structure of globular proteins. Based on knowledge of the secondary structure of the existing proteins, the model predicts the secondary structure of local sequences of amino acids with a success rate of 64.3%. Sayeed et al (1995) developed a back propagation neural network to predict the sensory attributes of a snack food. The performance of the trained neural network was reasonable as indicated by correct prediction rates ranging from 78 to 98%. Ruan et al (1995) designed a neural network that accurately predicted (>94%) the rheological properties of dough from the torque developed during mixing. They reported that the neural network could be used on line for process control.

Liao et al (1993) used a neural network to classify corn kernel breakage. The neural network model accurately discriminated the broken kernels from the whole corn kernels.

Fang et al (1998) developed back propagation neural networks for the prediction of ground wheet samples. Compared to conventional statistical models the accuracy of prediction was improved substantially as indicated by the significant reduction in not meansquare error and the improvement of coefficient of determination (r^2>0.98). Olajide et al (2007) used artificial neural network to predict oil yield from groundnut kernels in an hydraulic oil press. The neural network developed could predict oil yield than previously developed statistical model (R= 0.82). The neural network model developed could better predict the properties than the previously multiple regression model. Considering a number of input parameters that influence the oil yield from groundnut and the perceived non-linear nature of their relationship, this study is aimed at evaluating the suitability of Artificial Neural Networks (ANN) in predicting the oil yield from shea kernels.

Materials and Methods

In achieving the set goal of this study, an Artificial Neural Network (ANN) was trained and validated. A total of 96 data sets obtained from the experiment work of Olajide (2000) were used in this study. About 60 sets of these data sets were assigned to the training set while the remaining 36 sets were used as the validation sets. There are five input variables, which are: applied pressure (X_1), pressing time (X_2), moisture content (X_3), heating temperature (X_4) and heating time (X_5). The desired output is the oil yield from the sheakernel. The statistical description of the data set is given in Table 1 The ANN was trained using standard back propagation architecture with Levenberg Marquadart training algorithm and this architecture used comprised of two layers. Table 2 shows the Architecture of the network used. The tansigmoidal function was used as the transfer function in the hidden layer due to its suitable application for the data set of this kind. The output layer was made up of pure linear transfer function. The optimal hidden layer was determined by varying the total number of neurons from 1 to 20. The stop criteria were based on Mean square Error (MSE) on the validation set for model generalization. The optimum hidden layer comprised of 17 neurons. All these were executed on a commercial simulator MATLAB6R12.

Table 1: Statistical description of the variables

Variables	Number of Variables	Average Value	Minimum Value	Maximum Value	Standard deviation
Applied Pressure (X_1)(Mpa)	96	15.00	5	25	4.40
Pressing Time (X_2) (Min)	96	5	3	7	0.88
Moisture Content (X_3) (%)	96	11	9	15	1.32
Heating Temperature (X_4) °C	96	110	90	130	8.80
Heating Time (X_5) (Min)	96	40	20	60	8.80
Oil Yield (%)	96	33.85	18.28	46.70	6.42

Table 2: Architecture of the network used

Network Used	Levenberg- Marquadart Back propagation neural Network
Learning Methods	Supervised
Transfer Funtion	Sigmoid, purelin
No of input	5
Hidden layer	2
No of output	1

The algorithm model for Shea kernel oil yield prediction is as shown below. Incremental training style is used where the weights and biases of the network are updated each time an input is presented to the network. Its training function is trainbr. The performance function is set to the learning function used, which is invoked, by setting the learning parameter (lr)

```
net = newff([7 15;9 13;3 5;1 2;4 6],[24 1],{'tansig','purelin'},'trainlm');
net.trainParam.epochs = 100;
net.trainParam.goal = 0;
net.trainParam.lr = 0.1
net.trainParam.show = 25;
net = train(net,p,t);
[pn,minp,maxp,tn,mint,maxt] = premnmx(p,t);
a = sim(net,p)
```

Where p=supplied inputs
t =supplied targets/outputs
a =network outputs

Results and Discussion

The values of the experimental oil yields used to train the network and the corresponding output given by the ANN is as shown in Table 3. The standard deviation and mean value of 6.42 and 33.98 was calculated for the experimental yield while corresponding ANN outputs was 7.127 and 33.98 respectively. The closeness of both values for the standard deviation about the same mean further confirms the degree of reliability of the network in predicting sheakernel oil yield.

Fig 1 represent a graphical representation of the experimental oil yield to train the network and corresponding yield given by the ANN. The closeness of the points on the plot further confirms the reliability of the network in predicting oil yields from groundnut kernels provided the five inputs are supplied accordingly.

The values of the experimental oil yield used to validate the neural network and the corresponding output given by the ANN is as shown in Table 4. The standard deviation and mean value of 5.57 and 35.35 was calculated for experimental yield while the corresponding ANN outputs was 5.58 and 35.34 respectively. The closeness of both confirms the degree of reliability of the network.

Fig 2 represents a graphical representation of the experimental oil yield to validate the network and the corresponding yield given by the ANN. The closeness of the points on the plot further confirms the reliability of the network in predicting oil yields from groundnut kernels provided the five inputs are supplied accordingly.

From Table 5 mean square error (MSE) of 0.0064 for training data set and 0.0006 for validation data set were obtained. For the statistical method compared to the corresponding values of 0.0006 and 0.0007 for the ANN.

The correlation coefficient of 0.82 and 0.84 were obtained for training and validation datasets using the statistical method as compared to corresponding values of 0.962 and 0.964 for the ANN.

