Artificial Intelligence in Agriculture 4 (2020) 39–47

Contents lists available at ScienceDirect

Artificial Intelligence in Agriculture

journal homepage: http://www.keaipublishing.com/en/journals/artificial-intelligence-in-agriculture/

Evaluation of optimization techniques in predicting optimum moisture content reduction in drying potato slices

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ARTICLE INFO

Article history:
Received 26 December 2019
Received in revised form 5 April 2020
Accepted 6 April 2020
Available online 14 April 2020

Keywords:
Moisture content
Potato
Adaptive neuro fuzzy inference systems
Artificial neural network
Response surface methodology

ABSTRACT

The use of artificial intelligence models in predicting the moisture content reduction in the drying of potato (*Ipomoea batata*) slices was the focus of this work. The models used were adaptive neuro fuzzy inference systems (ANFIS), artificial neural network (ANN) and response surface methodology (RSM). The parameters considered were drying time, drying air speed and temperature. The capability and sensitivity analysis of the three models were evaluated using the correlation coefficient (R^2) and some statistical error functions such as the average relative error (ARE), root mean square error (RMSE), Hybrid Fractional Error Function (HYBRID) and absolute average relative error (AARE). The result showed that the three models demonstrated significant predictive behaviour with R^2 of 0.998, 0.997 and 0.998 for ANFIS, ANN and RSM respectively. The calculated error functions of ARE (RSM = 1.778, ANFIS = 1.665 and ANN = 4.282) and RMSE (RSM = 0.0273, ANFIS = 0.0282 and ANN = 0.1178) suggested good harmony between the experimental and predicted values. It was concluded that though the three models gave adequate predictions that were in good agreement with the experimental data, the RSM and ANFIS gave better model prediction than ANN.

1. Introduction

The need for food security is one of the global challenges of our time. In addition to insufficient production of needed agricultural products, one of the major challenges with the issue of food security is inadequate post-harvest processing and insufficient preservation techniques. This is in addition to the fact that most of the agricultural food crops are perishable and seasonal. If these agricultural products are not adequately preserved and stored, they will spoil and become unhealthy for human consumption. Food preservation is very important because it enhances preservation, storage and easier transportation of such agricultural products while mitigating unexpected rise in prices of agricultural products (Akinola et al., 2006).

Spoilage of agricultural products is caused mainly by the activities of the microorganisms and enzymes in the food. The growth of the microorganisms normally leads to faster rate of spoilage. The presence of water in the form of moisture content is the major factor that aids the growth and activities of the microorganisms because it increases their metabolic activities. Without water or in the presence of limited amount of water, agricultural products will become inhospitable for the microorganism and inhibit their growth and activities thereby preserving the product for a longer time (Rajeev et al., 2012).

The sweet potato (*Ipomoea batata*) is highly nutritious and is rich in carbohydrates, digestive starch, essential amino acid, etc. It equally contains some important elements such as calcium, iron, potassium etc. which are necessary for proper maintenance of the human body. Nigeria is one of the biggest producers of potato. Ugonna et al. (2013) reported that Nigeria is the fourth biggest producer of potato in Sub-Saharan Africa with production yield of about 843,000 t per year. The major drawback in potato production is that it decays easily after harvesting due to its high moisture content which aids the growth and activities of microorganisms. Hence, there is need to increase its preservation especially through drying.

Drying is one of the post-harvest handling processes that involves the removal of moisture from products due to simultaneous heat and mass transfer (Onu, 2017). Drying is a thermo-physical process that can reduce the moisture content to a minimal acceptable limit that hinders the growth and activities of microorganisms in agricultural products (Ravinder et al., 2014; Sajith and Muraleedharan, 2004; Shahzad et al., 2013; Wankhade et al., 2012). Moisture content removal should be done in such a manner that desired quality of the product is not affected for prolonged time (Correia et al., 2015; Brooks et al., 2008,

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https://doi.org/10.1016/j.aiia.2020.04.001

Akanbi et al., 2006). The drying of potato can be enhanced by optimizing the major factors involved. This will lead to more efficient and cost effective preservative method.

Response surface methodology (RSM) is an advanced tool for developing, improving and optimizing a process where an output variable depends on several input variables (Nwabanne et al., 2017; Mansour and Mostafa, 2011). RSM reveals the interactive relationships between the process parameters and needs only relatively few experimental runs to determine the optimum response and propose a predictive model (Adepoju and Olawale, 2014; Ohale et al., 2017). As an improved systematic approach to process variation, RSM considers all the input variables involved simultaneously and their effect on the response in a way that is difficult to depict with mathematical formulations (Onu, 2014; Okpe et al., 2018). RSM has been used in optimizing several processes such as the extraction of *Terminalia catappa* L. kernel oil (Agu et al., 2020); in predicting the optimum process parameters for production of activated carbon from rice husk (Iheanacho et al., 2019), in adsorption of malachite green using Nteje clay (Onu and Nwabanne, 2014), in optimizing chromium VI reduction by isolated acinetobacter (Nur et al., 2019), in determining the optimum extraction yield of *Ferulago angulata* through supercritical fluid (Gholamhossein et al., 2016).

Artificial neural network (ANN) is an information processing paradigm whose functioning is inspired by the technique used by the brain and other biological nervous systems in processing information (Assidjo et al., 2008). It was derived from artificial intelligence (AI) research in the efficient description of multivariate nonlinear processes with adequate data and the application of correct training algorithm (Mingyi et al., 2017). An artificial neural network usually has input layer (consisting of the input variables), hidden layers (neurons), and an output layer (the output). ANN is usually applied in complex systems because it is robust and effective with special ability to describe nonlinear relationships between the independent variables and the dependent variable by the training and retraining of the input-output systems (Nur et al., 2019; Pareek et al., 2002). Artificial Neural network modeling is essentially black box in nature with the major merit being that it employs multiple input variables in predicting output variables even without prior knowledge of the process relationships (Mojtaba et al., 2012). Furthermore, in application of engineering to agriculture, it serves as a better alternative for conventional empirical modeling based on linear and/or polynomial regressions (Ngankham and Ram, 2011). ANN was employed in predicting the quality characteristics of apples during convective dehydration (Karina et al., 2013), in optimum extraction of artemisinin from *Artemisia annua* (Josh et al., 2014), in predicting the microwave-assisted extraction procedure (Mansour and Mostafa, 2011).

