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PREDICTION OF COCOYAM DRYING PARAMETERS USING ARTIFICIAL NEURAL NETWORK

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Abstract: **This paper presents a model developed using artificial neural network (ANN) to predict the drying parameters of cocoyam (*Xanthosoma sagittifolium* L.) slices dried using an oven. To obtain data for developing the model, 311 drying experiments were performed on cocoyam slices of thickness ranging from 2 mm to 8 mm subjected to varying temperatures ranging from 40°C – 70°C in 10°C increments. The input variables for the model include: cocoyam slice thickness, drying time and the drying air temperature while the outputs were the moisture content and drying rate. After series of simulation runs, it was found that the ANN architecture of 3-8-2 gave the optimum prediction performance. In assessing the performance of the developed model using statistical error metrics, it was found that the model had a mean squared error of 9.2 x 10^{-4}, a root mean square error of 0.0303 and a correlation coefficient (R) of 0.99645. Overall, the results from the model's prediction were found to be consistent with experimental data. To the best of the authors' knowledge, this study is one of the few available studies on cocoyam drying parameters modelling using ANN. This indicates that ANN can effectively describe the drying process of cocoyam owing to its good accuracy and applicability to a wide range of situations.**

Keywords: **Artificial Neural Network, Drying, Cocoyam, Modeling, Moisture content.**

1. INTRODUCTION

1.1 Background of the Study

Agricultural products especially those of the plant origin (for example cocoyam) are now frequently used for a wide range of activities and are increasingly processed into a wide range of products. These agricultural products have over the years been underexploited in the regions of which they are produced especially in the developing countries (Balami *et al.*, 2012).

Cocoyams are monocotyledonous herbs that belong to the family Araceae and are grown primarily for their roots which are edible (Onwueme, 1982; Bolarin *et al.*, 2017). There are two major species of cocoyam grown in Nigeria and many other parts of the world viz: *colocasia exculanta*(taro) and *xanthosoma sagittiffolum* (tannia) (Ndukwu and Nwabuisi, 2011), however, Owusu-Darko *et al.*, (2014) classified cocoyams as (old-taro: *Colocasia esculenta*; new tannia: *Xanthosoma sagittifolium*) Generally, cocoyams are root crops produced in regions of tropical and sub-tropical developing countries**.**

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According to Ndukwu and Nwabuisi (2011), Nigeria is the largest producer of cocoyam with the root crop ranking fifth in the nation's food system after rice, cassava, yam and maize. Although, they are less important than other tropical root crops such as yam, cassava and sweet potato, they are still a major staple in some parts of the tropics and sub-tropics (Bolarin *et al.*, 2017, Owusu-Darko *et al*., 2014).

Cocoyams are relatively smaller in size compared to other tuber crops and also weigh lesser and less denser to other tubers. It also spoils easily when exposed to sunlight, humidity and other climatic condition, and breaks easily when exposed to much cold. It is not completely spherical like other tubers. Due to its high water content, the tendency of it to get spoilt if not properly preserved is high (Balami *et al*, 2012). According to Ndukwu and Nwabuisi (2011), an estimated 40% of cocoyam is lost due to post harvest rot. This magnitude of rot is discouraging farmers and as a result it is consumed shortly after harvest. It also contains mucilage which makes processing difficult.

Drying operations can help in reducing the moisture content of food materials for avoidance of microbial growth and deterioration, for shelf life elongation, to minimize packaging and improving storage for easy transportation. Though there are many ways in which drying can be achieved, but the choice of method depend on the material and the sanitary level required (Kabiru *et al.*, 2013, Inyang, *et al.* 2018). The use of drying of foodstuffs is very common to improve food stability and minimize chemical and physical changes during storage. Hence, drying is the most extensively used technique for food preservation (Singh *et al.*, 2014). Moreover, there are various types of drying techniques that can be applied to reduce the water and which attains the purpose of food preservation as has been shown in Singh *et al*. (2014) and Inyang, *et al.* (2017).

