Feed forward neural network and its reverse mapping aspects for the simulation of ginger drying kinetics

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Abstract: In the present study, simulation and modeling features of hot air-drying kinetics of ginger was investigated by an artificial neural network system (ANNs). Mapping of moisture ratio (MR) of the drying process as a function of drying temperature (TD), slice thickness (ST) and drying time (DT) was accomplished based on the ANN architecture. A tale strategy of the reverse neural system was built up to anticipate the drying process of ginger slices under given TD and ST for desired moisture content. Further, proportional odd displaying (POM) approach was applied for the tangible assessment of the dried samples. The ANN architecture, 3-5-1 was chosen as the best for modeling drying behavior of the ginger slices. Simulation of the ginger drying process was assured from the sensitivity analysis implemented based on the inversion of 3-5-1 ANN architecture. Effective diffusivity of the drying process as evaluated by the use of ANN (3-5-1) incorporated Fick's law approach varied from 6.92×10^{-11} to 2.87×10^{-11} m^2 s^{-1}. Ginger samples treated at TD of 60°C and ST of 7 mm (60-7) showed best quality based on the analysis of color properties. Further, the results of POM demonstrated the most elevated adequacy for the same ginger dried samples. Hence, the current investigation will help to enhance the viable simulation and control during the hot air drying of ginger.

Keywords: ginger drying, ANN, reverse ANN, proportional odd modeling, simulation

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1 Introduction

Ginger (*Zingiber officinale*) is a perpetual herbaceous plant grown for its edible rhizome (underground stem). In tropical countries, fresh ginger root is frequently used up as spice, whereas dried ginger is internationally used as a medicinal plant. With the maturity of the rhizome, flavor and aroma of the ginger become stronger.Ginger powder as got from fresh ginger can be utilized straightforwardly as flavor or in therapeutic use and furthermore for the extraction of ginger oleoresinand ginger oil. During internal chewing, ginger acts as a sialagogue due to the presence of stimulant, aromatic and carminative properties. In order to export ginger as medicinal herb with retention of quality parameters, it is required to cut proper slices, dry efficiently and also store safely (Hoque et al., 2013; An et al., 2016; Akpinar and Toraman, 2016).

In 2019, the global production of ginger was 4,081,374 tons. India was the leading producing country accounting for 43.81% of total global production (FAOSTAT, 2020). But in India, ginger drying products are yet to be exploited in the market and proper control of the ginger drying process is a challenge in the North-Eastern states. The regional consumption pattern of ginger includes ginger tea,

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pickles and mostly used as spices.Ginger is very much beneficial for health and is used as a natural remedy worldwide. Surplus wastage amount of ginger has been seen throughout the North-Eastern states as a reason of poor processing and preservation knowledge.

Drying is one of the most important methods for the preservation of fruits and vegetables. In agriculture products, drying is mainly applied to reduce the moisture content up to safe level allowing proper storage over an extended period. Drying instigated moisture expulsion process assists to prevent growth and propagation of microorganisms causing rot and minimization of the moisture interceded deteriorative responses in the food items (Wankhad et al., 2013). In the North Eastern regions of India, it is very problematic to control the ginger drying process up to a safe moisture level. Due to insufficient sun shine intensity, sun drying also cannot be used for the efficient reduction of ginger moisture level. Improper drying leads to the problem of aflatoxin (toxic metabolites)contamination during storage of ginger making the product unfit for the human consumption. Natural drying of ginger namely solar drying requires longer period and produces inferior quality product with high loss of volatile oil (Prasad et al., 2006; Deshmukh et al., 2014).Hence, it is required to apply economic and appropriate drying technology for the drying of ginger.

Simulation of the drying process is required for the adequate control of moisture reduction parameters. Although various researches related to ginger drying has been reported, simulation study of the ginger drying process is still a challenging and pioneering aspect of research (Hoque et al., 2013; Alakali and Satimehin, 2004; Akpinar and Toraman, 2013; Afolabi et al., 2014; Fudholi et al., 2013; Jayashree et al., 2014) .Though various mathematical modeling techniques are used for the modeling of drying process, artificial neural network (ANN) approach shows accurate prediction of moisture parameters with adequate control of the process. If there should be an occurrence of nonlinear and various multiple processing systems, ANN is perceived as an amazing and promising technique. Because of high learning capacity and ability of distinguishing, ANN can demonstrate complex nonlinear relationships with a suitable decision of free parameters or weights.

ANN models are created dependent on an improved model of human brain operations. Without requiring the priori models, ANN can inside self-adjust and relate complex non-direct connections among information and yield factors. On the off chance that a phenomenological model of the procedure isn't accessible or too complex to even think about deriving, this turns out to be more helpful. For portraying drying attributes of numerous agricultural products, for example, mango ginger, carrots, tomato, bael etc. ANN ideas have been effectively applied (Murthy and Manohar, 2014; Erenturk and Erenturk, 2007; Movagharnejad and Nikzad, 2007; Mohebbi et al., 2011; Khawas et al., 2016; and Dash et al., 2020). Likewise, ANN is usable for information recorded during normal production, and henceforth, ANN favored as an option for the recreation of such procedure.

ANN based simulation for the ginger drying process is important aspect for efficient controlling of the drying process. Further inverse mapping of neural network helps for strenghtning prediction of output based input parameter. Very few studies had been reported related to neural network inversion and it’s impact on the simulation of ginger drying process. The objectives of the present study were modeling of the tray drying process of ginger by using ANN and simulation of its performance by applying inverse neural network and proportional odd modeling approach.

