Modelling Moisture Ratio of Dehydrating Yam Slices Using the Levenberg-Marquardt Back-propagation Artificial Neural Network Technique

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ORIGINAL RESEARCH

Abstract- This study predicts the moisture ratio history data of dehydrating yam slices from partial data using Artificial Neural Network (ANN) techniques. The moisture ratio history data at 65 °C, 75 °C, 85 °C, and 95 °C were recorded for the dehydration of 1.5 mm, 3.0 mm, and 4.5 mm thick yam slices in a RefRACTANCE Window Dryer. The Artificial Neural Network within MATLAB software (v. 8.5), using the Levenberg-Marquardt back-propagation algorithm, was trained with some of the data. After training, the Neural Network software predicted the moisture ratio of the primary variables not used in training. The predicted and experimental values were compared. The results showed that, the Artificial Neural Network (ANN) model using the Levenberg-Marquardt back-propagation training algorithm could accurately predict the experimental results not used in training., the predicted and observed data values fitted each other with correlation coefficient (R²) values of 0.97, 0.99 and 0.99, respectively, for the three-process condition considered. The high R² establishes a strong correlation between the experimental and predicted values. This work is essential as it establishes that Artificial Neural Network (ANN) techniques, using the Levenberg-Marquardt back-propagation training algorithm, can predict food samples moisture ratios of in a drying process when data is incomplete.

Keywords- Artificial Neural Network, Levenberg-Marquardt Back Propagation, Moisture Ratio, Drying, yam slices

1 INTRODUCTION

Tubers such as yam (Dioscorea spp.), cassava (Manihot esculenta Crantz), and sweet potato (Ipomoea batatas L.) are worldwide staple foods (Roy et al., 2006; Nuani et al., 2022). For preservation, these tubers are cut into slices, dried, and turned into powder, becoming ingredients for various cuisines. Predicting the amount of moisture in the tuber slices during the dehydrating process is becoming important because of the need to know the energy requirements of dryers without experimenting with the entire range of process conditions. Predicting moisture content in dehydrated tuber slices using Artificial Neural Networks (ANN) appears promising.

Artificial neural network (ANN) techniques have increased considerably in the last few decades as a viable soft-computing technology (Huang, 2009; Ikram et al., 2022; Khudhair et al., 2022). As a result, ANN has found applications in many fields, including engineering, medicine, sciences, and economics, just to mention a few. These techniques involve constructing input-output mappings in which the outputs can be functions of the inputs and the variables in the network. Although there are several learning algorithms for training Artificial Neural Networks (Panchal et al., 2018; Hosseinzadeh et al., 2021), this study explores the Levenberg-Marquardt algorithm used.

Compared to the Bayesian Regularization method and the Scaled Conjugate Gradient method, the Levenberg-Marquardt method achieved results most rapidly in the ANN training (Jeong and Kim, 2005). However, the Levenberg-Marquardt training algorithm requires much memory. Jebur et al. (2018) examined the load-carrying capacity of model piles embedded in sandy soil. They developed a predictive model to simulate pile settlement using a Levenberg–Marquardt (LM) MATLAB algorithms, a new artificial neural network (ANN) approach h. There was close agreement between the experimental and predicted data with a Root Mean Square Error (RMSE) and Coefficient of Determination (R²) of 0.0025192 and 0.988, respectively.

Ye and Kim (2018) predicted the electricity consumption in buildings using an Optimized Back-Propagation (OBP) and Levenberg–Marquardt Back-Propagation (LMBP) artificial neural network technique; their results established that the LMBP technique gives better accuracy than the OBP technique. Çavuş et al. (2018) predicted the gender of wall lizards (Darevskia Bithynia) using a Levenberg–Marquardt Back-Propagation (LMBP) artificial neural network. 70, 15, and 15% of the 115 data values are randomly selected to train, validate, and test the LMBP Artificial neural network model. The evaluated performance regression coefficient (R²) values are 0.98, 0.97, and 0.96 for the network’s layer, with tangent sigmoid activation functions for training, testing, and all data. The mean square error (MSE) values for training and testing data are calculated as 0.015 and 0.016, respectively. The obtained results satisfactorily confirm the high ability of the Levenberg–Marquardt Back-Propagation Artificial Neural Networks in predicting the gender of wall lizards.