For most industrial applications, convectional hot air drying is widely applied. Hot air drying involves the uniform distribution of hot air on a material undergoing dehydration and can negatively affect important properties of the food products, such as the nutritional properties and phytochemical properties. Thus, the determination of a suitable drying model, drying conditions and the determination of the optimum operating parameters are indispensable in achieving great quality along with minimum product cost with maximum yield (Rodríguez *et al*., 2014; Onwude *et al*., 2016).

The critical aspect of drying technology is the modeling of the drying process (Demir *et al.,* 2007). The prediction of drying kinetics of agricultural products under various conditions is vital for equipment and process design, quality control, energy and fuel management, choice of appropriate storage, handling practices etc.

Ndukwu and Nwabuisi (2011) asserted that long storage of the product in fresh form is discouraged or not successful. Since cocoyam do not store long in fresh form, it is dried and processed into flour which can be prepared in many form for consumption. Therefore, it is necessary to predict the remove of moisture content of the sample (product) for preservation to avoid deterioration or spoilage. The aim of this study is to use ANN model to predict the moisture content and drying rate of cocoyam during the drying process under different drying conditions. Thus, by modeling the moisture content and drying rate, it will help preserve the product, avoid spoilage and deterioration. Hence, gives useful insight into the drying mechanisms, easy control of drying process, and optimum product output.

2. LITERATURE REVIEW

The most current and by far the most pervasive technology that has crossover appeal across various industries especially for predictive modeling is artificial intelligence (AI). The reasons are not far-fetched. AI-based models offer numerous advantages. According to Bahiraei *et al.* (2019), Artificial Intelligence based models have the ability to learn from patterns and once learned can carry out generalization and estimation at great speed; they are fault tolerant in the sense that they are capable to handle noisy data and they are capable of finding the relationship among nonlinear parameters (Agwu *et al.*, 2019).

Table 1 is a summary of previous research work on using AI techniques as modeling tools for the prediction of the drying rate and moisture content of various root crops. From the table, it is evident that most of the works focused on the drying of potato. No work considered the drying of cocoyam. The probable reason for the focus on potato is because of its rank on the food chain in most tropical and developing nations. A second observation from Table 1 is that the most widely used AI modeling technique adopted was the ANN method. This is due to the numerous advantages ANN offers and its wide range of applicability. First, drying is quite complex and uncertain and they can be considered as non-linear, time-varying properties and many unknown factors. Since ANNs perform better when parameters have non-linear relationships, then it comes as no surprise that it is widely used by most researchers on drying parameters modelling. Second, the ANN technology could be used in process control, medical diagnosis, forensic analysis, weather forecasting, financial applications, and investment analysis. In food science, ANNs are useful tools for food safety and quality analyses, such as modeling microbial growth and from this predicting food safety, interpreting spectroscopic data, and predicting physical, chemical, and functional properties of food products during processing and distribution (Huang *et al.*, 2007). In all, it is observed that ANNs permit an adequate and precise prediction of the drying process in industrial applications.

Table 1: Summary of previous ANN models for predicting drying rates of root crops

Author, year	Root crop dried	Modelling method used	Input parameters & number of data points	Output parameter
Islam et al. (2003)	Sweet potato slices	ANN 4-8-8-2	Air temperature, humidity, velocity, and product thickness 205 data points	Drying time
Singh and Pandey (2011)	Sweet potato	ANN 4-8-4-1	Temperature (T), air velocity (V), sample thickness (s) and time of drying (t) 1400 data points	moisture content
Azadbakht et al. (2018)	Potato cubes	ANN	temperature, air velocity, bed depth	drying time and process moisture loss
Elijah et al. (2020)	Potato slices	RSM, ANFIS, ANN	drying time, drying air speed and temperature 20 data points	moisture content
Ojediran et al. (2020)	Yam slices	ANFIS	drying time, air temperature, air velocity, and yam slice thickness	moisture ratio
Rezaei et al. (2021)	Potato slices	ANN 2-3-1 ANN 2-2-2-1	First ANN model inputs: time and power density Second ANN model inputs: shrinkage and power density	moisture ratio

3. MATERIALS AND METHODS

3.1 Preparation of Samples

The cocoyams (*Xanthosoma sagittifolium* L.) were bought at Itam market in Uyo, Akwa Ibom State and were identified in University of Uyo Botany and Ecological Department to confirm the family and species. They were peeled and sized into 30 mm in diameter using a locally fabricated peeler. Thereafter, they were cut into various thickness of 2 mm, 4 mm, 6 mm and 8 mm.