2 Materials and methods

2.1 Raw material and sample preparation

For the present study, fresh ginger (*Zingiber officinale*) was procured from the local market of Nirjuli, Arunachal Pradesh (India). The ginger samples were chosen and washed with normal water to eliminate the residue and earth over their surface. The peeled ginger was cut with a sharp knife into slices of thickness 3 mm, 5 mm and 7 mm. The moisture content of the ginger samples was obtained

88.60% (wet basis) by using hot air oven at 105°C for 24 hours.

2.2 Experimental procedure for the thin layer drying of ginger slices

Drying was performed in a tray dryer (UOP 8-A Tray Dryer, Armfield, UK). The tray dryer is consists of a drying chamber, heater, electric blower and controllers for controlling the temperature and airflow velocity. The overall dimensions of the drying chamber of tunnel tray dryer are 0.3 m × 0.3 m × 0.4 m. Before starting an experimental run, the whole apparatus was operated for at least one hour to stabilize the air temperature and air velocity in the dryer. Different thickness (3, 5and 7 mm) slices were uniformly spread in thin layers on their respective Petri dish. Initial weights of samples were taken 100 g for 3, 5 and 7 mm thickness samples respectively. The experiments were performed at 60°C, 70°C and 80°C drying temperature with constant air velocity at 2.75 m s^{-1}. During each set of drying experiments, weights of the petri dishes were taken at an interval of 30 min. The experiments were continued until three constant readings were obtained. The process flowchart for the ginger drying process is illustrated in Figure 1.

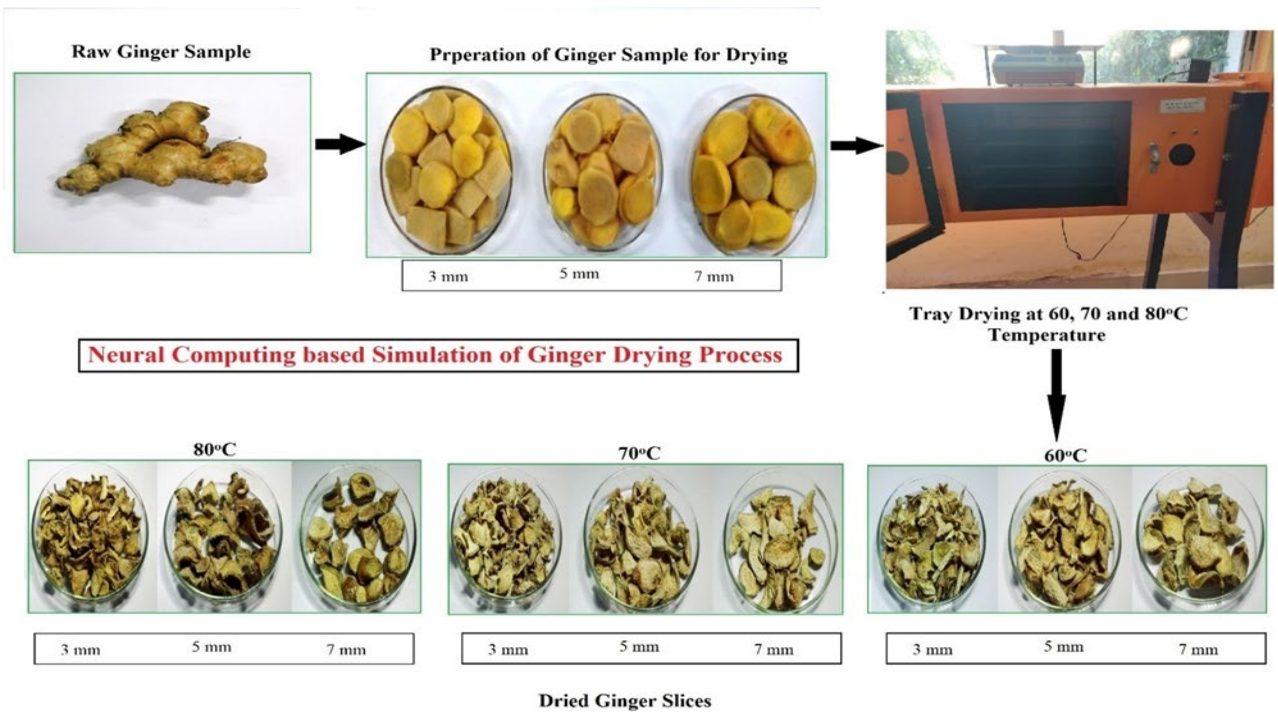


Figure 1 Flowchart for the tray drying of ginger slices

2.3 Determination of drying parameter of ginger slices

2.3.1 Moisture content

The moisture content of the dried ginger samples were determined by using the following equations (Sarkar et al., 2020; Chakraborty et al., 2019).

$$MC\ (\%db) = \frac{W_w}{W_d} \times 100 \quad (1)$$

$$MC\ (\%wb) = \frac{W_w}{W_w + W_d} \times 100 \quad (2)$$

where, W_d stands for dry weight (g), W_w refers to weight of water (g), MC is moisture content (%).

2.3.2 Moisture ratio (MR)

Moisture ratio (MR) was determined by using the following mathematical expression (Sarkar et al., 2020; Chakraborty et al., 2016).

$$MR = \frac{M - M_e}{M_O - M_e} \quad (3)$$

Here, M stands for moisture content at each drying time, M_o and M_e refer to initial and equilibrium moisture content of the material.

2.4 Color analysis of the dried ginger slices

Hunter color measuring system (Model: UltraScan VIS, Make: Hunter Lab, USA) was used for the color measurement of fresh and dried ginger samples. As color parameter of the samples L^*, a^* and b^* values were determined, where L^* refers to lightness (0 = black, 100 = white), a^*refers to red-purple (positive values) and bluish-green (negative values) and b^* refers to yellowness (positive values) and blueness (negative values) features (Hoque et al., 2013).