Adaptive neuro fuzzy inference systems (ANFIS) is an adaptive network that is based on Takagi-Sugeno fuzzy inference system (You et al., 2017). It is an artificial intelligence model that has effective self-learning function and mechanism (Ling et al., 2014). ANFIS is a nonlinear computational intelligent system that adapts itself by forming rules to survive with changing environment and uncertainty. It is a synergetic system of fuzzy inference and artificial neural network that uses a generated influential tool from numerical data to predict output (Adem et al., 2018; Ling et al., 2014). The major strength of ANFIS is that it enhances fuzzy controllers with self-learning capability for achieving minimum steady state error (Kiran and Rajput, 2011).

Therefore, the aim of this work is to contribute to the ongoing efforts in ensuring food security by modeling the predictive behaviour of moisture content reduction in potato drying using ANN, RSM and ANFIS models which will enhance the post-harvest preservation of potato.

2. Materials and methods

2.1. Sourcing and preparation of samples

Fresh potato tubers used in this work were sourced from the local Eke Awka market in Anambra State, Nigeria. The tubers were washed, peeled, sliced to a thickness of 1.5 mm. The slices were then washed to remove dirt.

2.2. Drying experimental procedure

The drying experiment was conducted using a conventional hot-air dryer fabricated in Faculty of Engineering, Nnamdi Azikiwe Univeriesty, Awka, Nigeria. One of its features is that the temperature and air velocity can be regulated. One hundred grams (100 g) of the sample was used for each run of the experiments. The fan and heater were started and allowed to run without load until a stabilized (steady) drying temperature and air speed were observed in the drying chamber. Thereafter, the drying chamber was loaded with the samples for the experiments. The actual temperature of the drying chamber was 30 °C lower than the set temperature of the dryer. The speed of the air was measured by a speed meter (hot wire anemometer, model 20004 AHYK, China), with the precision of 0.01 m/s, while the temperature was measured by digital thermometer and the mass of the sample was obtained using a digital weighing balance (M-Metlar, model M311L, China). Three replicates of the experiments were conducted and the average used to reduce experimental error.

2.3. Determination of moisture content

The moisture content was determined by using the gravimetric method as given in eq. 1.

$$MC = \frac{M_1 - M_2}{M_2} \times 100 \tag{1}$$

where MC is the moisture content of the sample after drying in dry basis (d/b), M_1 is the initial mass before drying, M_2 is the mass after oven drying.

2.4. RSM, ANN and ANFIS modeling

The three most commonly used RSM methods are the Box-Behnken, central composite design (CCD) and the factorial design (Mohammad et al., 2014). CCD is a five-level design that incorporates the axial points in the design of the experimental runs while the Box-Behnken and the factorial design are three-level designs. The RSM modeling was performed by applying the CCD. This was done to study the interactive effects of the independent input variables on the moisture content which serves as the response. The independent input variables were drying time (minutes), drying air speed (m/s) and drying temperature (°C). These independent variables were varied at five different levels: +1 and −1 (factorial points), 0 (center point) and +α and −α (axial points). The coded values of the process parameters were determined by the equation given by Rajeshkannan et al. (2012) in Eq. (2).

$$N_i = \frac{X_i - X_o}{\Delta X} \tag{2}$$

where N_i is the coded value of the ith variable, x_i is the real value of the ith test variable, x_o is the real value of the ith test variable at the center point, Δx is the step change of the variable. The values of the five factor levels of the three input variables were given in Table 1.

Table 1
Factors levels of independent variables for the hot air dryer.

Independent factors	−α	Low level (−)	Medium level (0)	High level (+)	+α
Time (mins)	64.2	80.0	130.0	180.0	195.8
Air speed (m/s)	0.60	1.00	2.25	3.50	3.90
Temperature (°C)	55.3	60.0	75.0	90.0	94.7

The aim of the optimization was to minimize the moisture content which will increase its shelf life and preservation. Design expert version 11.0.1 was used in generating the factor levels and the experimental runs, analysis of variance (ANOVA) and regression analysis.

The quadratic model was used to express the behaviour of the system response which is the moisture content (Y) as a function of the independent input variables in Eq. (3). The input variables were drying time (X_1), drying air speed (X_2) and temperature (X_3).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{11} {X_1}^2 + \beta_{22} {X_2}^2 + \beta_{33} {X_3}^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_2 + \beta_{23} X_2 X_3 + \varepsilon \tag{3}$$

where β_0 is the offset term or model constant; $\beta_1, \beta_2, \beta_3$ are the linear or first order terms; β_{11} β_{22} β_{33} are the pure quadratic or squared terms; β_{12} β_{13} β_{23} are the interactive terms of the quadratic function; ε is the random error term that allows uncertainties between the experimental and predicted values.

According to Arulkumar et al. (2011), the total number of experimental runs N, in CCD is given by Eq. (4).

$$N = 2^n + 2n + n_c, \tag{4}$$

where n is the number of independent factors or input variables and n_c is the number of center points or null points chosen. The term 2^n corresponds to the core (factorial) points, 2n corresponds to the star-like or axial points and n_c corresponds to the center points. Therefore, by using six (6) center points, a total of twenty (20) experimental runs were utilized in the optimization process. This consists of 8 core points, 6 star-like points and 6 center points. The distance of the star-like point, α, used was 1.316. The center points aids in minimizing experimental error while allowing the reproducibility of the data (Khodadoust et al., 2014). The star-like points or axial points were used for the rotatability of the experimental runs which makes the variance of the model prediction to be equidistant from the design center (Sahu et al., 2010). The experiments were performed in random in order to avoid systematic error.

