Journal of Applied Sciences

ISSN 1812-5654

OPEN ACCESS Journal of Applied Sciences

ISSN 1812-5654
DOI: 10.3923/jas.2022.262.272

CrossMark

Research Article
Modelling the Drying Properties of Tomato in a Hot-Air Dryer Using Hybrid ANN-GA Technique

[1]J.B. Hussein, [2]M.O. Oke, [2]R.I. Ajetunmobi and [3]F.F. Agboola

[1]Department of Food Science and Technology, Modibbo Adama University, Yola, Adamawa, Nigeria
[2]Department of Food Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo, Nigeria
[3]Department of Computer Science, Modibbo Adama University, Yola, Adamawa, Nigeria

Abstract

Background and Objective: Drying, a simultaneous heat and mass transfer method, is an essential process to reduce post-harvest losses of tomatoes. Thus, knowledge about the drying properties of tomatoes is necessary for designing and optimizing the drying systems. The study, therefore, investigated the modelling of the drying properties of tomatoes in a hot-air oven using the hybrid ANN-GA technique. **Materials and Methods:** The tomatoes were pretreated in water blanching (WAB), ascorbic acid (ASA) and sodium metabisulphite (SMB). After that, sliced into 4, 6 and 8 mm and dried at 40, 50 and 60°C air temperatures following the Taguchi experimental design. The drying properties (effective moisture diffusivity (D_{eff}), activation energy (E_a) and specific energy consumption (SEC)) of the dried tomatoes were determined and modelled each by hybrid ANN-GA. The highest and lowest values of correlation coefficient (R) and mean square error (MSE), respectively were used as the stopping criteria for the developed model, while R^2, RMSE and MAE were used to validate the reliability of the ANN-GA hybrid network. **Results:** The result shows a variation of 0.98×10^{-10} to 6.36×10^{-10} m^2 sec^{-1} for D_{eff}, 12.23 to 25.76 kJ mol^{-1} for E_a and 0.6247 to1.9514 kWh kg^{-1} for SEC. The results of hybrid ANN-GA ($R^2 = 0.9934$, RMSE $= 1.83\times10^{-11}$, MAE $= 1.54\times10^{-11}$ for D_{eff} and $R^2 = 0.9587$, RMSE $= 0.0656$, MAE $= 0.0501$ for SEC) proved it that is capable of better prediction accuracies and generalization capability. **Conclusion:** The results found in this study can serve as an operational guide for drying tomato fruit on both pilot and industrial scales.

Key words: Modelling, hot air drying, drying properties, tomatoes, hybrid ANN-GA

Citation: Hussein, J.B., M.O. Oke, R.I. Ajetunmobi and F.F. Agboola, 2022. Modelling the drying properties of tomato in a hot-air dryer using hybrid ANN-GA technique. J. Appl. Sci., 22: 262-272.

Corresponding Author: M.O. Oke, Department of Food Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo, Nigeria

Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Tomatoes (*Solanum lycopersicum* L. var) and tomato-based products provide a wide variety of nutrients and many health-related benefits to consumers. It can be consumed raw in salads or as an ingredient in many dishes, drinks and eaten as tomato-based products. Fresh tomato is high in moisture content (90-95%), making it prone to high post-harvest losses[1]. Therefore, drying is an essential process to reduce these post-harvest losses. Drying, a simultaneous heat and mass transfer method, represents an energy-intensive operation of some industrial significance. Due to this high energy requirement, the overhead drying cost of most crops is usually high, resulting in the high price of dried food products. Consumers who demand healthy dried products require simulation and further optimization of the drying conditions to minimize detrimental quality changes during drying processing[2]. Thus, knowledge about the drying properties of tomatoes is necessary for designing and optimising the dryer systems. Among these properties, effective moisture diffusivity (D_{eff}), activation energy (E_a) and specific energy consumption (SEC) are the most critical parameters in the convective drying process of tomatoes[3]. The D_{eff} indicates the flow of moisture out of tomato in the drying process, E_a is the minimum required energy to activate the drying process, while SEC measures the energy needed to evaporate a unit mass of water from the tomato product.

Convective hot-air drying has been extensively employed as a preservation technique. However, using this method, food materials are exposed to elevated drying temperatures, which leads to an increase in shrinkage and toughness, reduction of both the bulk density and rehydration capacity of the dried product and also causes severe damage to flavour, colour and nutrient content[4]. The significant drawback of the convective hot-air drying method from an energy point of view is the more extended drying period, higher drying temperature and high energy consumption[5]. Thus, the desire to reduce these problems and achieve a fast and effective thermal process leads to the modelling and optimization of the drying procedures.

Artificial Neural Networks (ANN), a computational tool whose acting is inspired by that of the human brain[6], has been recognized as promising tools for dynamic modelling and capable of handling complex systems with nonlinearities and interactions between decision variables[7]. ANNs has been successfully used to describe the drying characteristics of a variety of agricultural materials like blueberries[8], jackfruit bulbs and leather[9], tomato slices[10], mushroom[11] and strawberries[12]. On the other hand, the genetic algorithm (GA) is a search technique used to find suitable optimization and search problems solutions. GA belongs to a particular class of evolutionary algorithms that use methods inspired by evolutionary biologists such as inheritance, mutation, selection and crossover to optimize the most critical parameters of neural network structures that significantly influence its performance efficiency[13]. Nevertheless, some significant limitations are attributed to the individual use of ANNs and GA. Therefore, hybridizing the two techniques is considered the most reliable and promising way to eliminate all these constraints and lead to a better solution[14]. Thus, this research aims to explore the ability of coupled ANN-GA in predicting the drying properties of the tomato slices.

MATERIALS AND METHODS

Study area: The experiment was carried out from December, 2018 to January, 2021 at the Department of Food Science and Technology Laboratory, Modibbo Adama University, Yola, Adamawa State.