2.5 Sensory analysis of the dried ginger slices

Sensory analysis of the ginger samples were performed for the overall acceptability of the dried ginger slices. Total twenty number judges were invited for scoring the dried ginger samples in five point hedonic scale (1: poor, 2: medium, 3: fair, 4: good and 5: excellent). For the sensory analysis total 9 dried ginger samples were considered.

3 Theoretical considerations

3.1 Artificial neural network (ANN) modeling

Moisture ratio (MR) of the ginger drying process was simulated by applying artificial neural network (ANN). A relationship between the independent variables viz. temperature of drying (TD), slice thickness (ST) and drying time (DT) and dependent variable namely moisture ratio (MR) was developed by applying ANN. ANN architecture was formulated on the basis of feed forward algorithm. A forward course based information stream viz. from input to output layer was highlighted for the execution of the feed forward ANN. As a versatile boundary of the network, a genuine number amount specifically loads were related with the associations of two neurons. The information were acquainted with the hidden layer with the assistance of weights and input layer neurons. The hidden layer of the ANN was associated for performing two sorts of tasks. Based on the following equations, weighted inputs were summed up along with bias values.

$$sum = \sum_{i=1}^{n} X_i w_i + T_i \quad (4)$$

Where, W_i refers to connection weights, T_i refers to bias values as associated with hidden and output layers and X_i refers to input parameter for i^{th} neuron.

Once the summation was completed, assessed output is allowed to be set for an activation function. The space in the non-linearity of the input data is shifted with the assistance of the activation function, thatled to the shifting of space in the non-linearity of the input data. For the current research activation function is represented as tansigin Equation 5, was utilized during execution of the feed forward ANN design.

$$f(sum) = \frac{2}{1+exp\,(-2sum)} - \quad (5)$$

Input to output layer was presented by utilizing the acquired output of the hidden layer. Therefore, final output of the output layer was delivered in the comparable way (Desai et al., 2008; Dash et al., 2020, Chakraborty et al., 2020). ANN is applied in aggregation of training, testing and validation stages.In the current investigation, MATLAB R2015a programming was utilized for the execution of ANN. Neural network was formulated with three neurons in the input layer and one neuron in the output layer were observed. The values of coefficient of determination (R^2) and mean square error (MSE) were for the evaluation of hidden layer neurons.

3.2 Reverse mapping of ANN

In the present study, inversion of developed feed forward network, also known as reverse mapping was applied in order to predict ginger drying time (DT) for a given TD, ST and final moisture content. Mathematical relationship for the output of feed forward ANN as a function of weight and input values were inversed in order to determine output based input parameters.

Feed forward ANN

$$Y=f(W,X) \quad (6)$$

Reverse ANN

$$f^{1}:Y=X \quad (7)$$

For the inversion of feed forward neural network, non linear programming (NLP) method was used. NLP is a straight forward method adapting mathematical programming approach for the inversion of neural network. This method is advantageous over other methods (Hazarika and Dutta, 2014). In the present study, for the implementation of inversion approach feed forward relationship was initially developed by considering MR as a function TD, ST and DT. Weight and bias values as obtained from the feed forward ANN were used for the formulation of reverse ANN algorithm. This algorithm helps to determine DT for known TD and ST up to a desired moisture content of ginger during tray drying process.

3.3 ANN integrated moisture diffusivity modeling of ginger drying process

In case of food material drying generally occurs in falling rate period, which is mainly governed by moisture diffusion process. Hence, effective diffusivity is mentioned as an important parameter for the drying of food materials. Fick's diffusion equation is generally used for the explanation of effective diffusivity. Evaluation for the moisture transport phenomenon of drying is done by using Fick's second law (Dash et al., 2020; Chakraborty et al., 2016; Wang et al., 2007). The general form of the Fick's second law is expressed by the following mathematical equation.

$$\frac{\partial M}{\partial t} = \left(D_{eff}\frac{\delta^2 M}{\delta L^2}\right) \quad (8)$$

Effective moisture diffusivity was determined by using the following equation

$$MR = \frac{M_t - M_e}{M_0 - M_e} = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\times exp\left(-\frac{(2n+1)^2\pi^2 D_{eff}t}{4L^2}\right) \quad (9)$$

For long term drying n is equal to 1. Hence, Equation 9 can be reduced to the form given in Equation 10.

$$MR = \frac{M_t - M_e}{M_0 - M_e} = \frac{8}{\pi^2}exp\left(-\frac{\pi^2}{4}\frac{D_{eff}t}{L^2}\right) \quad (10)$$

Here, *MR* stands for moisture ratio, M_0 is initial moisture content (wb), M_t refers to moisture content (wb) at time t, M_e is the equilibrium moisture content (wb), D_{eff} is effective moisture diffusivity (m^2 s^{-1}), *t* is drying time (s) and *L* is half of the thickness of the slab (m).

In this study, a combined approach of ANN and Fick's second law based mathematical modeling was applied for the determination of moisture diffusivity. Best ANN architecture with information of weight and bias values was integrated with Fick's second law of moisture diffusivity. For a given TD, ST and DT, moisture diffusivity of the ginger drying process was determined.