The acceptability of the quadratic model depended on the *p*-value of the analysis of variance and the value of the correlation coefficient (R^2). The difference between the experimental and the predicted values was utilized in determining the significance of the regression model obtained. The three-dimensional (3D) surface plots were employed in the study of the interactive effects of the input variables.

The ANN and ANFIS were simulated by utilizing the Neural Network of MATLAB 8.5 software 2015 version. The ANN design can be satisfactorily modeled using the RSM generated experimental data (Mourabet et al., 2014; Nazerian et al., 2018). Thus, twenty (20) experimental runs were used in the ANN modeling. The input layer consisted of drying time (minutes), drying air speed (m/s) and temperature (°C) while the corresponding moisture content served as the target or output layer as seen in Fig. 1.

About 70% of the experimental runs were used to train the network, 15% was used in testing the network while the remaining 15% was used to validate the result. These represented 14 experiments, 3 experiments and 3 experiments respectively. According to Kiran and Pragnesh (2016), using more data sets in training reduces processing time in ANN learning and improves the generalization capability of models. The 15% used in testing the network was to provide an independent measure of network performance during and after training. In the validation, the network generalization was measured by network validation and halted when generalization stopped improving in order to avoid over fitting.

The learning algorithm utilized in modeling the ANN process was the Levenberg-Marquardt. In order to enhance reduction of network error, the response and the input variables were normalized between 0 and 1 (Mourabet et al., 2014). Trainlm was used as the training function because it regularizes the bias value using the algorithm of the Levenberg-Marquardt.

The appropriate number of hidden neurons was determined by trial and error method with the aim of getting the lowest possible error between the predicted and the measured values. Large number of neurons leads to unwanted over-fitting and complicated network topology while very few neurons reduces the convergence rate of the network (Mingyi et al., 2017).

The ANFIS model was stimulated as a five-layered neural network that employed the fuzzy inference system principle. Fig. 2 is the ANFIS architecture. The nodes in the first and fifth layers represent the overall input and output variables respectively. The nodes in the second layer acted as the membership function for the input variables while the neurons in the third layer represented fuzzy rules indicating the preconditions and the consequences of the rules. Each individual node in the fourth layer was an adaptive node with a node function. The fifth layer was made up of only one node that gave the summation of the incoming signals as the overall output.

The model predictions by the RSM, ANN and ANFIS were compared by plotting the comparative parity plots of the model prediction with the experimental data. Equally, some statistical models were used to evaluate the magnitude of the error between the experimental values and the predicted values.

In addition to the correlation coefficient (R^2), the error functions used include Average relative error (ARE), root mean square error

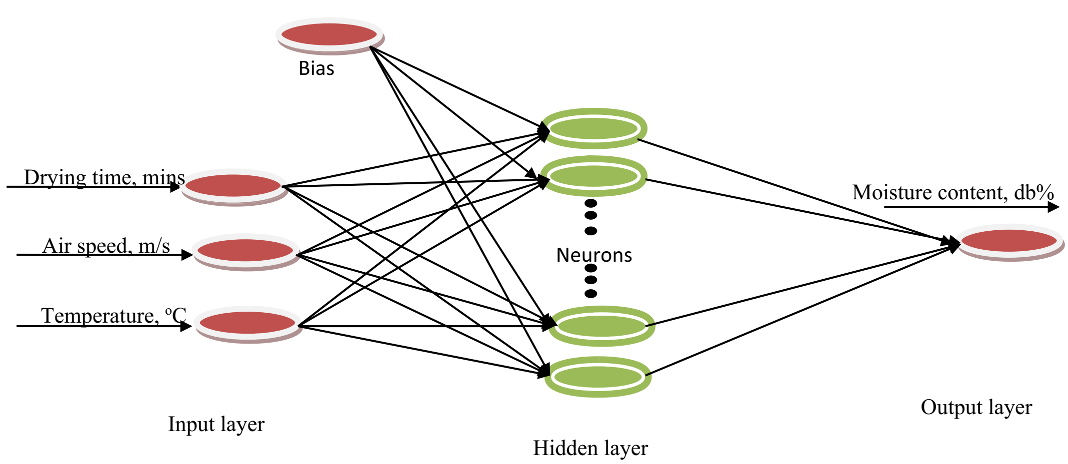

Fig. 1. ANN architecture of the drying process.

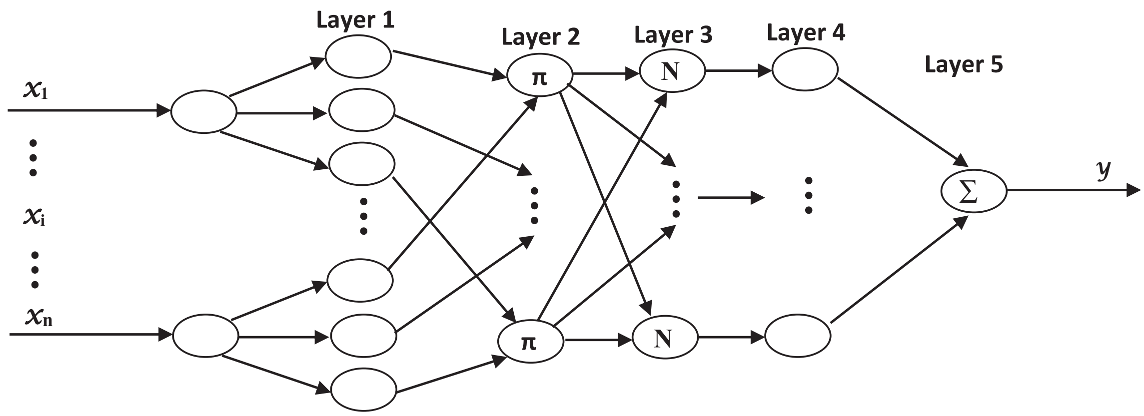

Fig. 2. ANFIS architecture.