The current investigation aims to use the Levenberg-Marquardt Back-Propagation Artificial Neural Network technique, as developed by MATLAB, to predict the

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amount of moisture in dehydrating yam slices when partial data is available. (Sapna et al., 2012; Jayalakshmi and Santhakumaran, 2010; Yadav et al., 2022). The importance of this work is to show that ANN can be used to predict the amount of moisture in yam slices that are dehydrated when partial moisture ratio history data is available.

2. METHODS AND MATERIAL
2.1 SAMPLE PREPARATION
White yam tubers (Dioscorea alata) were purchased from the local market with lengths between 45 cm to 60 cm and maximum diameters between 11.3 and 16.4 cm. The tubers were carefully cut into 1.5, 3.0, and 4.5 mm thick slices with a Mandolin slicer. Then, using a Refractance Window™ Dryer, the yam slices were dehydrated at temperatures of 65 °C, 75 °C, 85 °C, and 95 °C, respectively, in the dryer. In this study, the Refractance Window™ dryer used was similar to that fabricated by Akinola and Ezeorah (2018). First, the moisture content of the yam slices as dehydration progressed was determined using a moisture analyser (OHAUS Corporation, MB45, Parsippany, NJ, USA). Next, recorded was the dehydrated yam slices' moisture content vs time data. Finally, the moisture ratio was determined from the moisture content using Equation 1.

\[
MR = (MC_i - MC_e)/(MC_i - MC_0)
\]

Where:
- \(MC_i\) is the moisture content at any time
- \(MC_e\) is the equilibrium moisture content
- \(MC_0\) is the initial moisture content

2.2 EXPERIMENTAL PROCEDURE
The experiment procedure consists of some dehydration experiments to gather dehydrating yam slices' moisture ratio history data. First, in different experiments, 1.5, 3.0, and 4.5 mm thick yam slices were dried in a Refractance Window™ dryer at 65 °C, 75 °C, 85 °C, and 95 °C. Consequently, moisture-ratio history data values were collected. This moisture ratio history data is for use with the Artificial Neural Network model. Secondly, the Artificial Neural Network software developed by Matrix Laboratory Co. Ltd. (MATLAB) was trained, tested, and validated using a fraction of the moisture-ratio history data values obtained for yam slices. Finally, the expected moisture-ratio history data values were calculated for yam slice variables excluded in training the Neural Network. Finally, the predicted and experimental data moisture-ratio values were compared.

2.3 NEURAL NETWORKS BASICS
In the MATLAB ANN toolbox software, each connection between artificial neurons is characterized by a weight value. Each neuron of the input layer receives data from experiments that will be the output of this layer. The information is drying time, dryer temperature, and yam slice thickness in this situation. Next, the output from the input layer passes to the neurons of the hidden layer weighted by a bias (Figure 1). Finally, each neuron computes the weighting sum of all the neurons in the hidden layer and passes the output to the output layer. A bias can be introduced at this stage, and each neuron activates the output. The mechanics of all these computations are built into the MATLAB software Version 8.5.

2.4 TRAINING, VALIDATING AND TESTING THE NETWORKS
The study will use the Artificial Neural Network software within MATLAB employing the Levenberg-Marquardt back-propagation algorithm. First, 70% of the recorded moisture-ratio history data will be used to train the ANN software. Next, the software will predict the moisture ratio of the primary variables not used to train the Neural Network. Finally, predicted and experimental moisture ratio values will be compared.

2.5 ASSESSING THE TRAINED NETWORK
The ability and the performance of the proposed algorithm can be evaluated using different performance measuring indicators suggested in the open literature. In this study, the accuracy of the network predictions is assessed by determining the Mean Square Error (MSE) (Jebrur et al., 2018); the goal is to set the error to zero. The Levenberg-Marquardt algorithm stops when the MSE during the training and testing is minimal. This means the model has created a high degree of correlation between the input and output variables. i.e., the R² approaches unity. The method of calculating MSE is discussed extensively in the literature (De Myttenaere et al., 2015; Ogunnaiake, 2011) and the equation for estimating MSE is presented in equation 2.