3.4 Proportional odd modeling (POM) for the sensory evaluation of dried ginger

POM is a multivariate expansion of summed up straight models, permitting displaying of the probabilities related with every class of responses under the impacts of exogenous factors, including the direct indicator. For a five point hedonic scale, the responses of consumers attitude can be taken on estimations of the set {1, 2, 3, 4, 5}, with the end goal that 1 <2 <3 <4 <5. The approach of POM evaluates probabilistic mentality of customers by considering the impacts of the co-factors and non-quantifiable elements (specialist impact). Under this context $\pi_j(x)$ is considered as the marginal probability *(j = 1, 2, 3, 4, 5*). This probability is used for the evaluation of product acceptance under each of the response category (Meullenet et al., 2003; Lemos et al., 2015; Borah et al., 2016). For the j^{th} response category, the accumulated probabilities can be expressed by the following equation:

$$\gamma_j(X) = \pi_1(X) + \cdots + \pi_j(X) \quad (11)$$

Based on the accumulated probabilities, POM can be expressed by Equation 12.

$$ln[(\gamma_j(X))/(1-\gamma_j(X))] = \lambda_j - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{p-1}X_{p-1}) \quad (12)$$

Here, λ_j is the intercept, β_{p-1} represents slope and X_{p-1}represents covariable's vector (p stands for number of samples).

If $ln[(\gamma_j(X))/(1-\gamma_j(X))] = L_j$, the proportional odd models for all the scales (j-1) can be given as follows

$$L_1 = \lambda_1 - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{p-1}X_{p-1}) \quad (13)$$

$$L_2 = \lambda_2 - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{p-1}X_{p-1}) \quad (14)$$

$$L_3 = \lambda_3 - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{p-1}X_{p-1}) \quad (15)$$

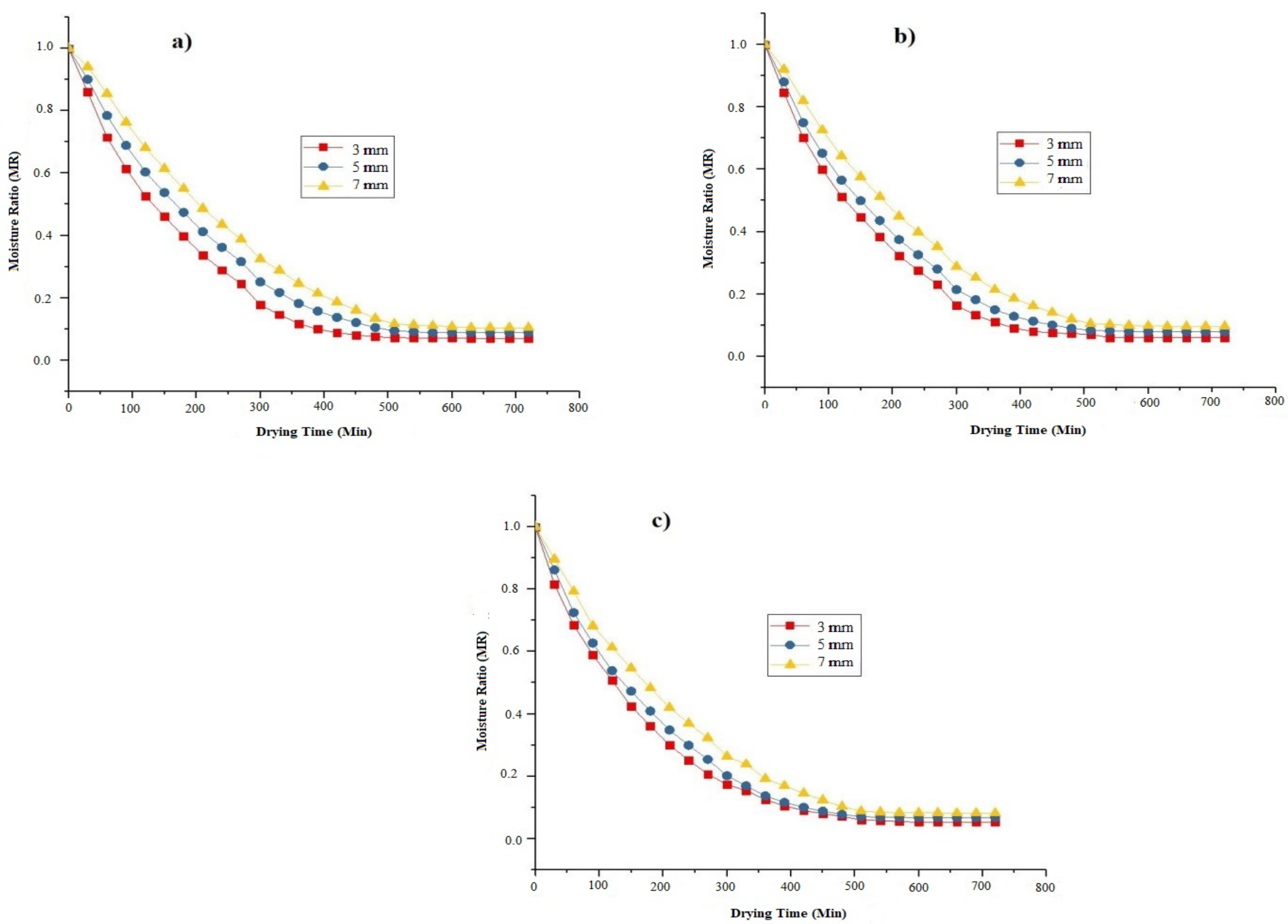
$$L_4 = \lambda_4 - (\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_{p-1}X_{p-1}) \quad (16)$$

In the present study, POM based sensory evaluation was performed by considering overall acceptability of the dried ginger slices. POM analysis was performed in R software (R 3.4.1).

4 Results and discussions

4.1 Drying behavior of ginger slices

From Figure 2 tray drying behavior of ginger under various slice thickness (ST) and temperature of drying (TD) can be observed. It can be seen that drying mainly occurs under the falling rate period up to the final moisture content varying from 6% to 9 % wb. As a result, moisture diffusion was higher and hence the drying rate was higher. The effect becomes more prominent with the increase of the temperature. From the results negative effect of ST and positive effect of TD can be observed on the drying rate of the ginger slices. In our study, we observed that shortest period of ginger drying for the combination at TD of 80 °C and ST of 3 mm (80-3). Similar results were obtained during the drying process under isothermal conditions, a noticeable shift in the rate of moisture decline was observed at same temperatures and time reported by various researchers (Lee et al., 2019; Hoque et al., 2013; Loha et al., 2012).