(RMSE), Hybrid Fractional Error Function (HYBRID) and the absolute average relative error (AARE) given in Eqs. (5)–(9).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{i,pre} - Y_{i,\,exp}\right)^2}{\sum_{i=1}^{n}\left(Y_{i,\,exp} - Y_m\right)^2} \tag{5}$$

$$\mathrm{ARE} = \frac{100}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}\left[\frac{\mathrm{q_{e,cal}} - \mathrm{q_{e,\,exp}}}{\mathrm{q_{e,\,exp}}}\right] \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}-1}\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(\mathrm{q_{e,\,exp}} - \mathrm{q_{e,cal}}\right)^2} \tag{7}$$

$$HYBRID(\%) = \frac{1}{N-P}\sum_{n-p}^{n}\left[\frac{q_{exp} - q_{cal}}{q_{exp}}\right] \times 100 \tag{8}$$

$$\mathrm{AARE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}\left[\frac{\mathrm{q_{cal}} - \mathrm{q_{exp}}}{\mathrm{q_{exp}}}\right] \tag{9}$$

where n is the number of experimental runs, q_{cal} is the predicted values of the model under investigation, q_{exp} is the experimental values obtained in the drying process and p is number of input variables.

3. Results and discussion

3.1. Experimental result

The experimental result of the design matrix together with the coded and actual factors was given in Table 2. The experiments were used to evaluate the single and interactive effects of the drying time, drying air speed and drying temperature on the moisture content reduction of potato. The lowest moisture content of 18.9% dry basis (db) was obtained at drying time of 180 min, drying air speed of 3.5 m/s and dryer temperature of 90 °C.

3.2. Modeling and prediction using RSM

The linear, two factor interaction (2FI), quadratic and the cubic models were compared to determine the model that best described the drying process in Table 3. The suggested best model was based on the model with the lowest standard deviation value and the highest correlation coefficient. The cubic model was aliased because the CCD does not contain enough runs to support a full cubic model (Oguanobi et al., 2019). The model fitting using regression analysis showed that the quadratic model best described the relationship between the output and input variables with relatively high correlation coefficient (R^2) of 0.9961 and standard deviation of 1.49. The same trend of quadratic model was reported in extraction of artemisinin from *Artemisia annua* (Josh et al., 2014)

The adjusted R^2 of the quadratic model was 0.9925 which was in good agreement with the predicted R^2 of 0.9651. The adjusted R^2 was very close to R^2 which indicated good correlation of experimental data (Samaram et al., 2015; Mazaheri et al., 2017; Betiku and Ajala, 2014). The relatively small PRESS statistic of 196.92 suggests that the quadratic model best fits the data point and can be used to navigate the design space (Nwabanne et al., 2017). Therefore, the quadratic regression model of the drying process was given in their actual values in Eq. (2). The regression terms with positive sign indicated synergistic effect, while those with negative sign indicate an antagonistic effect (Onu and Nwabanne, 2014). The model quadratic model in terms of the actual factors was given in Eq. (10).

$$\begin{aligned} Y_{(MC)} = {} & +165.02-1.3435\times{}_1-6.332\times{}_2+0.7622\times{}_3 \\ & +0.0374X_1X_2+0.00505X_1X_3-0.066X_2X_3+0.0020068 \\ & \times{}_1{}^2-0.003831\times{}_2{}^2-0.012215\times{}_3{}^2 \end{aligned} \tag{10}$$

Analysis of variance (ANOVA) in Table 4 was used in further analysis of the suggested quadratic model.

Table 2
: CCD matrix of the input variables and the response.

S/N	Point Type	Coded Values			Actual values			Response (Moisture content)
		X_1	X_2	X_3	X_1	X_2	X_3	
1	Factorial	−1	−1	−1	80	1	60	90.4
2	Factorial	+1	−1	−1	180	1	60	39.3
3	Factorial	−1	+1	−1	80	3.5	60	71.2
4	Factorial	+1	+1	−1	180	3.5	60	32.2
5	Factorial	−1	−1	+1	80	1	90	66.9
6	Factorial	+1	−1	+1	180	1	90	33.7
7	Factorial	−1	+1	+1	80	3.5	90	45.5
8	Factorial	+1	+1	+1	180	3.5	90	18.9
9	Axial	−1.316	0	0	64.2	2.25	75	77.4
10	Axial	+1.316	0	0	195.8	2.25	75	35.0
11	Axial	0	−1.316	0	130	0.605	75	58.8
12	Axial	0	+1.316	0	130	3.9	75	36.2
13	Axial	0	0	−1.316	130	2.25	55.26	53.6
14	Axial	0	0	+1.316	130	2.25	94.74	31.9
15	Center	0	0	0	130	2.25	75	47.5
16	Center	0	0	0	130	2.25	75	47.8
17	Center	0	0	0	130	2.25	75	47.6
18	Center	0	0	0	130	2.25	75	47.3
19	Center	0	0	0	130	2.25	75	47.3
20	Center	0	0	0	130	2.25	75	47.5

Table 3
Model summary statistics of the RSM.

Source	Standard deviation	R-squared	Adjusted R^2	Predicted R^2	PRESS	Remark
Linear	4.98	0.9297	0.9166	0.8727	718.71	Not suggested
2FI	4.17	0.9600	0.9415	0.9126	493.49	Not suggested
Quadratic	1.49	0.9961	0.9925	0.9651	196.92	Suggested
Cubic	0.17	1.0000	0.9999	0.9999	0.44	Aliased

Table 4
ANOVA of the RSM process.