Sample preparation: Tomato fruit samples were obtained from the Modibbo Adama University of Technology, Yola, Adamawa State Teaching and Research Farm prepared using standard methods[15]. Thirty-six kilograms of tomatoes were divided into three equal portions of 12 kg each. The first portion (12 kg) was blanched (WAB) in boiling water for 1 min and the water drained. The second portion (12 kg) was dipped into 5% ascorbic acid (ASA), while the residual quantity (12 kg) was dipped into 5% sodium metabisulphite (SMB). The tomato to dipping solution ratio was 1:10 (w/v) and the dipping time was 5 min as Hussein *et al.*[5] described. After the pretreatment process, each portion was sliced with Tomato Slicer (NEMCO 56610-13/16" Roma) to a thickness of 4, 6 and 8 mm, respectively. The moisture content of the fresh fruits was determined according to the method described by Hussein *et al.*[1]. The moisture content of the fresh was 94.22 ± 0.28 g water per 100 g sample on a wet basis.

Drying procedure: The drying was conducted using a convective hot air oven (TO008GA-34, AKAI-Tokoyo, Japan). A weighing system (A digital electronic balance (OEM, Freebang-SKU323367) of 0.001 g accuracy) was integrated into the dryer to weigh the samples without taking them out of the oven. The pretreated samples were dried at three levels of drying air temperatures of 40, 50 and 60°C with tomato thickness of 4, 6 and 8 mm following the Taguchi experimental design. A constant airflow velocity of 1.5 m sec^{-1} was maintained throughout the drying processes. Moisture loss of the sample was recorded at 5 min intervals for the 1st hr, 10 min intervals for the 2nd hr and 15 min intervals after that until a constant weight was achieved. The final stage of drying was the point when subsequent weight loss was less than 0.001 g. The final drying time and final moisture content corresponding to each power level were recorded.

Determination of moisture ratio: The moisture ratio of tomato slices at a given time, t, was calculated using a relationship described by Tunde-Akintunde and Oke[16]. The values of M_e are relatively small compared to M_t and M_i, therefore, the error implied in the simplification is negligible in this study:

$$\text{Moisture ratio (MR)} = \frac{M_t - M_e}{M_i - M_e} = e^{-kt} \tag{1}$$

where, M_i and M_e are the instantaneous and equilibrium moisture contents, respectively (% dry weight basis):

M_t = Dry basis moisture content at any time 't'
k = Drying rate constant per minute
t = Drying time (min)

Determination of moisture effective diffusivities (D_{eff}): The moisture transfer within the food material is mainly by molecular diffusion in the falling drying rate period. Assuming that uniform initial moisture distribution throughout the sample, negligible external resistance to movement and tomato slices releasing the moisture from the top and bottom surface occurs. Then, the solution to the equation developed by Cakmak and Yildiz[17] can be applied:

$$MR = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\exp\left(-\frac{(2n+1)^2 D_{eff}\pi^2}{4l^2}t\right) \tag{2}$$

Where:
D_{eff} = Effective moisture diffusivity ($m^2\ sec^{-1}$)
t = Drying time (sec), m and n is a positive integer
l = Half thickness of a thin layer

But for long drying time, only the first term of equation 3 is significant[15,18] therefore, the solution becomes:

$$MR = \frac{8}{\pi^2}\exp\left(-\frac{D_{eff}\pi^2}{4l^2}t\right) \tag{3}$$

The equation above can be further simplified to a straight-line equation as:

$$\text{In}\,(MR) = \text{In}\left(\frac{8}{\pi^2}\right) - \left(\frac{D_{eff}\pi^2}{4l^2}t\right) \tag{4}$$

The effective moisture diffusivity values were then determined by plotting experimental drying data in terms of In (MR) versus drying time (t). A plot of In (MR) versus drying time gives a straight line with a slope:

$$\text{Slope} = -\frac{D_{eff}\pi^2}{4l^2} \tag{5}$$

Therefore, knowing the tomatoes slice thickness and the slope from the above plot, the moisture diffusivity (D_{eff}) was calculated.

Determination of activation energy: The dependence of the effective diffusivity on the different drying temperatures can be predicted appropriately using the Arrhenius equation which is given by Workneh and Oke[18]:

$$D_{eff} = D_o \exp\left(-\frac{Ea}{R(T+273.15)}\right) \tag{6}$$

Where:
D_o = Constant in the arrhenius equation ($m^2\ sec^{-1}$)
E_{ah} = Activation energy for hot air drying of the product ($KJ\ mol^{-1}$)
T = Temperature of hot-air (°C)
R = Universal gas constant (8.31451 $kJ\ molK^{-1}$)

Equation 7 above can be rearranged into the form:

$$\text{In}\,(D_{eff}) = \text{In}\,(D_o) - \frac{Ea}{R(T+273.15)} \tag{7}$$

The activation energy for moisture diffusion was obtained from the slope of the graph of In (D_{eff}) against (-1/T+273.15).

Specific energy consumption (SEC) during hot air oven drying: The SEC consumed for drying a kilogram of tomato slices is calculated using the equation below as described by Motevali *et al.*[19] and Samadi and Loghmanieh[20]:

$$SEC = \left(\frac{\rho_a A_v C_{pa} \Delta T}{M_w}\right)t \tag{8}$$

Where:

SEC	=	Specific energy consumption (kWh kg^{-1} water)
ρ_a	=	Density of air at a temperature (kg m^{-3})
A	=	Cross-sectional area of channel that samples are placed (m^2)
V	=	Air velocity (m sec^{-1})
C_{pa}	=	Specific heat capacity of air in constant pressure (kJ/kg°C)
t	=	Total drying time (h)
M_w	=	Mass of water evaporated (kg)

Hybrid artificial neural network-genetic algorithm (ANN-GA) modelling design: The ANN-GA model was developed by the feed-forward back-propagation described by Arab *et al*.[21]. The input, output and hidden layers were used as the learning algorithm while the hyperbolic tangent sigmoid (tansig)and linear (purelin) at the hidden and output layer, respectively, were used as the transfer functions. In training the developed network, a Levenberg Marquardt algorithm was used for back-propagation with a gradient descent with momentum weight and bias learning function[21]. After 1000 epochs or iterations, the training was terminated with a 0.01 level MS error performance function. Three input variables corresponding to different levels, slice thickness and drying temperature were used as units in the ANN model input layer. At the same time, the drying characteristics, specific energy consumption and dried tomato quality indices are saved as the output layer.