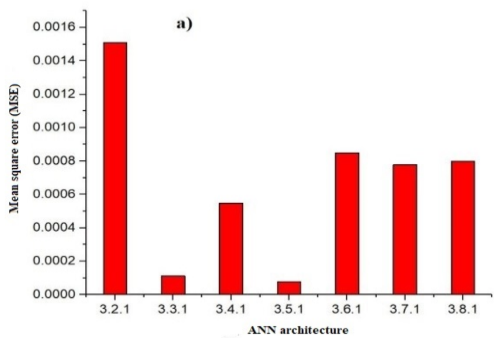
(a)60°C; (b)70°C; and (c)80°C

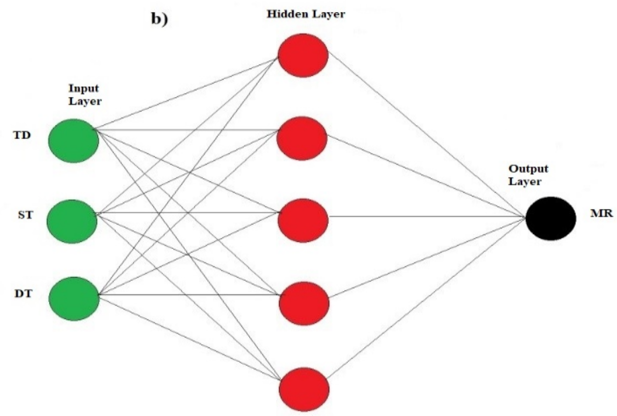
Figure 2 Drying curves for the ginger slices dried at different temperature

4.2 Modeling of ginger drying kinetics by using ANN

The drying kinetics of ginger was modeled by applying artificial neural network (ANN). Mapping of moisture ratio (MR) was accomplished as a function of temperature of drying (TD), slice thickness (ST) and drying time (DT). ANN was performed by using 224 experimental data. For the execution of ANN, the data was divided as 70%, 15% and 15% for training, testing and validation respectively. The transfer function, tansigwas utilized for the assessment of final output during each run. ANN structure was formulated by considering TD, ST and DT as independent and MR as dependent variables. Hence, input and out layers of the formulated ANN structure consisted of three and one neurons respectively. The methodology of ANN analysis is represented in Figure 3.

Based on trial and error approach, the number of hidden layer neurons was determined. Learning rate of the neural network varied from 0.5 to 1 during total iterations of 2000 for each run. For accurate execution of the training process, total iteration was repeated in combination of ten runs for each architecture. By comparing average MSE values for each ANN structure, best architecture was selected. Figure 3a shows the selection of best architecture. The ANN architecture, 3-5-1 was selected as the best for the drying analysis of ginger slices. The coefficient of determination (R^2) value for the best ANN architecture was more than 0.99. Figure 3b delineates the best ANN architecture.





(a) ANN architecture; (b) best ANN architecture

Figure 3 Selection of ANN architectures

4.3 Reverse mapping of ANN for the simulation of ginger drying process

Reverse mapping of the feed forward ANN or inversion of ANN was done for the simulation of ginger drying process. Weight and bias values of 3-5-1 architecture was used for the inversion of the network. As discussed in the methodology section, NLP method was implemented for the inversion process. In order to estimate drying time for given TD, ST and MC values, inverse neural network was used. Generally for the modeling of drying process, the main objective is to determine the required drying time for reducing the moisture content of the food material up to a desired value under given set of conditions. Inverse neural network is an effective approach in order to accomplish desired simulation of the drying process. In the present study, inversion of the developed feed forward ANN architecture (3-5-1) was done to determine tray drying time of ginger slices at TD of 65°C and 75°C for desired ST of 3 and 6 mm. The programming for the inversion of feed forward neural network was done in MATLAB R2015a. Table 1 shows the results of the reverse ANN as decided for the required drying conditions. Hazarika and Dutta (2014) reported similar aspects for the estimation of required input conditions based on reverse ANN.

Table 1 Simulation of ginger drying process by using reverse ANN technique

Temperature of drying-TD (°C)	Slice Thickness-ST (mm)	Moisture content-MC (%wb)	MR	DT (min)
65	3	8	0.09	475
65	6	8	0.09	600
75	3	8	0.09	400
65	3	10	0.12	380
65	6	10	0.12	520
75	3	10	0.12	380
65	3	12	0.14	365
65	6	12	0.14	485
75	3	12	0.14	345
65	3	14	0.16	345

65	6	14	0.16	445
75	3	14	0.16	320

4.4 ANN based modeling of moisture diffusivity

In this study, ANN based modeling approach was implemented for the estimation of effective diffusivity. 3-5-1 ANN architecture was integrated with Fick's second law for determining effective diffusivity of ginger drying under different conditions. The flowchart for the ANN based estimation of effective diffusivity is illustrated in Figure 4. Effective diffusivity of the drying process varied from 6.92×10^{-11} to 2.87×10^{-11} $m^2\ s^{-1}$ with the variation of ST and TD. The effect of ST and TD on the effective diffusivity of the ginger drying process. A rising trend of effective diffusivity with the elevationin values of ST and TD can be observed from the figure. Table 2 demonstrates significant effect of TD (A) and ST (BB) on the effective diffusivity. These outcomes are conflicting with the discoveries detailedby Hoque et al. (2013), Akpinar and Toraman (2013), and Murthy and Manohar (2014).The equation of effective diffusivity (D_{eff}) as a function TD (A) and ST (B) can be expressed as follows.