The correlation coefficient of 0.96 followed the same trend reported by investigations carried out by Olajide et al (2007), Ruan et al (1995), Fang et al (1988) and Sayeed et al (1985).

The correlation coefficient between the ANN outputs and the expected experimental yields was calculated to be 0.96 showing a strong agreement between both sets of values. The standard deviation for the expected experimental yields was calculated to be 5.57 with a mean of 35.3 while the standard deviation for the corresponding ANN outputs was found to be 5.68 with a mean of 35.34. The closeness of the values for both standard deviations confirms the reliability and generalization of the developed network model. Figure 4 shows the Sheakernel oil yield (expected from experiment and ANN) plotted against the experiment number. The closeness of the points on the plot still further confirms the reliability of the developed model in predicting oil yields from sheakernel provided the five required inputs are supplied accordingly.

Table 3: Average ANN training outputs and experimental training outputs for Sheakernel oil yield

S/No.	Experimental Yield (%)	ANN Output (%)
1	22.84	22.84
2	32.76	32.76
3	27.48	27.51
4	41.04	40.99
5	25.67	25.73
6	31.15	31.23
7	31.38	31.45
8	43.09	43.00
9	27.25	27.08
10	37.84	37.89
11	29.16	29.16
12	44.27	44.39
13	29.45	29.45
14	38.48	38.48
15	34.38	34.45
16	46.70	46.66
17	18.28	18.28
18	30.32	30.52
19	33.37	33.22
20	34.71	34.66

Table 4: ANN testing outputs and expected experimental outputs for Sheakernel oil yield

S/No.	Experimental Yield (%)	ANN Output
21	26.63	26.72
22	32.52	32.59
23	20.36	20.40
24	37.42	37.57
25	38.79	38.81
26	36.32	36.44
27	38.72	38.59
28	38.53	38.49
29	38.08	38.48
30	38.42	38.49
31	39.09	38.69
32	38.71	38.68

Table 5: Result of oil yield prediction by statistical method and ANN model

Model	Training dataset		Validation dataset	
	MSE	Correlation index	MSE	Correlation index
Statistical	0.0064	0.8200	0.0068	0.8420
ANN	0.0006	0.9640	0.0007	0.9660

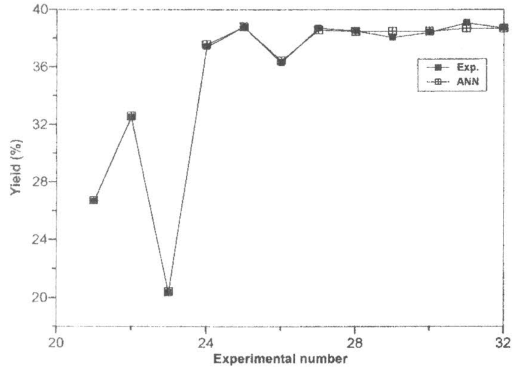

Fig.1: Sheanut oil yield vs. experimental number (validation)

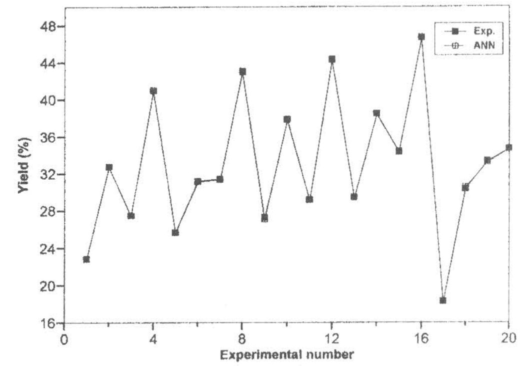

Fig.2: Sheanut oil yield vs. experimental number (testing)

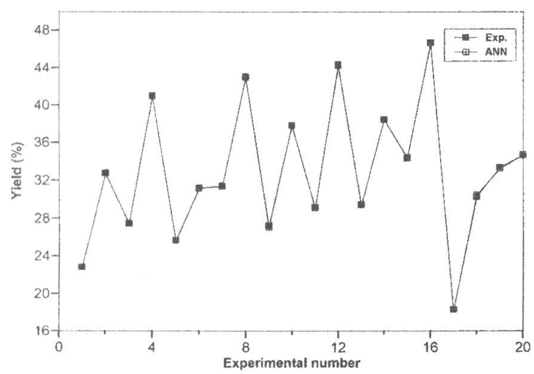

Fig. 3: Sheanut Oil Yield vs. Experimental Number (Testing)

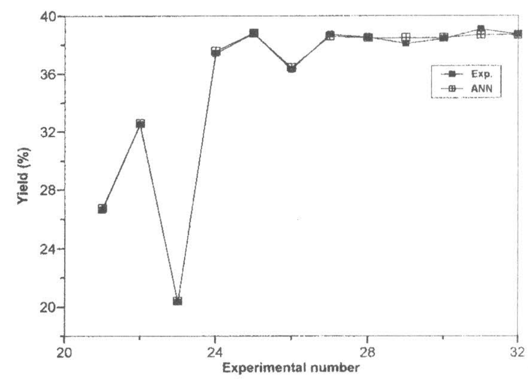

Fig. 4: Sheanut Oil Yield vs. Experimental Number (Testing)

Conclusion

Back propagation neural network model was trained and validated for the prediction of oil yield from shea kernels. The network had five input variables. The network performed well during validation. The accuracy of prediction was significantly improved compared to statistical models. The network model had R=0.96 which showed that the neural network model was capable of learning the relationships among the input and output variables for given data set.

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