During the training process, GA was applied to optimize the ANN structure to determine the prime neuron numbers in the hidden layer. In this technique, an elite population was chosen for crossover using a roulette wheel selection method. The generation number of 1000, an initial population of 50, a crossover rate of 0.85 and a mutation rate of 0.01 were adopted to develop the best ANN structure[21]. The stop criterion was based on the MSE with the lowest level as the network performance function for the training dataset. In each generation, the fitness of every individual in the population was evaluated by the fitness function, the chromosomes which had a better fitness value when compared to their predecessors were then used for the next iteration[22].

The three genetic operators, namely selection, crossover and mutation, were implemented. The process by which the chromosomes with the best fitness values were chosen as parents for breeding is called selection. The process by which GA selects a pair of parent solutions (best fitness value) to produce progeny, which inherits many characteristics of the parents, is called crossover. At the same time, the process which brought out diversity in the population is called a mutation. The process continues until a maximum number of generations set is reached. The stages of the hybrid model to optimize the initial values of the weights in ANN with a genetic algorithm are shown in Fig. 1.

To obtain fast convergence minimum mean square error and ensure that the targets (output data) reproducibly fall into

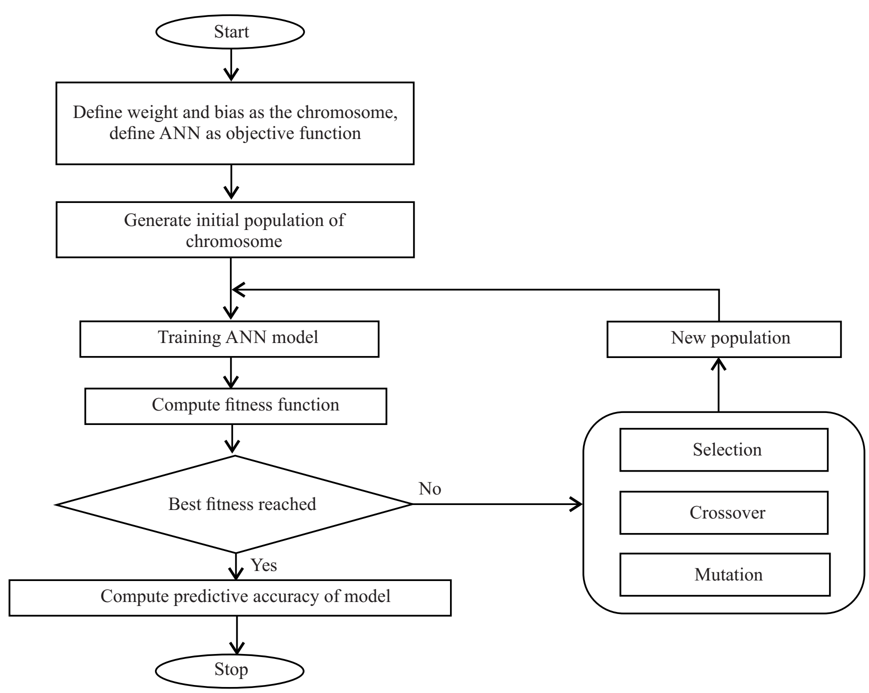

Fig. 1: Stages of the hybrid ANN-GA network

the specific range of the new feed-forward network, each data set (input and output data) was normalized (0, 1) to make the problem more straightforward for the network before training[21,23]. Also, the data samples were randomly divided into three, 70% for training, 15% for testing and the reaming 15% were used for validation. Training data were used to present the cause-erect relationship for the model to learn and test data were used to assess the model's quality[21]. Validation is done by presenting the network to test a data set not used for training and then evaluating the system's performance. The performance and effectiveness of simulating tools with hybrid ANN-GA were calculated using three criteria, namely, regression coefficient (R^2), mean square error (MSE) and mean absolute error (MAE). These are defined in equations 9, 10 and 11 as described by Nazghelichi *et al.*[24]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_0 - y_e)^2}{\sum_{i=1}^{n}(y_0 - y_m)^2} \quad (9)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_0 - y_e)^2 \quad (10)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_0 - y_e|^2 \quad (11)$$

Where:

n = Number of experiments used for developing the model
y_0 = Predicted value of the model
y_e = Actual or experimental value
y_m = Average of actual values

RESULTS AND DISCUSSION

Drying characteristics of pretreated tomato slices: Figure 2 shows the change in moisture ratio of pretreated tomatoes slices with drying time in a hot air oven. The total drying time required to dry pretreated tomato slice to the equilibrium moisture content of 15.67-0.12 % (dry basis) in water blanched (WAB), ascorbic acid (ASA) and sodium metabisulphite (SMB) pretreatments ranged from 17-22$^1/_2$, 12-17 and 11$^1/_2$-15 hrs, respectively for all thickness and temperature ranges understudied. The experimental run (SMB, 4 mm, 60°C) had the lowest value while the highest was obtained for the (WAB, 4 mm, 40°C) sample. The drying curve showed a common trend similar to a typical drying curve, which clearly shows how drying followed a falling rate period and the drying process was accelerated by increasing the drying temperatures. The downward trends of the drying curve imply