3.2 Drying experiments

The initial weight of the sample used in drying process was 200 g of the cocoyam for the different thickness (size).The laboratory oven model used was Wiseven 105. The oven was switched on for 30 minutes (Ayim *et al.*, 2012) to simulate and keep the inside at required operating temperature which gives steady state of operation before placing the samples inside the oven. The cocoyam slices were placed in a single layer on a wire mesh tray and placed inside the oven at different temperatures of 40 °C, 50 °C, 60 °C and 70 °C. Every 30 minutes the wire mesh tray was removed from the oven and weighed using a digital weighing balance (ohaus), (Omolola *et al*., 2015, Sridhar and Madhu, 2015). The drying continued until constant weight was achieved under those drying conditions. The convective oven (Wiseven 105) was used to determine the initial and final moisture content at 105 °C (Ruiz, 2005), also, the dynamic equilibrium moisture contents for the different products were calculated (Saeed *et al.*, 2008). The moisture ratio was determined. The initial moisture content of cocoyam was 71.7%, before the drying process.

3.3 Data acquisition and preparation

The inputs parameters (temperature, thickness and time) and outputs (moisture content and drying rate) datasets used to develop the artificial neural network (ANN) model for predicting the moisture content and drying rate. Thence, input and output datasets obtained for each of the mentioned input and output variables were 317. The statistical descriptions of the input and out variables were done using mean square error and coefficient of determination (R^2). During the network training stage, to ensure that the ANN training algorithm will adjust the network weights and biases effectively, the input and output variables were scaled (normalized) to 0 – 1 using Equation 1. Also, normalizing these input and output datasets prevents the sensitivity of the ANN transfer function—sigmoidal to large data values (Okon *et al.*, 2020).

$$Xscaled = \frac{X-Xmin}{Xmax-Xmin} \tag{1}$$

where $Xscaled$ is the scaled (normalized) parameter (input or output), x denotes the actual parameter, $Xmin$ and $Xmax$ represent the minimum and maximum values of the actual parameter, respectively.

3.4 Artificial neural network (ANN) model development

In this study, the neural fitting tool (nftool) in MATLAB 2015a mathematical software was exploited to develop the ANN model for predicting drying parameters. The acquired datasets (i.e., 311 of each input and output variables) training set of (70%), a test set of (15%) and validation set of (15%). One major challenge in developing the ANN model, especially with MATLAB software is how to select the optimal network architecture (topology). In most cases, researchers use a trial-and-error approach to arrive at the optimum network architecture. Hence, the established ANN architecture was 3 – 8 - 2, that is, three neurons at the input layer, 8 neurons at the hidden layer and two neurons at the output layer. Another hiccup in the ANN model development is the choice of the network learning or training algorithm. In this case, three basic training algorithms: The Levenberg–Marquardt algorithm minimizes the sum of the error function of the form:

Hence, the Levenberg–Marquardt algorithm will be applied to train the network to develop the ANN model for predicting drying parameters. Now that the ANN model topology and learning algorithm are known, the datasets meant for developing the model were exported to the nftool environment in the MATLAB software. The basic settings used in the software for the training process are in Table 2. During the training process, the network error is figured out using the training data (311 datasets) and learning algorithm (trainlm in MATLAB) to adjust the weights and biases of the neurons until the ANN learns the correct input–output behaviour of the data. Thus, Equation 2 applies for the network weights adjustment:

$$\Delta\omega(t) = \alpha\frac{\delta E}{\delta\omega(t)} + \beta\Delta\omega(t-1) \tag{2}$$

where α and β are assumed constants called the learning rate and momentum factor, respectively, E is the error function (in which MSE was used), ω is the weight vector, and t is the iteration (epoch in MATLAB) number (Huang *et al.* 1996).