$$D_{eff} = -4.63\times10^{-11} + 8.64\times10^{-13}A + 4.96\times10^{-12}B + 5.00\times10^{-13}AB - 1.48\times10^{-14}A^2 + 9.03\times10^{-13}B^2 \quad (17)$$

Table 2 ANOVA results for the effect of TD (A) and ST (B) on the effective diffusivity

Variables	degree of freedom	F value	p value
Model	5	15155.26	< 0.0001
A	1	1268.11	< 0.0001
B	1	73948.53	< 0.0001
A^2	1	7.83	0.0266
B^2	1	46.29	0.0003
AB	1	513.32	< 0.0001

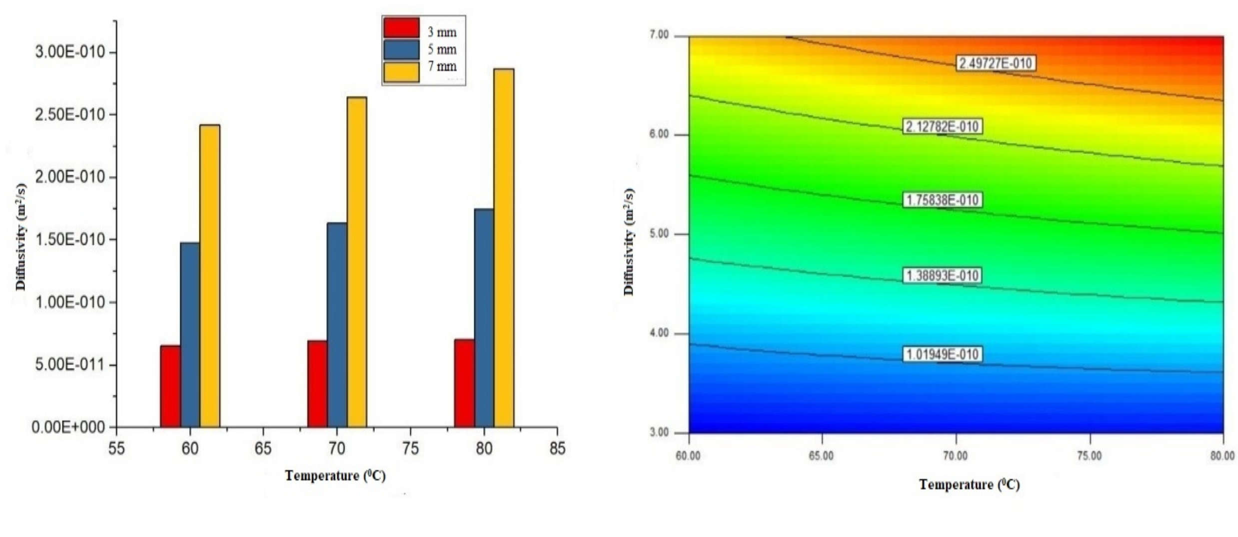


Figure 4 Effect of ST and TD on the effective diffusivity of the ginger drying process

4.5 Color analysis

The values of L^*, a^* and b^* were observed and compared between various dried samples. Figure 5 shows the color properties of various dried ginger samples. A rising trend of L^* and b^* was observed with the increase of ST, whereas increase in TD showed decreasing effect on L^* and b^*. In case a^* values, negative effect of ST and positive effect of TD was observed. Positive effect of drying temperature was observed due to the increased impact of activation energy on ginger slices during the drying process, whereas increase in ST tried to retard the heavier impact on the color intensity. Among all the dried ginger samples, 60-7 indicated best quality for color properties. The sliced and blanched asparagus was dried at 50°C, 60°C and 70°C of drying temperature and there were some differences in colour indexes .Where as the lightness decreased at 60^{o}C but again increased at 70^{o}C were reported for ginger similer result were reported (Hoque et al., 2013).