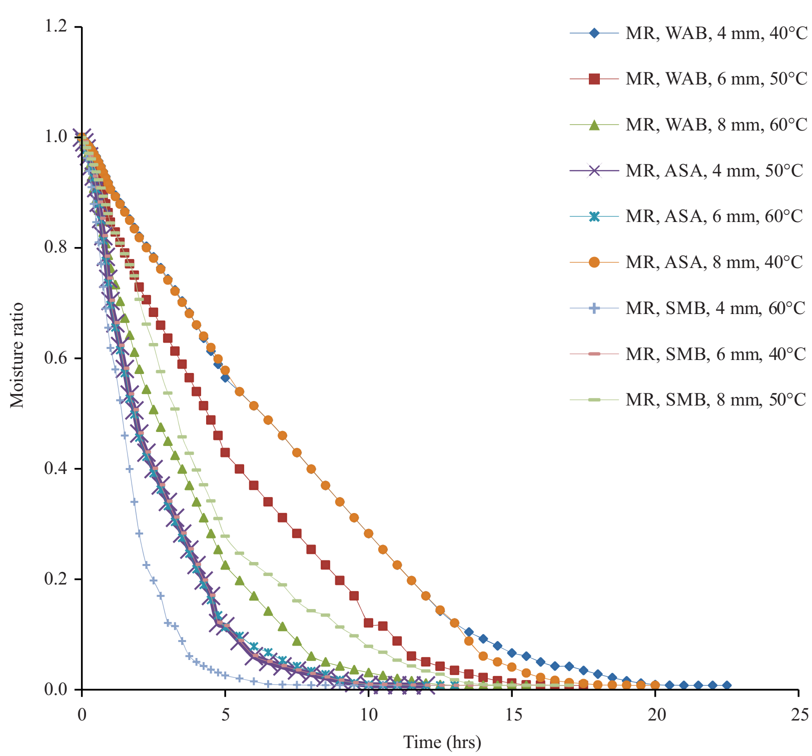

Fig. 2: Drying characteristic curve of pretreated tomato slices by hot air oven at a different drying temperature

that moisture content reduces with increasing drying temperatures. At no point in the drying, operations were the moisture removal at a constant rate. This confirms that the whole drying operation of the tomato samples largely took place in the falling rate period. This indicated that discussion is the most likely physical mechanism governing moisture movement in tomato slices. This result was in agreement with previous studies on the drying of various foods as reported by Hussein *et al.*[25].

The mechanisms of mass transfer in food are complex. In convective hot air oven drying, the water migrates from the inside to the surface of the product under the effect of various mechanisms which can be combined[15]. The method of slopes was used to calculate the effective moisture diffusivity coefficient. The slope of graphs of Ln (MR) versus time for the experimental drying was determined. The values of the D_{eff} of the pretreated tomato samples varied between 0.98×10^{-10} to 6.36×10^{-10} m^2 sec^{-1}. These values obtained in this study lie within the general range of 10^{-12} to 10^{-8} m^2 sec^{-1} for drying agricultural materials[25]. They are also in comparison with the values reported by Akanbi and Adeyemi[26] for tomatoes dried at 45-75°C (3.72-12.27×10^{-9} m^2 sec^{-1}), Doymaz[27] for tomatoes dried at 55-70°C (3.91-7.53×10^{-10} m^2 sec^{-1}) and Workneh and Oke[18] for hot air and microwave-assisted hot air drying of tomato slices at 40°C to 80°C (1.68 -52.2×10^{-9} m^2 sec^{-1}). The differences between the results obtained with the previous works can be as a result of drying methods used, varieties of the tomatoes and the proposed model used for the calculations.

Activation energy is the minimum energy required to begin the drying process. It is also the energy needed to initiate the moisture diffusion within the sample to be dried[18]. The effective moisture diffusivity is dependent on the different drying temperatures and can be appropriately predicted using the Arrhenius equation. The activation energy was obtained from a graph of Ln D_{eff} versus 1/Tabs. The E_a values were 12.23, 23.29 and 25.76 kJ mol^{-1} for the tomato slice with WAB, ASA and SMB pretreated, respectively. This shows that SMB pretreated is more sensible to moisture diffusion than the other. The activation energy obtained for this drying process is within the general range of 12.7-110 kJ mol^{-1} [25] for most agricultural and food materials as presented by several other reports.

The SEC in the drying of pretreated tomato slices ranges from 0.6247 to 1.9514 kWh kg^{-1} as presented in Fig. 2. The experimental run (SMB, 6 mm, 40°C) had the lowest value while the highest was obtained for the (WAB, 8 mm, 60°C) sample. It was observed that the SEC increases with increasing the slice thickness and drying temperature. In other words, each factor causing an increase in input energy rate also causes the specific energy consumption to increase. This result corroborates with what was reported by Pillai *et al.*[28] for plaster of paris. It was also observed that the highest SEC was obtained for WAB samples and also the thickest ones. This was probably since the energy utilized to transfer heat to the internal regions of the slice is higher since the heat transfer distance is higher. Similar results have been observed for ginger slices by Afolabi *et al.*[29].