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (MR_{exp} - MR_{mod})^2
\]

Where:
- \(MR_{exp}\) is the experimental value,
- \(MR_{mod}\) is the predicted network output
- \(N\) is the number of data points

3 RESULTS AND DISCUSSIONS
3.1 THE MOISTURE RATIO HISTORY DATA
The initial moisture content of yam slices was determined to be 65.98% wet basis using an MB45 moisture analyser (OHAUS Corporation, MB45, Parsippany, NJ, USA). The moisture content history data and subsequently the moisture ratio history data were gathered as prepared by the procedure described in Section 2.2. Figure 2 presents...
a plot of the moisture content history for 1.5, 3.0, and 4.5 mm thick yam slices at 65 °C. The line graphs indicate that the moisture ratio decreased exponentially and that the yam slices dehydrated faster with a decrease in yam slice size. Line graphs with similar characteristics are observed for yam slices 1.5, 3.0, and 4.5 mm thick at 75, 85, and 95 °C.

3.2 Predicting the Moisture Ratio

Twelve (12) dehydration experiments using a Refractance Window™ dryer were performed in this study. Variation in Moisture content with time was recorded during the experiments. Later, Moisture ratio history data (MRHD) values and the dehydration experiments were done at 65 °C, 75 °C, 85 °C, and 95 °C for yam slices 1.5, 3.0, and 4.5 mm. MRHD values from 11 of the 12 sets were used in training, validating, and testing the MATLAB ANN toolbox. Finally, the moisture ratio values for the 12th set were predicted using the trained and tested software. Then, the researchers compared the predicted and experimental 12th MRHD values. In this study, the training, the validation, and the testing of the Neural network were done by randomly selecting data values for the 11 sets of experiments in the proportion of 70, 15, and 15%, respectively and three situations were tested, namely process conditions A, B, and C.

Fig. 2: Experimental Drying Curves for Different Yam Slices at 65 °C

Investigations with process condition A involved using MRHD values from the dehydration experiments performed with yam slices 1.5 mm thick at 65 °C, 75 °C, and 85 °C, yam slices 3.0 mm thick at 65 °C, 75 °C, 85 °C, and 95 °C, and yam slices 4.5 mm thick at 65 °C, 75 °C, 85 °C, and 95 °C. The trained artificial neural network was then used to predict the moisture ratio for 1.5 mm thick yam slices at 95 °C.

Similarly, investigations with process condition B were performed with the MRHD values for dehydration experiments performed when the yam slices were 1.5 mm thick at 65 °C, 75 °C, 85 °C, and 95 °C, 3.0 mm thick yam slices at 65 °C, 75 °C, and 95 °C and yam slices 4.5 mm thick at 65 °C, 75 °C, 85 °C, and 95 °C. The prediction was performed for the moisture ratio for 3.0 mm thick yam slice size at 85 °C, using the trained artificial neural network.

Finally, investigations with process condition C, a fraction of the dehydration MRHD values for experiments performed when the yam slice was 1.5 mm thick at 65 °C, 75 °C, 85 °C, and 95 °C, 3.0 mm thick yam slices at 65 °C, 75 °C, 85 °C, and 95 °C and 4.5 mm thick yam slices at 65 °C, 75 °C, and 85 °C. The ANN was then used to predict the moisture ratio for Yam slices 4.5 mm thick at 95 °C.

3.3 Performance of the Training, Validation, and Testing of Artificial Neural Network

The training dataset’s purpose is to learn the patterns presented in the dataset by updating ANN biases and weights (Trigo 2000; Jaeel et al. 2016). The MATLAB software incorporates the Levenberg-Marquardt back-propagation algorithm. This training process ends when the error value is sufficiently small (Yadav et al., 2014). Figures 3, 4, and 5 display the model’s performance under training, respectively, for the process Conditions, considered. The training process terminates to avoid overfitting once the cross-validation error increases. The results reveal that the training process ended with Process Conditions A, B, and C having minimum MSE values of 1.12E-03, 5.26E-04, and 4.80E-04, respectively, at Epoch values of 12, 43, and 34.]