The ANN model used a supervised learning process, because of the provision of the targets data: moisture content and drying rate as the network outputs. The generalization of the network predictions during the training phase was tested with the random 15% of the ANN model development datasets (311) and validated with the remaining 15% of the datasets (i.e., 47 validation set). Based on the stopping criteria for the network training, that is, mean square error (MSE) and the number of the epoch; which by default in MATLAB software are 0.00001 and 1000, respectively, the weights and biases that yield the lowest error from the supervised datasets were the best generalization (Agwu *et al*., 2019; Okon *et al*., 2020).

Table 2: Parameter settings for ANN model

Parameters	Values
Training data set (217)	70 % of dataset
Testing data set (47)	15% of dataset
Validation data set (47)	15% of dataset
Number of input neurons	3 (T, X, t)

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Number of hidden layer	1
Number of neurons in hidden layer	8
Number of output neurons	2
Output activation function	purelin
Learning algorithm	Levenberg–Marquardt (trainlm)
Mean square error (MSE)	1.0e-05
Number of epochs	1000
Training rate	0.7

4. RESULTS AND DISCUSSION

4.1 Performance of the ANN model

The network training process was iterated several times to ensure that the model predictions were consistent. Thus, the developed ANN model is a three-layer (i.e., input, hidden and output layers) feed-forward network with 8 neurons in the hidden layer (Figure 1). As earlier mentioned, the training algorithm—Levenberg–Marquardt was the best design for training the neural network as the mean square error (MSE) obtained was 0.0010431 at 25 epochs (iterations). Then, the performance plots that showed the training, testing, validation and overall predictions of the developed ANN model to the actual datasets are in Figure 3. The outcome of the training is shown in Figure 1.