Source	Sum of squares	df	Mean squares	F-value	*p*-Value (Prob > F)
Model	5622.49	9	624.72	280.27	<0.0001
X_1 – Drying time	3690.92	1	3690.92	1655.85	<0.0001
X_2 – Drying air speed	742.21	1	742.21	332.98	<0.0001
X_3 – Temperature	814.97	1	814.97	365.62	<0.0001
$X_1 X_2$	43.71	1	43.71	19.61	0.0013
$X_1 X_3$	114.76	1	114.76	51.49	<0.0001
$X_2 X_3$	12.25	1	12.25	5.50	0.0410
X_1^2	175.38	1	175.38	78.68	<0.0001
X_2^2	0.0002497	1	0.0002497	0.000112	0.9918
X_3^2	52.63	1	52.63	23.61	0.0007
Residual	22.29	10	2.23	–	–
Lack of Fit	22.11	5	4.42	–	–
Pure Error	0.18	5	0.036	–	–
Cor Total	5644.78	19	–	–	–
PRESS = 96.92		–	–	–	–
C.V. = 3.06		–	–	–	–
Adequate Precision = 65.209		–	–	–	–

The *p*-value gave information whether a statistical hypothesis is significant or not and how significant it is (Agu et al., 2020). The model F-value of 280.27 and *p*-value of <0.0001 showed that the quadratic model chosen was significant. The individual model terms were tested for their significance based on the *p*-values of each term. A significance level of 95% was chosen hence, all the terms whose p-values are <0.05 were significant otherwise, they were termed insignificant (Gholamhossein et al., 2016).

Relatively lower *p*-value and higher F-values showed better significance effect of the model term on the response (Josh et al., 2014; Tan et al., 2008). Therefore, all linear terms of drying time (X_1), drying air speed (X_2) and temperature (X_3), the interactive terms of X_1X_2, X_1X_3 and X_2X_3 and the squared terms of X_1^2 and X_3^2 were significant. Only the squared model term of X_2^2 was found to be insignificant. The model term found to have the significant effect on the response was drying time (X_1) followed by temperature (X_3) while the interaction of X_2X_3 and the squared term of X_3^2 have the least effect on the response.

The insignificant model term was eliminated and the final quadratic model equation was given in Eq. (11).

$$Y_{(MC)} = +165.02 - 1.3435 \times {}_1 - 6.332 \times {}_2 + 0.7622 \times {}_3 + 0.0374X_1X_2 + 0.00505X_1X_3 - 0.066X_2X_3 + 0.0020068 \times {}_1{}^2 - 0.012215 \times {}_3{}^2 \quad (11)$$

The coefficient of variation (C.V.) of 3.06% obtained shows the reproducibility and repeatability of the quadratic model since its numerical value was <10% (Chen et al., 2011). Adequate precision of 65.209 suggests adequate model efficacy because it is >4 (Oguanobi et al., 2019; Krumar et al., 2007).

The Normal plot of Residuals and the Predicted vs Actual plots in Fig. 3 (a and b) are graphical estimations that compares of the nature of the residuals depicting the correlation between the experimental values and the predicted value. The plot of predicted against actual revealed that the points were closely distributed to the straight line of the plot. Therefore, it is concluded that the residuals followed a normal distribution (Iheanacho et al., 2019). The Normal plot of Residuals showed that the points were firmly aligned to the straight line of the plot however; some little disperse like a "S" shape was observed as anticipated (Nwabanne et al., 2017). These plots show minimal divergence of the points from the diagonal.

The response surface plots were utilized in investigating the main and interactive effects between the combination of the independent factors and the response (Iheanacho et al., 2019; Nwabanne et al., 2017). This was done by varying any two of the input variables while keeping the other constant at its null point. The three dimensional (3-D) plots of the interactive effects are shown in Fig. 4 (a–c). Fig. 4 is the interactive effect of temperature and drying air speed. The two factors showed significant combined effect on the moisture content reduction of the drying process. Minimal moisture content was observed at temperature of about 75 °C and drying air speed of 2.5 m/s. The figure equally depicted that the combined effect was mainly as a result of singular effect of temperature because the drying air speed showed little effect. Fig. 4b is the plot of the interactive effect of temperature and drying time while Fig. 4c is for drying air speed and temperature. These two figures show that the interactive effects of these combinations are

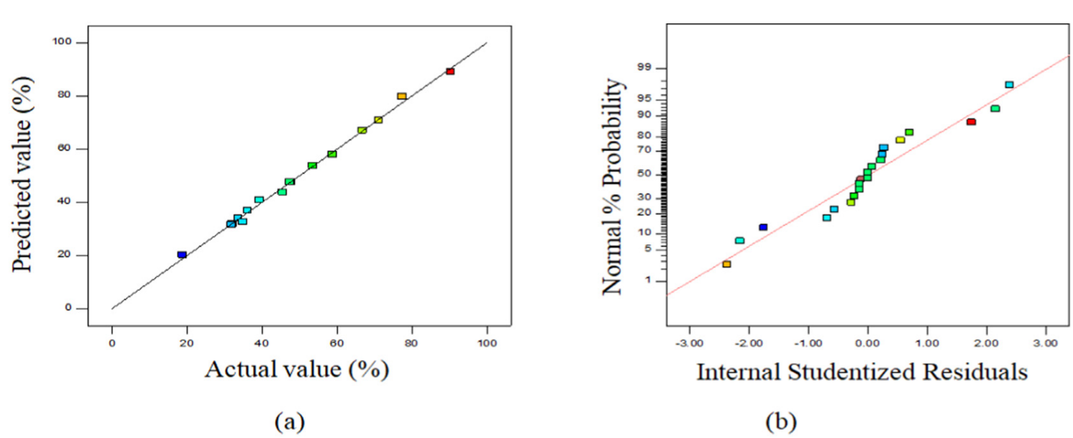

Fig. 3. Plot of predicted vs actual values (a) and Normal plot of residuals (b).