Modelling the effect of drying conditions on D_{eff} of hot air-dried pretreated tomato slice using ANN-GA: The experimental results obtained from the hot air drying process of pretreated tomato slice was used to develop the ANN-GA prediction model considering pretreatment, slice thickness and drying temperature inputs to the network. In contrast, the moisture diffusivity served as the network output. Several runs were performed to provide an efficient parameterization for this hybrid method. The regression analysis between hybrid ANN-GA outputs and the experimental data indicated a precise and effective prediction of the ANN-GA model with a correlation coefficient of 0.99728 for training in Fig. 3 and 0.99647 for testing in Fig. 4. The MSE values were 2.82×10^{-22} and 4.66×10^{-22} for training and testing. It was observed that

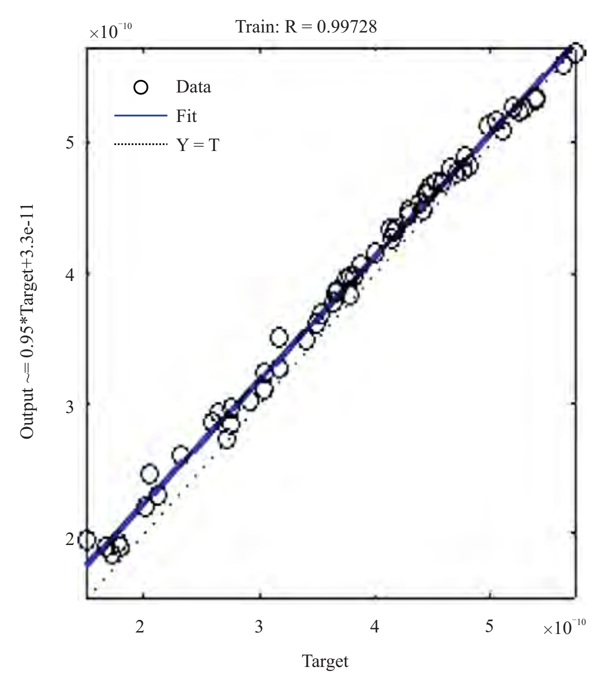

Fig. 3: Regression analysis for training datasets for effective moisture diffusivity in hot-air drying with ANN-GA model

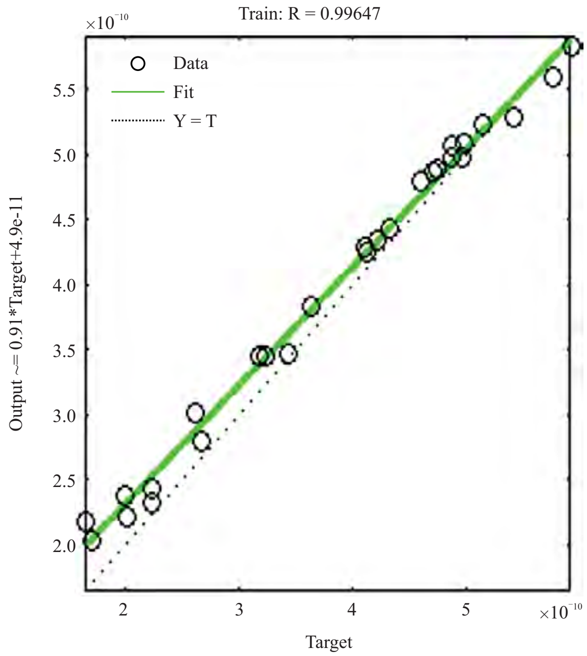

Fig. 4: Regression analysis for testing datasets for effective moisture diffusivity in hot-air drying with ANN-GA model

the network performances (MSE and R) are almost constant after a generation number of 440. Hence, G_{max} of the hybrid ANN-GA model was obtained as 440 in this study. Thus, a value of 440 was used as G_{max} of the hybrid ANN-GA model to predict the moisture diffusivity of the predicted tomato slice.

The validation process is performed to validate the reliability of the hybrid ANN-GA network developed. The predicted and experimental value of the D_{eff} was plotted in Fig. 5. The R^2 of the simulated regression plot was 0.99340. The RMSE and MAE were 1.83×10^{-11} and 1.54×10^{-11}, respectively. The obtained R^2, RMSE and MAE values for the moisture diffusivity show that the investigated prediction models simulate the experiments satisfactorily. The developed network had an excellent generalization in predicting the moisture diffusivity of the tomato slice from the drying process. Therefore, it can be concluded that the prediction ability of the network is reliable. This network can be employed to correctly model the drying time of the tomato slice in the hot-air drying process. Taheri-Garavand *et al.*[30] reported a similar result for modelling the moisture content of dried Basil leaves via FFNN and GA to get the best optimum point. Hybrid ANN-GA has also been successfully used to