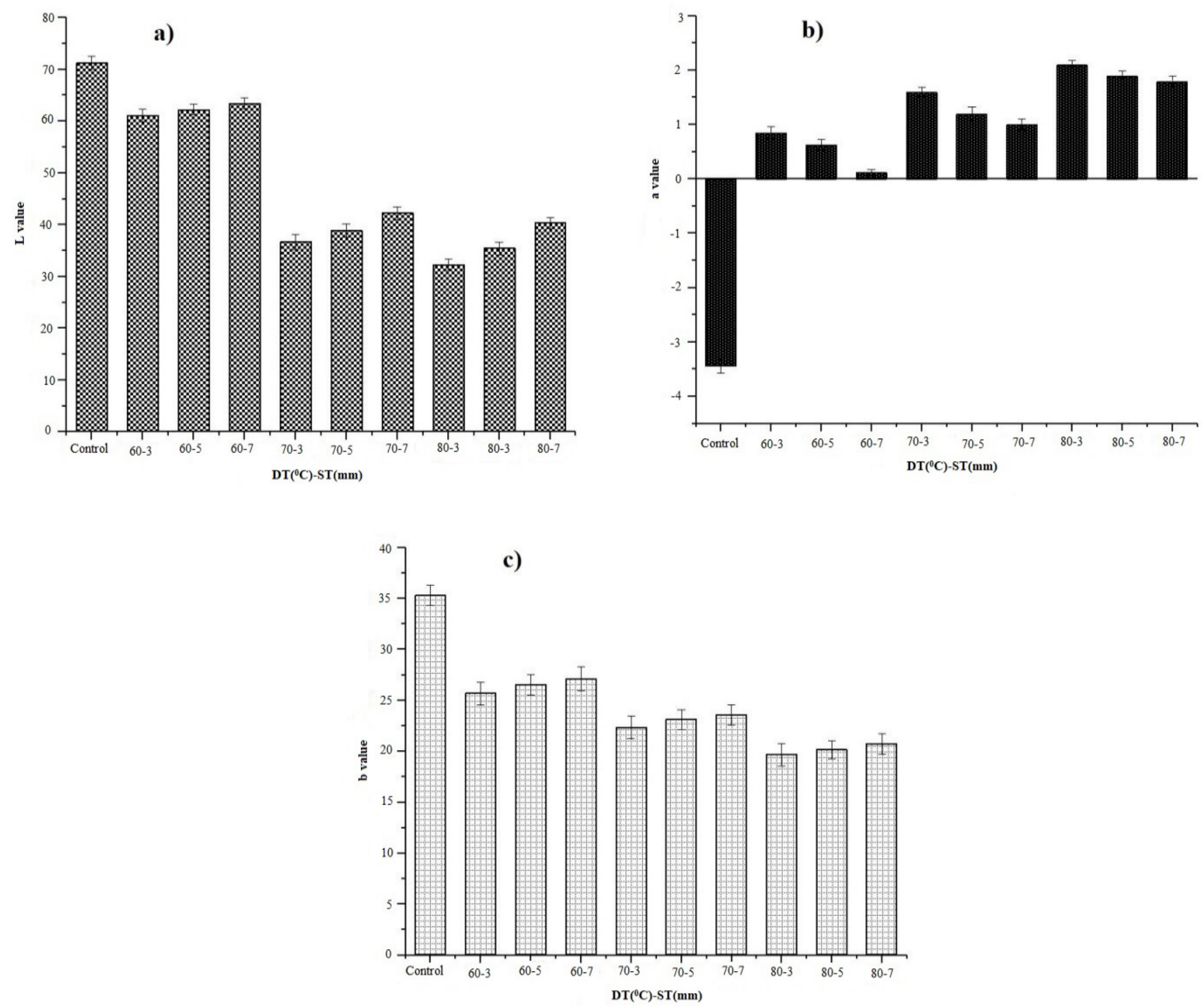


Figure 5 Color properties of different ginger dried samples

4.6 Application of POM for the sensory evaluation of dried ginger slices

Proportional odd modeling (POM) was applied for the sensory evaluation of dried ginger slices. Sensory evaluation was performed for overall acceptability of the dried ginger slices. Total twenty number judges gave scores for the overall acceptability of the dried samples in five point hedonic scale. The results of POM are represented in Table 3. 60-3 was considered as the reference sample for the POM analysis. By comparing the estimated coefficients with the reference sample, the ranking of the dried ginger samples can be written as 60-7>60-5>60-3>70-7>70-5>70-3>80-7>80-5>80-3. Hence, from the results of the POM it can be concluded that TD of 60^{o}C and ST of 7 mm (60-7) is the best dried ginger sample with highest overall acceptability.

Table 3 Results of POM for the sensory evaluation dried ginger slices

Coefficients:	Estimated values	Standard Error	t value
60-5	0.2423	0.6013	0.403
60-7	1.0033	0.6547	1.5324
70-3	-2.2305	0.6515	-3.4237
70-5	-1.2266	0.6138	-1.9985
70-7	-0.5025	0.6023	-0.8342

80-3	-4.2083	0.6597	-6.3788
80-5	-4.1212	0.6601	-6.243
80-7	-2.5903	0.6072	-4.2661
Intercepts:			
1|2	-4.4022	0.5537	-7.9511
2|3	-2.305	0.4722	-4.8814
3|4	-0.7804	0.4261	-1.8316
4|5	-0.2976	0.4233	-0.703

5 Conclusion

In the present investigation, simulation of the ginger drying process was studied by applying artificial neural network (ANN) and its inverse modeling aspects. Mapping of moisture ratio (MR) of the drying process as a function of temperature of drying (TD), slice thickness (ST) and drying time (DT) was accomplished based on ANN modeling approach. The ANN architecture, 3-5-1 was observed most suitable forpredicting the drying behavior of ginger slices. A novel technique of inverse neural network was established to predict the drying time of ginger slices under given TD and ST for desired final moisture content. Effective diffusivity of the drying process as estimated by the application of ANN (3-5-1) integrated Fick's law approach varied from 6.92×10^{-11} to 2.87×10^{-11} m^2 s^{-1}. Color analysis of the dried products showed best quality for the ginger samples treated at TD of 60°C and ST of 7 mm (60-7). Further, proportional odd modeling (POM) approach, applied for the sensory evaluation of the dried products also showed highest acceptability for the 60-7 ginger dried products. Therefore, the present study will be helpful as a pioneering aspect of research in order to efficiently control and simulate the ginger drying process.

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Conflict of Interest

The authors declare no conflict of interest.

References

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. *Journal of Food Research*, 3(5): 103.

Akpinar, E. K., and S. Toraman. 2013. Estimation of the moisture diffusivity and activation energy in thin layer drying of ginger slices. *International Journal of Nutrition and Food Engineering*, 7(6): 415-418.

Akpinar, E. K., and S. Toraman. 2016. Determination of drying kinetics and convective heat transfer coefficients of ginger slices. *Heat and Mass Transfer*, 52(10): 2271-2281.

Alakali, J. S., and A. A. Satimehin. 2004. Drying kinetics of ginger. *Nigerian Food Journal*, 22(1): 105-111.

An, K., D. Zhao, Z. Wang, J. Wu, Y. Xu, and G. Xiao. 2016. Comparison of different drying methods on Chinese ginger (Zingiber officinale Roscoe): Changes in volatiles, chemical profile, antioxidant properties, and microstructure. *Food Chemistry*, 197: 1292-1300.