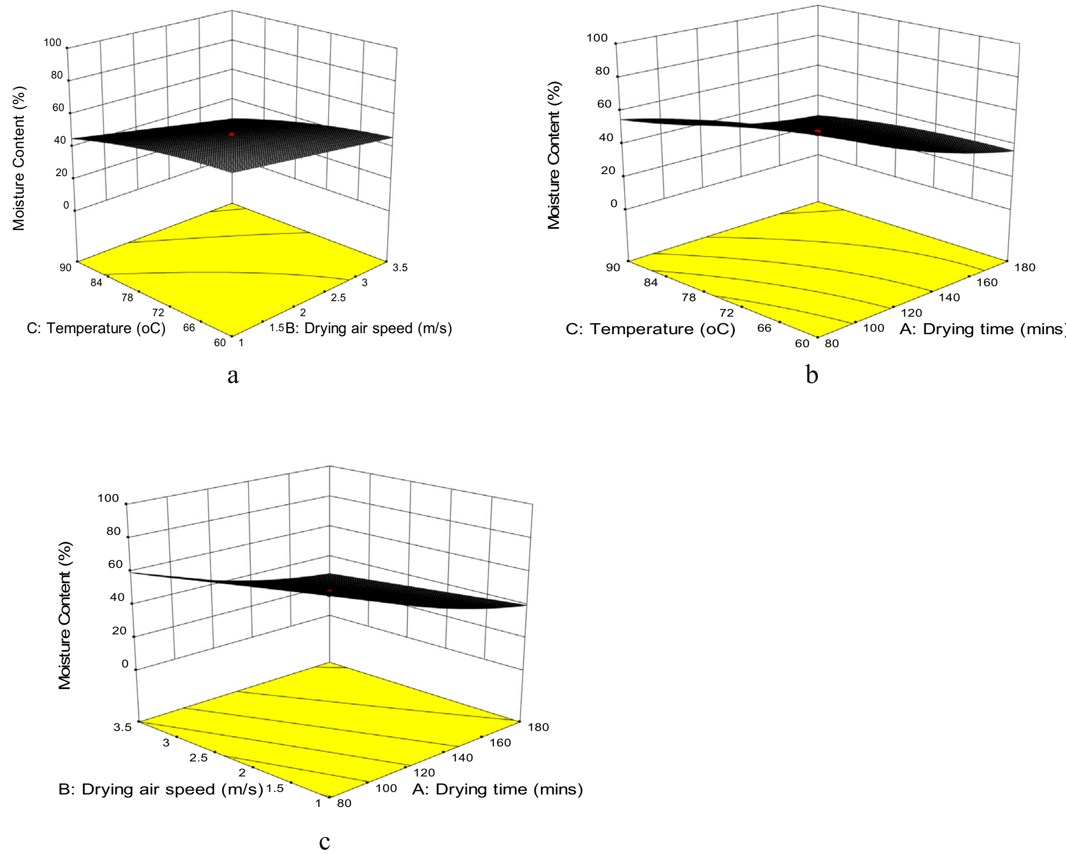

Fig. 4. a–c: 3-D surface interactive plots of the input variables.

relatively less significant than that of temperature and drying air speed. It was found that increasing the drying time reducing the moisture content of the potato slices. Again, drying air speed seems to have the least effect on the drying process among the three independent factors considered. The elliptical nature of the 3D curves suggested good correlation between the two variables (Iheanacho et al., 2019). These results indicated that the quadratic model selected is appropriate for the modeling. Similar trend was reported by Oguanobi et al. (2019).

3.3. Modeling and prediction using ANN

The drying process was equally modeled using the Artificial Neural Network. As explained earlier, 70% of the experimental runs were used for training of the neural network while the rest were used for testing and validation. This was to prevent over-training and over-parameterization (Jamil et al., 2018). The correlation coefficient and the minimum value of mean squared error (MSE) were used as performance check to determine the optimum number of neurons in the hidden layer. MSE is the mean squared difference of the output and input. Correlation coefficient values (R^2) was used to validate the correlation between input variables and the output. These two were used to measure the predictability of the artificial neural network (Agu et al., 2020). Through trial and error method, the number of neurons for optimal performance was obtained as five in the trainlm algorithm. Gholamhossein et al. (2016) reported six neurons for efficient extraction of *Ferulago angulata*.

Based on enough neurons (5) in the hidden layer and the consistency of the input data, a two-layer feed-forward neural network with sigmoid hidden neurons and linear output neurons were employed in multi-dimensional mapping of the process inputs in Fig. 5.

The regression plots with respect to the targets for the training, validation, testing and overall network process are presented in Fig. 6. A mean square error (MSE) of 0.0000396 and correlation coefficient of 0.99947 was obtained for the training. The correlation coefficient obtained was very close to that reported by Gholamhossein et al. (2016). Correlation coefficients of 0.9343, 1.000 and 0.9698 were equally obtained for the validation, testing and overall neural network process respectively. The fit is reasonably good for the data sets, with correlation coefficient values in each case were very close to unity. The data fell reasonably along a 45-degree line, where the network outputs were equal to the targets. Based on these performance values, it was concluded that the network response was satisfactory and that the output adequately tracked the target in the drying of potato.

The plot of the best validation performance was presented in Fig. 7. The performance of the network process for validation was analyzed to determine the reliability of the training process. The training network showed a validation performance with mean square error of 0.00656 at epoch 4. This did not indicate any over-fitting problem with the training network since the error was very small.