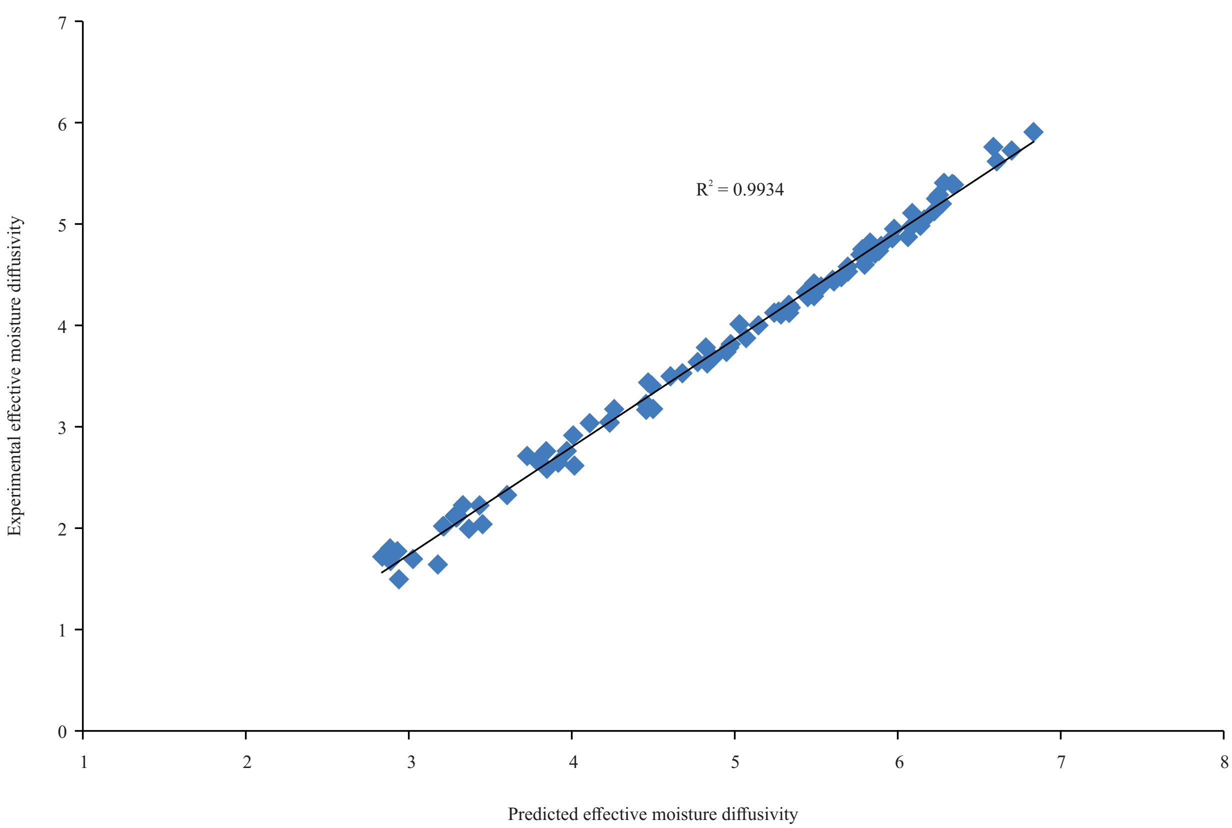

Fig. 5: Relationship between the experimental and predicted moisture diffusivity in hot-air drying using ANN-GA model

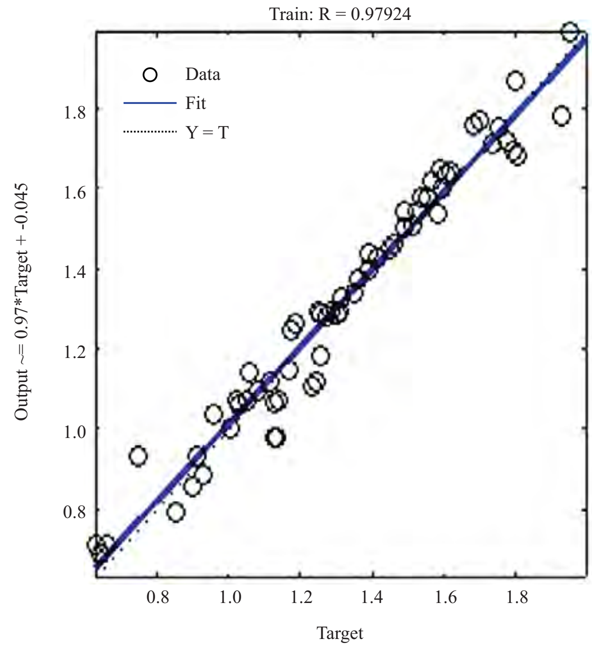

Fig. 6: Regression analysis for training datasets for specific energy consumption in hot-air drying with ANN-GA model

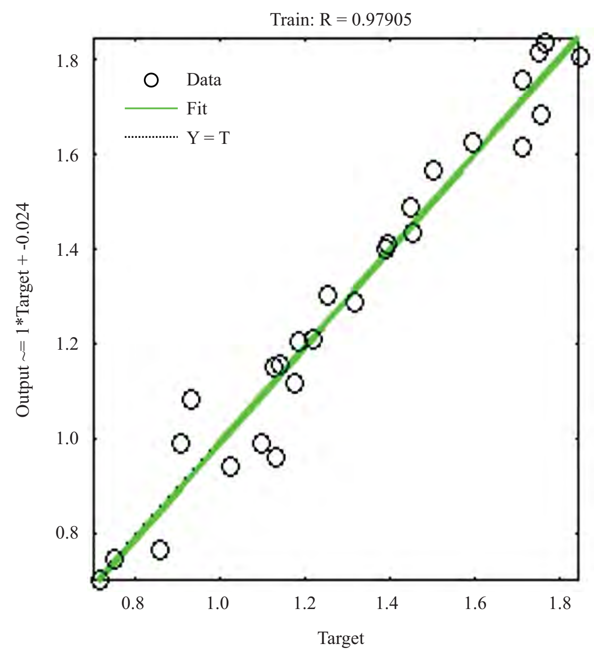

Fig. 7: Regression analysis for testing datasets for specific energy consumption in hot-air drying with ANN-GA model

model and optimize the drying process of fruits and vegetables. Such as the drying process of banana slices by Mohebbi *et al.*[31], kiwifruit by Fathi *et al.*[7] and papaw slices by Yousefi[32].

Modelling the SEC during hot air drying using ANN-GA: The experimental results obtained from the hot-air drying process of pretreated tomato slice was used to develop the ANN-GA prediction model considering pretreatment, slice thickness and drying temperature inputs to the network. At the same time, the SEC served as the network output. Several runs were performed to provide an efficient parameterization for this hybrid method. The regression analysis between hybrid ANN-GA outputs and the experimental data indicated a precise and effective prediction of the ANN-GA model with a correlation coefficient of 0.97924 for training in Fig. 6 and