Borah, P. K., S. Chakraborty, A. N. Jha, S. Rajkhowa, and R. K. Duary. 2016. In silico approaches and proportional odds model towards identifying selective adam17 inhibitors from anti-inflammatory natural molecules. *Journal of Molecular Graphics and Modelling*, 70: 129-139.

Chakraborty, S., S. P. Gautam, P. P. Das, and M. K. Hazarika. 2019. Instant controlled pressure drop (dic) treatment for improving process performance and milled rice quality. *Journal of The Institution of Engineers (India): Series A*, 100(4): 683-695.

Chakraborty, S., M. Sarma, J. Bora, S. Faisal, and M. K. Hazarika,. 2016. Generalization of drying kinetics during thin layer drying of paddy. *Agricultural Engineering International: CIGR Journal*, 18(4): 177-189.

Dash, K. K., S. Chakraborty, and Y. R. Singh. 2020. Modeling of microwave vacuum drying kinetics of bael (Aegle Marmelos l.) pulp by using artificial neural network. *Journal of The Institution of Engineers (India): Series A*, 101(4): 1-9.

Desai, K. M., S. A. Survase, P. S. Saudagar, S. S. Lele, and R. S. Singhal. 2008. Comparison of artificial neural network (ANN) and response surface methodology (RSM) in fermentation media optimization: case study of fermentative production of scleroglucan. *Biochemical Engineering Journal*, 41(3): 266-273.

Deshmukh, A. W., M. N. Varma, C. K. Yoo, and K. L. Wasewar. 2014. Investigation of Solar drying of ginger (Zingiber officinale): Emprical modelling, drying characteristics, and quality study. *Chinese Journal of Engineering*, 2014(1): 1-7.

Erenturk, S., and K. Erenturk. 2007. Comparison of genetic algorithm and neural network approaches for the drying process of carrot. *Journal of Food Engineering*, 78(3): 905-912.

FAOSTAT. 2020. Production quantities of Ginger by country 2019. Available at: http://www.fao.org/faostat/en/#data/QC/visualize.

Fudholi, A., M. H. Ruslan, M. Y. Othman, A. Zaharim, and K. Sopian. 2013. Mathematical modelling of solar drying of thin layer ginger. *Latest Trends in Renewable Energy and Environmental Informatics*, 273-278.

Hazarika, M. K., and A. K. Datta. 2014. Estimation of drying rate constant from static bed moisture profile by neural network inversion. *CIGR Journal*, 16(1): 253-264.

Hoque, M. A., B. K. Bala, M. A. Hossain, and M. B. Uddin. 2013. Drying kinetics of ginger rhizome (Zingiber officinale). *Bangladesh Journal of Agricultural Research*, 38(2): 301-319.

Jayashree, E., R. Visvanathan, and J. Zachariah. 2014. Quality of dry ginger (Zingiber officinale) by different drying methods. *Journal of Food Science and Technology*, 51(11): 3190-3198.

Khawas, P., K. K. Dash, A. J. Das, and S. C. Deka. 2016. Modeling and optimization of the process parameters in vacuum drying of culinary banana (Musa ABB) slices by application of artificial neural network and genetic algorithm. *Drying Technology*, 34(4): 491-503.

Lemos, T. D. O., M. D. C. P. Rodrigues, I. A. R. De Lara, A. M. S. De Araújo, T. L. G., A. L. F. Pereira, and L. V. T. De Paula. 2015. Modeling the acceptability of cashew apple nectar brands using the proportional odds model. *Journal of Sensory Studies*, 30(2): 136-144.

Lee, J. S., B. Kim, J. H. Kim, M. Jeong, S. Lim, and S. Byun. 2019. Effect of differential thermal drying conditions on the immunomodulatory function of ginger. *Journal of Microbiology and Biotechnology*, 29(7): 1053-1060.

Loha, C., R. Das, B. Choudhury, and P. K. Chatterjee. 2012. Evaluation of air drying characteristics of sliced ginger (Zingiber officinale) in a forced convective cabinet dryer and thermal conductivity measurement. *Journal of Food Process Technology*, 3(130):2.

Meullenet, J. F., R. Xiong, J. A. Hankins, P. Dias, S. Zivanovic, M. A. Monsoor, and H. Fromm. 2003. Modeling preference of commercial toasted white corn tortilla chips using proportional odds models. *Food Quality and Preference*, 14(7): 603-614.

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 and Bioproducts Processing*, 89(4): 362-366.

Movagharnejad, K., and M. Nikzad. 2007. Modeling of tomato drying using artificial neural network. *Computers and Electronics in Agriculture*, 59(1-2): 78-85.

Murthy, T. P. K., and B. Manohar. 2014. Hot air drying characteristics of mango ginger: Prediction of drying kinetics by mathematical modeling and artificial neural network. *Journal of Food Science and Technology*, 51(12): 3712-3721.

Prasad, J., A. Prasad, and V. K. Vijay. 2006. Studies on the drying characteristics of Zingiber officinale under open sun and solar biomass (hybrid) drying. *International Journal of Green Energy*, 3(1):79-89.

Sarkar, T., M. Salauddin, S. K. Hazra, and R. Chakraborty. 2020. Artificial neural network modelling approach of drying kinetics evolution for hot air oven, microwave, microwave convective and freeze dried pineapple. *SN Applied Sciences*, 2(9): 1-8.

Wang, Z., J. Sun, X. Liao, F. Chen, G. Zhao, J. Wu, and X. Hu. 2007. Mathematical modeling on hot air drying of thin layer apple pomace. *Food Research International*, 40(1): 39-46.

Wankhade, P. K., R. S. Sapkal, and V. S. Sapkal. 2013. Drying characteristics of okra slices on drying in hot air dryer. *Procedia Engineering*, 51(3): 371-374.