3.4. Modeling and prediction using ANFIS

The ANFIS model was structured using a hybrid-learning algorithm that encompasses the least square and the gradient method. Data

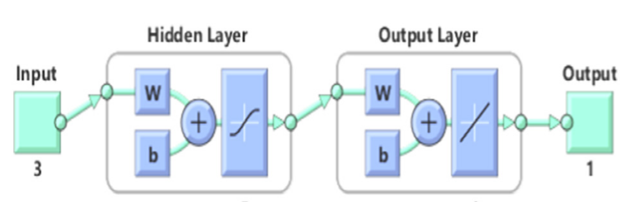

Fig. 5. The ANN network architecture showed five neurons in the hidden layer.

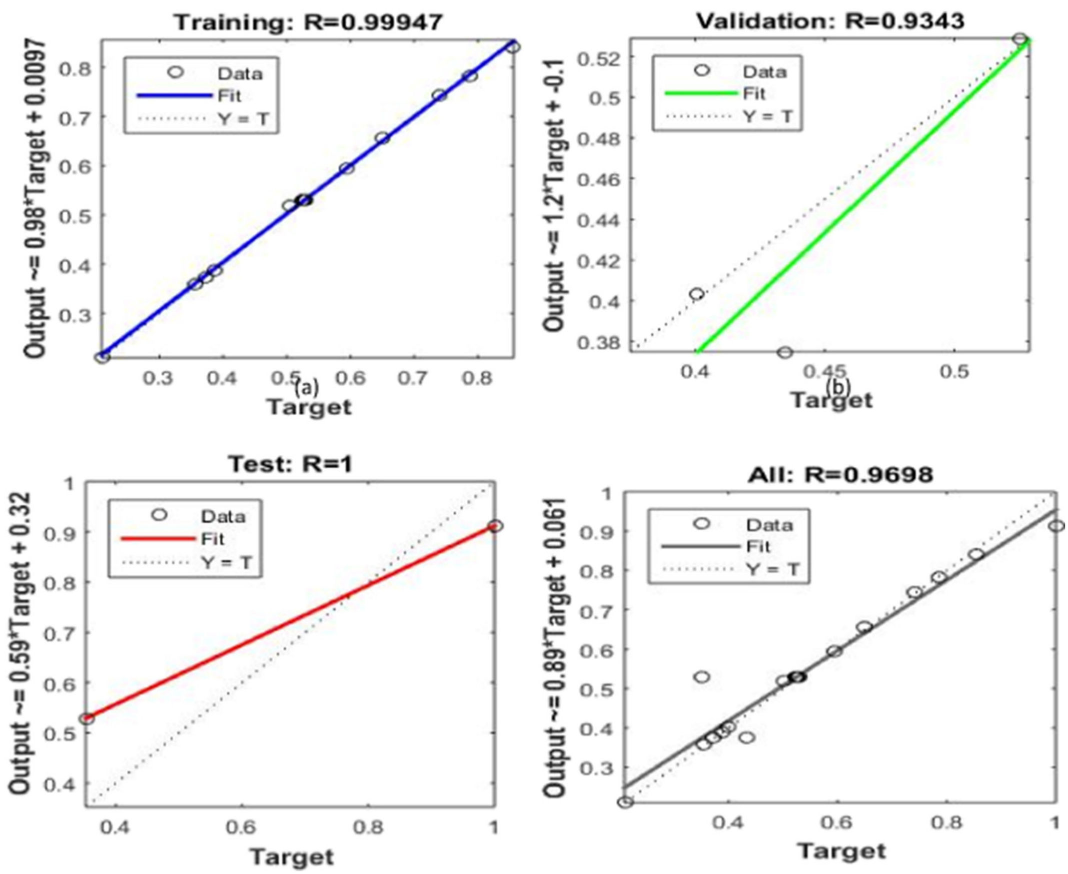

Fig. 6. Regression plots for training (a), validation (b), testing (c) and overall network (d) processes.

normalization was implemented before the training of the ANFIS model. Twenty seven fuzzy rules, nine input membership functions and twenty seven output membership functions were employed as shown in Fig. 8. The training was completed at epoch 2 with average training error of 0.03574 and average testing error of 0.57092. Kiran and Rajput (2011) reported a training error of 0.011555 at epoch 135 when modeling the effectiveness of an indirect evaporative cooling system. The total number of parameters was 54 which were evenly distributed between the linear and nonlinear parameters. The ANFIS model predicted the moisture content with a correlation coefficient of 0.998.

3.5. Comparison of the performances of the RSM, ANN and ANFIS models

The experimental values were compared with the predicted values of the RSM, ANN and ANFIS models in Table 5. In most of the axial and starlike combinations, the ANFIS model gave a residual of zero. The highest positive and negative residuals of 7.95 and −15.92 were

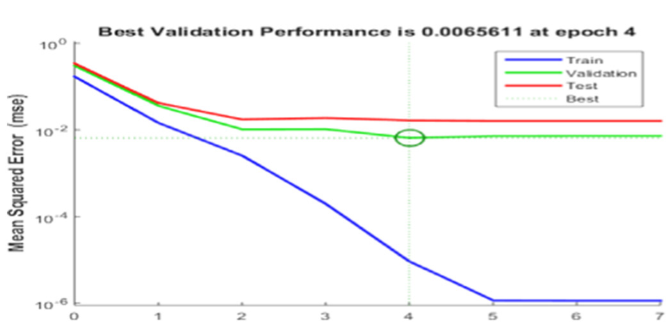

Fig. 7. Network validation performance of the training process.

observed in the ANN model. The three models were found to be reasonably accurate in predicting the moisture content of the drying process though the ANFIS with many residual of zero gave the best prediction.

The predictive capacity of the models was evaluated with closeness of the correlation coefficient to unity. Furthermore, smaller values of ARE, RMSE, HYBRID and AARE values indicates better predictive capacity. The statistical error analysis was given in Table 6.