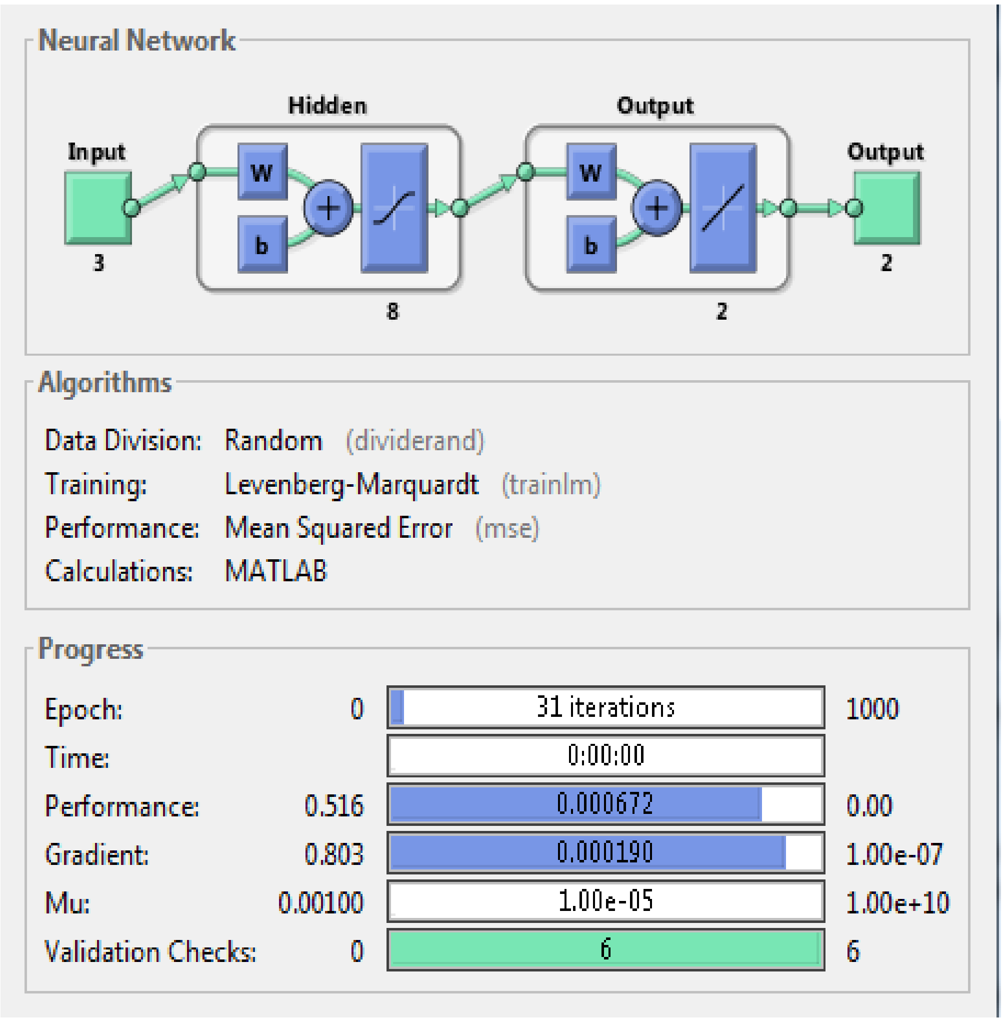

Figure 1: training performance

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The sample results showing the $\mathbf{R}^2$ - value and the MSE for training, validation and test is presented in Table 3.

Table 3: Result obtained for the sample

Property	Sample	MSE	R^2
Training	217	7.06290e-4	9.95946e-1
Validation	47	1.04313e-3	9.95681e-1
Testing	47	9.20691e-4	9.96450e-1