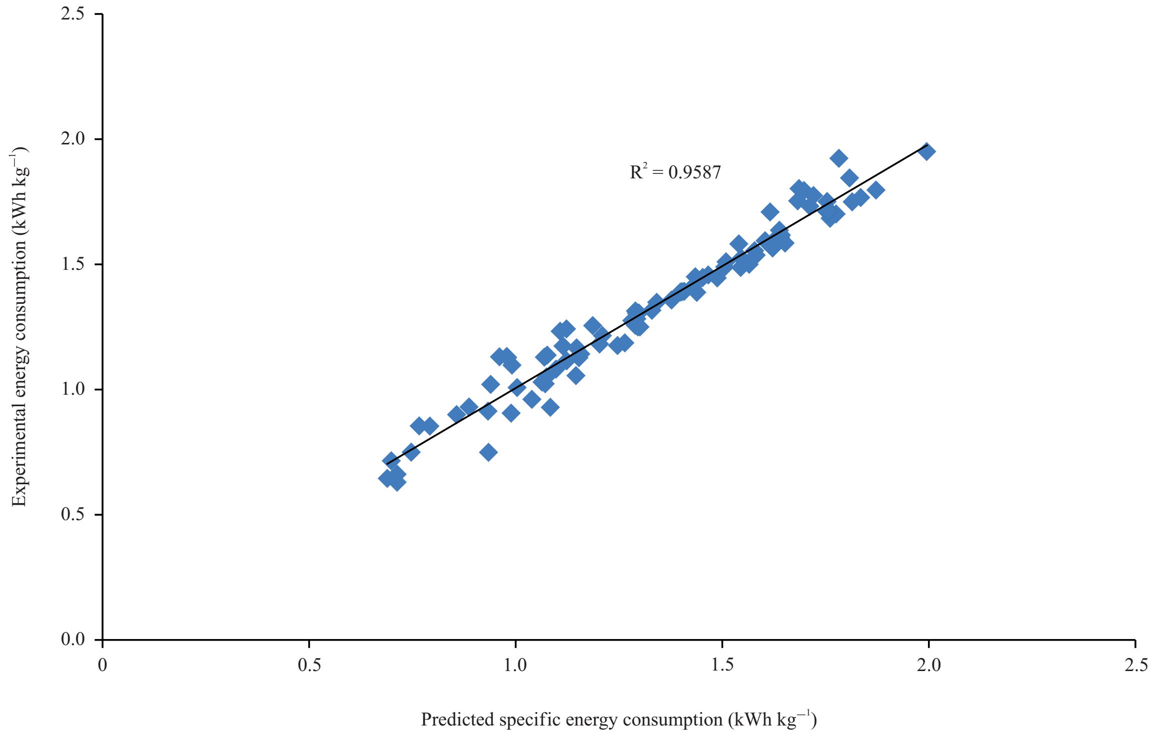

Fig. 8: Relationship between the experimental and predicted specific energy consumption in hot-air drying using ANN-GA model

0.97905 for testing in Fig. 7. The MSE value was 0.00419 and 0.00471 for training and testing, respectively. It was observed that the network performances (MSE and R) are almost constant after a generation number of 77. Hence, Gmax of the hybrid ANN-GA model was obtained as 77 in this study. Thus, a value of 77 was used as Gmax of the hybrid ANN-GA model to predict the SEC of the predicted tomato slice.

The validation process is performed to validate the reliability of the ANN-GA hybrid network. The predicted and experimental value of the SEC was plotted in Fig. 8. The R^2 of the simulated regression plot was 0.95870. The RMSE and MAE were 0.06558 and 0.05008, respectively. The obtained R^2, RMSE and MAE values for the SEC show that the investigated prediction models simulate the experiments satisfactorily. The developed network had an excellent generalization in predicting the SEC of the tomato slice from the drying process. Thus, the prediction ability of the network is reliable and this network can be employed to correctly model the SEC of the tomato slice in the hot-air drying process.

CONCLUSION

The moisture ratio curve shows that tomato drying follows a falling rate characteristic, an important design consideration. The activation energy of SMB pretreated tomato was highest, thus indicating that it is more sensitive to moisture diffusion than the other. The results of hybrid ANN-GA proved it that is capable of better prediction accuracies and generalization capability. The results found in this study can serve as an operational guide for drying tomato fruit on both pilot and industrial scales.

SIGNIFICANCE STATEMENT

This study discovered the modelling technique that can be beneficial for modelling the drying properties of tomatoes. The information reported herein could be to the pilot and industrial scales processors and serve as an operational guide for drying tomato fruits. This study will also help the researchers uncover the critical areas of drying properties that many researchers could not explore with the sole ANN model. Thus a new theory on modelling of drying properties of tomato may be arrived at with hybrid ANN-GA modelling technique.

ACKNOWLEDGMENT

The authors acknowledge the financial support provided by Modibbo Adama University, Yola through TET Fund PhD Study Fellowship Grant.