The R^2 values of RSM and ANFIS were 0.998 showing better correlation than that of ANN which was 0.970. The ARE value of the ANFIS was smaller than that of the RSM. The RMSE values were 0.0273, 0.0282 and 0.1178 for RSM, ANFIS and ANN respectively. This result showed that the RSM and ANFIS gave better significant prediction than the ANN in the drying of potato slices. RSM was reported to be better than ANN in optimizing the design parameters for a V perforated baffle (Sunil, 2015) though in most other cases, ANN gave a better prediction than RSM.

3.6. Model optimization and validation

Optimum moisture content value of 31.995% was predicted at a drying time of 180 min, drying air speed of 3.5 m/s and dryer temperature of 60 °C. The test re-test experimental validation technique was employed in validating the predicted optimal value. The experiment was carried out in triplicate and an average value of 32.65% was obtained. This showed close agreement with the predicted optimal value.

4. Conclusion

RSM, ANN and ANFIS models were used to predict the moisture content reduction of potato slices in a hot-air drying process. CCD was employed in the RSM analysis where a quadratic model with R^2 value of 0.9980 was obtained. Drying time had the most significant singular effect on the drying process followed by temperature. ANN model

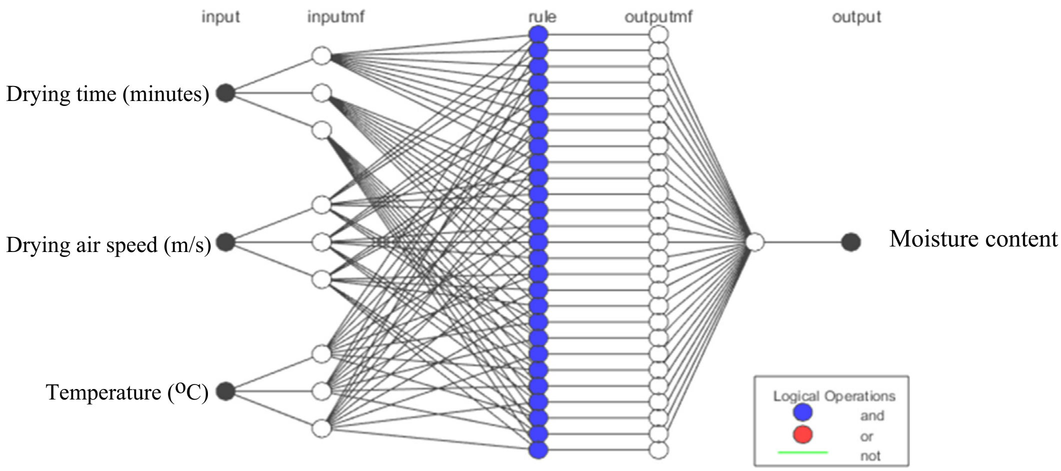

Fig. 8. ANFIS model structure of the drying process.

Table 5
RSM, ANN and ANFIS predicted values of the drying of potato slices.

Std run no.	Exp.	RSM		ANN		ANFIS	
		Predicted	Residual	Predicted	Residual	Predicted	Residual
1	90.4	89.07	1.33	82.45	7.95	90.4	0
2	39.3	40.94	−1.64	33.89	5.41	39.3	0
3	71.2	70.78	0.42	70.76	0.44	71.2	0
4	32.2	32	0.2	32.35	−0.15	32.2	0
5	66.9	67.11	−0.21	67.22	−0.32	66.9	0
6	33.7	34.12	−0.42	33.77	−0.07	33.7	0
7	45.5	43.87	1.63	46.83	−1.33	45.5	0
8	18.9	20.23	−1.33	18.99	−0.09	18.9	0
9	77.4	79.81	−2.41	76.1	1.3	77.4	0
10	35	32.58	2.42	35.09	−0.09	35	0
11	58.8	58.08	0.72	59.17	−0.37	58.8	0
12	36.2	36.9	−0.7	36.47	−0.27	36.2	0
13	53.6	53.84	−0.24	53.7	−0.1	53.6	0
14	31.9	31.65	0.25	47.82	−15.92	30.24	1.66
15	47.5	47.5	0	47.82	−0.32	45.24	2.26
16	47.8	47.5	0.3	47.82	−0.02	45.24	2.56
17	47.6	47.5	0.1	47.82	−0.22	45.24	2.36
18	47.3	47.5	−0.2	47.82	−0.52	45.24	2.06
19	47.3	47.5	−0.2	47.82	−0.52	45.24	2.06
20	47.3	47.5	−0.2	47.82	−0.52	45.24	2.06

gave R^2 of 0.970 with 5 neurons in the hidden layer. Mean square error of 0.00656 was obtained at epoch 4. ANFIS model also showed good predictive behaviour with R^2 of 0.998 and average training error of 0.03574 at epoch 2. The comparative analysis showed that the RSM and ANFIS were better in predicting the moisture content reduction of potato drying.

CRediT authorship contribution statement

Onu Chijioke Elijah: Conceptualization, Data curation, Investigation, Writing - original draft. **K. Igbokwe Philomena:** Project administration, Supervision, Visualization. **T. Nwabanne Joseph:** Formal analysis, Writing - review & editing, Supervision. **O. Nwajinka Charles:** Methodology, Formal analysis. **E. Ohale Paschal:** Software, Validation, Data curation.

Table 6
Statistical error analysis of the RSM, ANN and ANFIS models.

Error function	RSM	ANFIS	ANN
R^2	0.998	0.998	0.970
ARE (%)	1.778	1.665	4.282
RMSE	0.0273	0.0282	0.1178
HYBRID (%)	3.071	4.207	55.780
AARE	0.01496	0.01665	0.03154

Declaration of competing interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgment

The authors will like to acknowledge Engr. Chinedu Umebalu and Engr. Ugochukwu Emeka for assistance in the construction of the hot-air dyer.

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