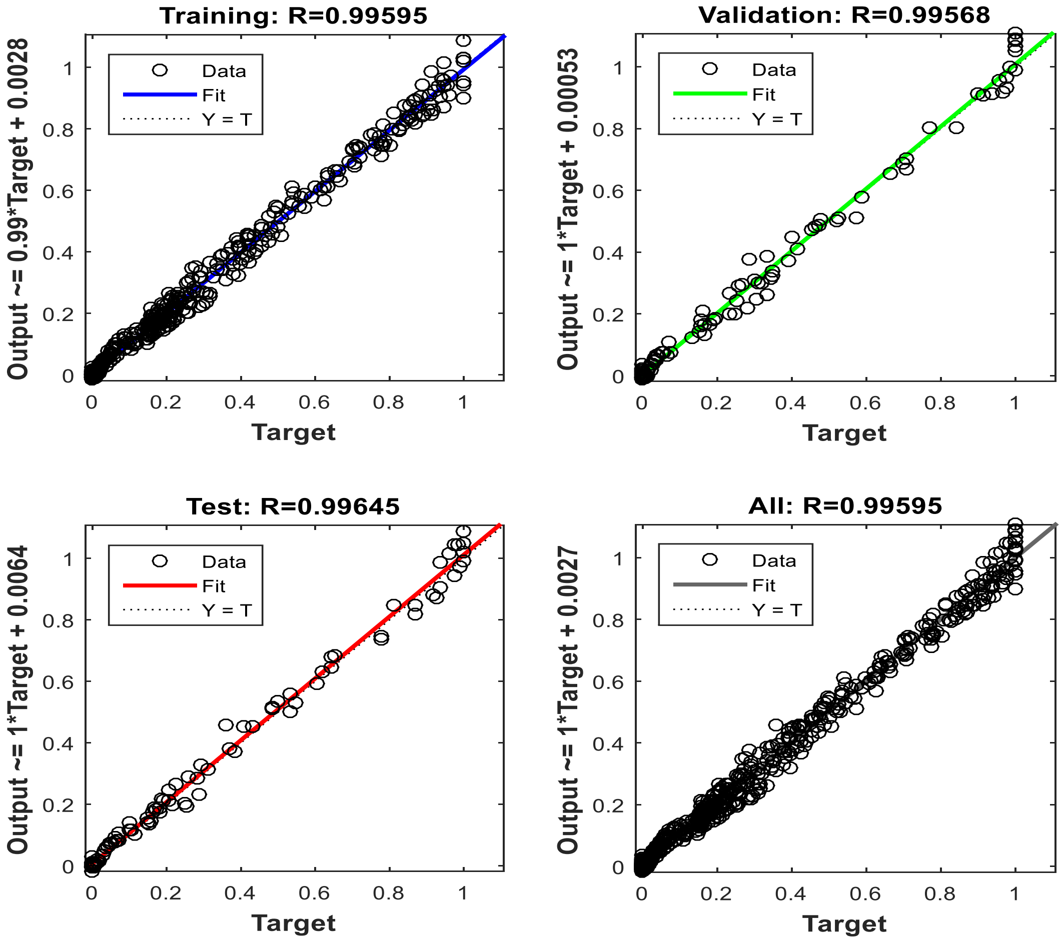

Figure 2: Regression values

The Regression plot is displayed in Figure 2; Figure shows that the prediction performance in terms of R-value is 99.595%. In this Figure 2, the ANN model predicted drying parameters fit very close to the datasets used. This prediction closeness resulted in a correlation coefficient (R) and MSE values of 0.99546 and 0.00070629 for training datasets, 0.995681 and 0.000104313 for validation 0.996450 and 0.000920691 for testing. Also, the overall predicted drying parameters by the developed ANN model compared to the actual drying data resulted in an R value of 0.99595. This R value implied that the ANN model predictions were very close to the actual temperature, thickness and time datasets.

From the results obtained, the empirical equation based on the Levenberg–Marquardt algorithm for predicting moisture content and drying rate. The transfer function 'purelin' correlated the linear relationship between the input and output variables, while 'tansig' calculated the layer's output from the network input.

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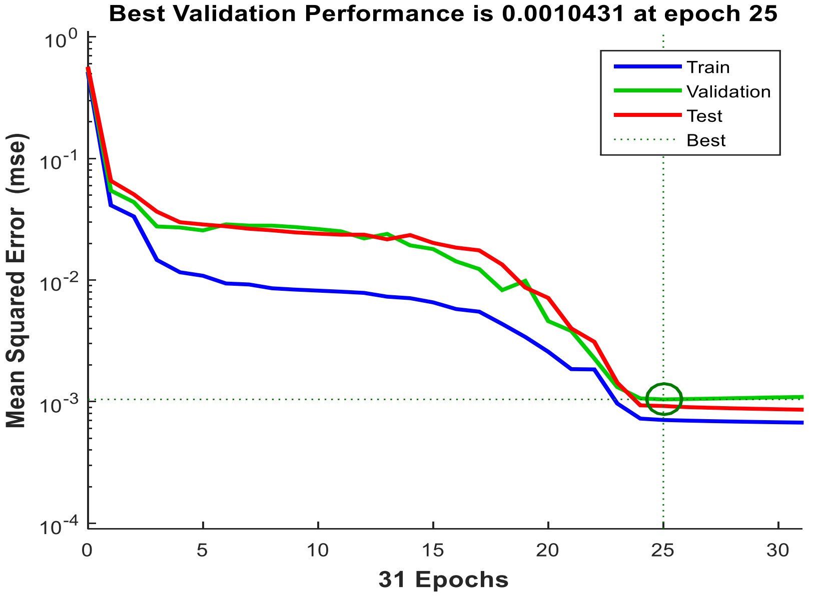

Figure 3: Optimum MSE validation performance

Figure 3 showed that an optimum validation performance 0.0010431 MSE was achieved at 25th iteration. For the optimum to be achieved, it trained for 31 iterations with an error performance of 0.000672 having carried out 6 validation checks. The optimum MSE performance is shown in Figure 3.

The comparative plots of the actual and predicted responses are shown in Figures 4 and 5 for moisture content and drying rate, respectively. The predicted and actual values data points are closed in the slope, which means a good agreement between these predicted and actual drying parameters (moisture content and the drying rate) (Al-Bulushi *et al*. 2009).

From Figures 4 and 5, the model output from ANN shows a good match with the experimental data. However, in order to quantify numerically how well the model's prediction matches actual values, the performance metrics of R^2 and MSE, are used to assess the model. This is summarized in Figure 2. From Figure 2, the assessment is based on the testing values only. Based on this, a combination of low MSE values coupled with high R^2 value (close to 1) makes the model a good one.