REFERENCES

1. Hussein, J.B., M.S. Sanusi and K.B. Filli, 2016. Evaluation of drying methods on the content of some bio-actives (lycopene, β-carotene and ascorbic acid) of tomato slices. Afr. J. Food Sci., 10: 359-367.
2. Scala, K.D. and G. Crapiste, 2008. Drying kinetics and quality changes during drying of red pepper. LWT Food Sci. Technol., 41: 789-795.
3. Chayjan, R.A., J.A. Parian and M. Esna-Ashari, 2011. Modeling of moisture diffusivity, activation energy and specific energy consumption of high moisture corn in a fixed and fluidized bed convective dryer. Span J. Agric. Res., 9: 28-40.
4. Maskan, M., 2001. Drying, shrinkage and rehydration characteristics of kiwifruits during hot air and microwave drying. J. Food Eng., 48: 177-182.
5. Hussein, J.B., M.O. Oke, O.O. Abiona and Q. Adebayo, 2020. Optimization of processing parameters for drying of tomatoes (*Solanum lycopersicum* L. var) slices using Taguchi technique. J. Food Process. Preserv., Vol. 45. 10.1111/JFPP. 15149.
6. Funes, E., Y. Allouche, G. Beltrán and A. Jiménez, 2015. A review: Artificial neural networks as tool for control food industry process. J. Sensor Technol., 5: 28-43.
7. Fathi, M., M. Mohebbi and S.M.A. Razavi, 2011. Application of fractal theory for prediction of shrinkage of dried kiwifruit using artificial neural network and genetic algorithm. Drying Technol., 29: 918-925.
8. Chen, C.R., H.S. Ramaswamy and I. Alli, 2001. Prediction of quality changes during osmo-convective drying of blueberries using neural network models for process optimization. Drying Technol., 19: 507-523.
9. Bala, B.K., M.A. Ashraf, M.A. Uddin and S. Janjai, 2005. Experimental and neural network prediction of the performance of a solar tunnel drier for drying jackfruit bulbs and leather. J. Food Process Eng., 28: 552-566.
10. Poonnoy, P., A. Tansakul and M. Chinnan, 2007. Artificial neural network modeling for temperature and moisture content prediction in tomato slices undergoing microwave-vacuum drying. J. Food Sci., 72: E042-E047.
11. Poonnoy, P., A. Tansakul and M. Chinnan, 2007. Estimation of moisture ratio of a mushroom undergoing microwave-vacuum drying using artificial neural network and regression models. Chem. Prod. Process Model., Vol. 2. 10.2202/1934-2659.1057.
12. Menli, T., V. Kirmaci and H. Usta, 2009. Modeling of freeze drying behaviors of strawberries by using artificial neural network. J. Therm. Sci. Technol., 29: 11-21.
13. Shopova, E.G. and N.G. Vaklieva-Bancheva, 2006. BASIC-A genetic algorithm for engineering problems solution. Comput. Chem. Eng., 30: 1293-1309.
14. Chiroma, H., A.S.M. Noor, S. Abdulkareem, A.I. Abubakar and A. Hermawan *et al*., 2017. Neural networks optimization through genetic algorithm searches: A review. Appl. Math. Inf. Sci. Int. J., 11: 1543-1564.
15. Hussein, J.B., K.B. Filli and M.O. Oke, 2016. Thin layer modelling of hybrid, solar and open sun drying of tomato slices. Res. J. Food Sci. Nutr., 1: 15-27.
16. Tunde-Akintunde, T.Y. and M.O. Oke, 2012. Thin-layer drying characteristics of tiger nut (*Cyperus esculentus*) seeds. J. Food Process. Preserv., 36: 457-464.
17. Çakmak, G. and C. Yıldız, 2011. The prediction of seedy grape drying rate using a neural network method. Comput. Electron. Agric., 75: 132-138.
18. Workneh, T.S. and M.O. Oke, 2013. Thin layer modelling of microwave-convective drying of tomato slices. Int. J. Food Eng., 9: 75-90.
19. Motevali, A., S. Minaei, M.H. Khoshtaghaza and H. Amirnejat, 2011. Comparison of energy consumption and specific energy requirements of different methods for drying mushroom slices. Energy, 36: 6433-6441.
20. Samadi, S.H. and I. Loghmanieh, 2013. Evaluation of energy aspects of apple drying in the hot-air and infrared dryers. Energy Res. J., 4: 30-38.
21. Arab, M.M., A. Yadollahi, A. Shojaeiyan and H. Ahmadi, 2016. Artificial neural network genetic algorithm as powerful tool to predict and optimize *in vitro* proliferation mineral medium for G×N15 rootstock. Front. Plant Sci., Vol. 7. 10.3389/fpls. 2016.01526.
22. Lim, M.H., Y. Yuan and S. Omatu, 2000. Efficient genetic algorithms using simple genes exchange local search policy for the quadratic assignment problem. Comput. Optim. Appl., 15: 249-268.
23. Gulati, T., M. Chakrabarti, A. Singh, M. Duvuuri and R. Banerjee, 2010. Comparative study of response surface methodology, articial neural network and genetic algorithms for optimization of soybean hydration. Food Technol. Biotechnol., 48: 11-18.
24. Nazghelichi, T., M. Aghbashlo and M.H. Kianmehr, 2011. Optimization of an artificial neural network topology using coupled response surface methodology and genetic algorithm for fluidized bed drying. Comput. Electron. Agric., 75: 84-91.
25. Hussein, J.B., M.Y. Soji, O.O. Abiona and M.O. Oke, 2018. Drying characteristics of osmotically pretreated red onion slices via hot air oven. J. Food Process Technol., Vol. 9. 10.4172/2157-7110.1000733.
26. Akanbi, C.T., R.S. Adeyemi and A. Ojo, 2006. Drying characteristics and sorption isotherm of tomato slices. J. Food Eng., 73: 157-163.
27. Doymaz, I., 2007. Air-drying characteristics of tomatoes. J. Food Eng., 78: 1291-1297.

28. Pillai, M.G., I. Regupathi, L.R. Miranda and T. Murugesan, 2010. Moisture diffusivity and energy consumption during microwave drying of plaster of Paris. Chem. Prod. Process Mod., Vol. 5. 10.2202/1934-2659.1316.
29. Afolabi, T.J., T.Y. Tunde-Akintunde and O.J. Oyelade, 2014. Influence of drying conditions on the effective moisture diffusivity and energy requirements of ginger slices. J. Food Res., 3: 103-112.
30. Taheri-Garavand, A., S. Rafiee, A. Keyhani and P. Javadikia, 2013. Modeling of basil leaves drying by GA-ANN. Int. J. Food Eng., 9: 393-401.
31. Mohebbi, M., F. Shahidi, M. Fathi, A. Ehtiati and M. Noshad, 2011. Prediction of moisture content in pre-osmosed and ultrasounded dried banana using genetic algorithm and neural network. Food Bioprod. Process., 89: 362-366.
32. Yousefi, A.R., 2017. Estimation of papaw (*Carica papaw* L.) moisture content using adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm-artificial neural network (GA-ANN). Iran. Food Sci. Technol. Res. J., 12: 767-779.