3.4 Training, Validating, and Testing Evaluation

For further evaluation of the reliability and the performance of the Levenberg-Marquardt MATLAB algorithm, the Training, Validating, and Testing phases are presented graphically in Figures 6, 7, and 8 for process conditions A, B, C, and C, respectively. For Process Condition A, the Training, Validating, and Testing phases had $R^2$ values of 0.98365, 0.99033, and 0.99316, respectively. Similarly, for Process Condition B, the Training, Validating, and Testing phases had $R^2$ values of 0.99796, 0.99588, and 0.99306, respectively. Finally, for Process Condition C, the Training, Validating, and Testing phases had $R^2$ values of 0.9971, 0.99625, and 0.99395, respectively. All the measured and predicted data values matched well and were close to the best-fit line with correlation coefficients close to unity. In all situations, the fact that $R$ is close to 1 substantiates the application of the Levenberg-Marquardt algorithm based on ANN as an effective predictive tool that behaves acceptably.

3.5 Validation of the Predicted Data

Validation that the predicted and experimental data moisture ratio values agree was done by plotting the observed and predicted values of moisture ratio in Figures 9, 10, and 11 from the three situations, respectively. A regression of the predicted and experimental data produces a slope of 1 and an intercept of 0. This linear relationship indicates that the results are acceptable for all 3 Process Conditions.
Furthermore, the coefficient of determination ($R^2$) was 0.97, 0.99, and 0.99, respectively, for the three situations considered. The results indicate a strong relationship between the predicted and experimental values whenever the $R^2$ values are above 0.95. The implication is that the experimentally determined moisture ratio and the expected moisture ratio for the process conditions considered do not vary significantly.

Fig. 3: Training, Validation and Testing Mean Square Error (MSE) for Process Condition A.

Fig. 4: Training, Validation and Testing Mean Square Error (MSE) for Process Condition B.

Fig. 5: Training, Validation and Testing Mean Square Error (MSE) for Process Condition C

Fig. 6: Training, validation and testing regression for Process Condition A.

Fig. 7: Training, validation and testing regression for Process Condition B.

Fig. 8: Training, validation and testing regression for Process Condition C.
4 Conclusions

A moisture ratio history database was created by conducting dehydration experiments on 1.5, 3.0 and 4.5 mm thick yam slices at 65 °C, 75 °C, 85 °C, and 95 °C. The MATLAB Artificial Neural Network toolbox using the Levenberg-Marquardt back-propagation algorithm was "trained" using 70% of the available data. Next, the verification of the Neural Network was performed with 15% of the data. Later, with the remaining 15%, the neural network predicted the moisture ratio for the primary input variables not used in training. Finally, the researchers compared the predicted and experimental moisture ratio values. There were three (3) Process Conditions, A, B, and C. In Case A, the predicted moisture ratio values were for yam slices 1.5 mm thick and at 95 ºC. The predicted moisture ratio values matched the equivalent experimental values with a regression coefficient of 0.97.

Similarly, in Process Condition B, the predicted moisture ratio values were for yam slices 3.0 mm thick and at 85 °C. The predicted moisture ratio values matched the equivalent experimental moisture ratio values with a regression coefficient of 0.99. Finally, with Process Condition C, the predicted moisture ratio values were for yam slices 4.5 mm thick and at 95 °C. Again, the predicted moisture ratio values matched the equivalent experimental moisture ratio values with a regression coefficient of 0.99. As the results have R² values above 0.90, there is a strong relationship between moisture ratio values predicted by the Artificial Neural Network and the experimentally determined moisture ratio values. The results obtained satisfactorily confirm the ability of the ANNs using the Levenberg-Marquardt training algorithm to predict the moisture ratio of dehydrating yam slices when partial data is available. This study is also pivotal in showing the influence of machine learning in food processing technology.

References


Jayalakshmi, T., and Santhakumaran, A. (2010, February). A Novel Classification Method for Diagnosis of Diabetes Mellitus Using Artificial Neural Networks. In 2010 International Conference on Data Storage and Data Engineering (pp. 159-163). IEEE. https://doi.org/10.1109/DSDE.2010.58