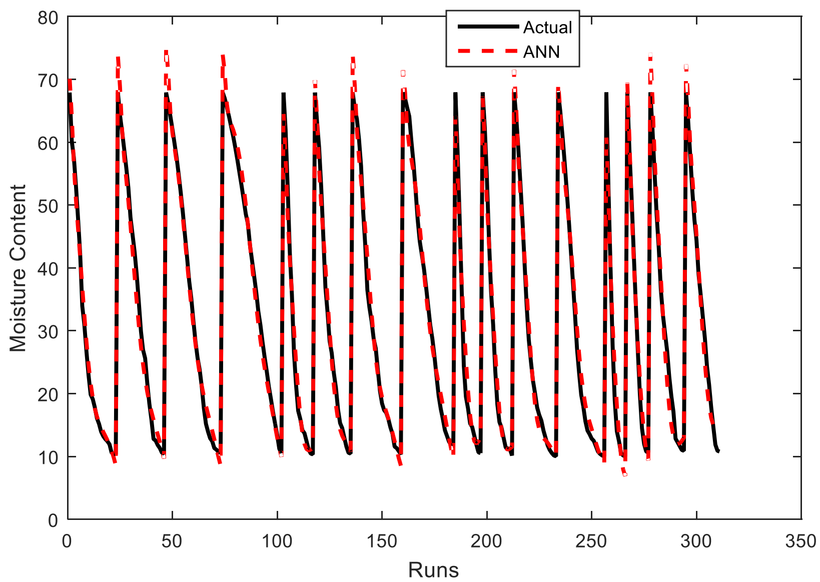

Figure 4: Moisture Content comparative analysis

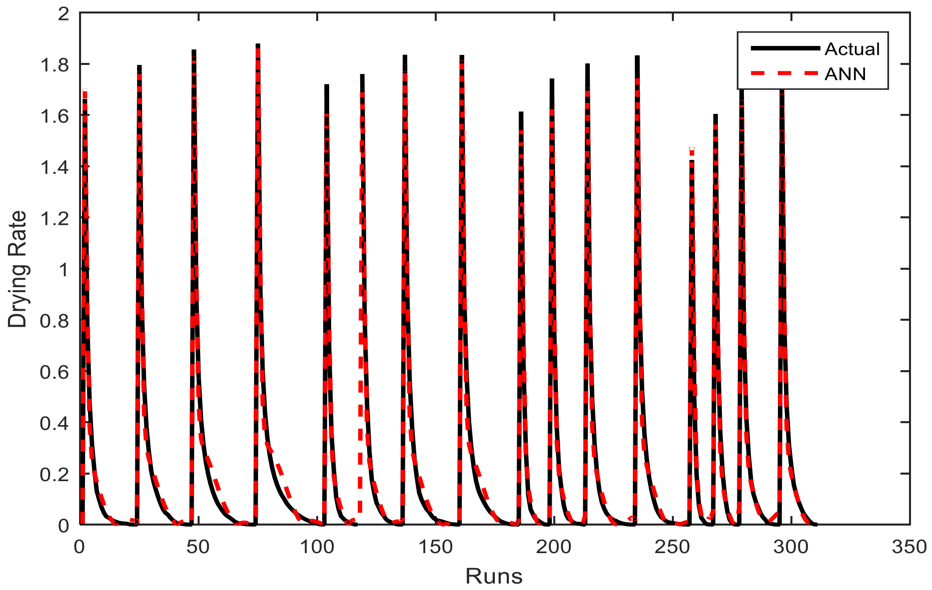

Figure 5: Drying rate comparative analysis

5. CONCLUSION

Based on the study, it is concluded that the moisture content and drying rate were predicted with R^2 of 99.6% and error performance of 0.000672 accuracy for cocoyam (*Xanthosoma sagittifolium* L.) slices when dried with an oven and this could be taken as optimum level. Artificial neural network for predicting desirable parameters in drying operation has been confirmed in this study as stated by other researchers. Nevertheless, ANNs offer an attractive possibility for control design that results in a controller with a higher level of robustness due to information contained in the model. However, with the ANN model, the man hours spent carrying out the compositional analysis can hopefully be reduced and reallocated to other high value-added tasks. The application of the artificial neural networks could be used for the on-line state estimation and control of the drying process. For future work, developing hybridize ANN model that optimizes the prediction of more parameters of the food materials will be necessary.

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