Modeling and Optimization of Parameters affecting Drying of Corn Kernels (Zea Mays) in Convective Tray Dryer

Shraddha Pandya

Department of Petroleum Engineering,
Assistant Professor, Parul University, Vadodara, Gujarat, India
Shraddha.g.pandya@gmail.com

Abstract*: *The present work involves the application of artificial neural network (ANN) and response surface methodology (RSM) for corn kernels drying in a convective tray dryer. The process parameters which affect most the drying of corn kernels namely: air velocity (2-5 m/sec), amount of feed (50-100 g), temperature (50-80 °C) and drying time (30-60 min). These parameters affect the drying process tremendously. Predictive modelling has been done using RSM and ANN. With ANN, experimental results have been evaluated to train, test and validate so that behaviour of the system can be predicted. There were 10 neurons used for ANN model; LM (Levenberg-Marquardt) showed as a suitable training function; MSE as a performance function; GDM as a learning suitable function for simulation of drying operation. The coefficient of determination values (R) is 0.99916 for training, 0.99071 for validation, 0.96091 for test and 0.97527 for all the results, value of MSE is 0.0002. Experimental and predicted moisture removal regression coefficient is 0.8085 and 0.9348 with RSM and ANN model, respectively. ANN model shows better behaviour than Box-Behnken design.

***Keywords*: Box-Behnken design, Corn kernels, Convective drying, Artificial Neural Network**

(Article history: Received: 5th February 2021 and accepted 13th June 2021)

I. INTRODUCTION

Drying is an essential industrial operation, widely used for agriculture products. It preserves material, decreases microbial activity and increases shelf life of the product for further processing. The moisture from agriculture product is removed through indirect heating. Conventionally, it is done utilizing solar heating and material is dried under sunshine. However, at commercial scale hot air at a moderate temperature is passed through the mass to minimize chemical and biochemical deterioration. In many instances, heat is not desired at all due to degradability of the product, in those situations unsaturated air at room temperature is allowed to flow through the bed of food material to be dried [1]. However, in countries like Canada, Europe and some part of US, sun is not available round the year. Therefore, it becomes essential making the drying process economically viable [2].

Currently, Indian growers produce nearly 24.2 million tonnes of maize per annum from close to 9.0 million hectares of land. India's yield of maize is approximately 3 tonnes per hectare, which put India at 91st place out of 168 maize growing countries [3,4]. A detailed experimental study is needed for optimizing the drying process of corn due to several applications of dried corn kernels. An engineering aspect is required where drying conditions under a certain process reaches its optimum response [5]. Using a suitable model, the final moisture content of the product can be predicted, and therefore, different models are used as evaluation tools for time of drying prediction and its optimum values prediction for better product quality. However, these models required a long computation time and the equations generated are complex to solve. These hindrances can be avoided in response surface methodology which is generally a quadratic model and less complex to solve [6,7,8].

The Box-Behnken method was used to find minimum numbers of experiments to determine the optimized parameters with the best response surface methodology and artificial neural network (ANN) using MATLAB software. Data obtained from designed experiments using RSM were used as input for ANN. Once trained network using experimental data developed then a predictive model for percentage of drying can be established. ANN develops better predictive models than response surface methodology [9,10,11,12].

II. MATERIAL AND METHOD

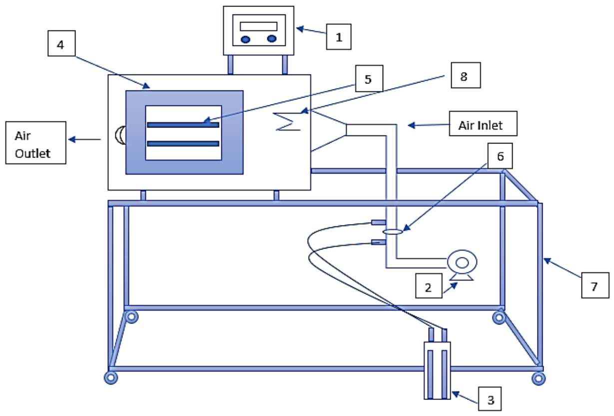
A. Material

Corn was brought from a local market at Ankleshwar, Gujarat, India. Corn silk and husk were removed before recovering corn kernels manually. Corn kernels were extracted in an appropriate homogeneous shape without any shrinkage. A specified amount of corn was purchased, and all experiments were performed as per conditions specified in the Box-Behnken design.

B. Method

Total initial moisture in corn kernels was evaluated by keeping it in an air-drying oven at 60 °C for 24 hours. Initial moisture content present in corn kernels was 62 % by weight. The equipment tray dryer consists of a drying chamber (40 x 30 x 30 cm^3), made of mild steel and insulated with glass wool (25 mm thick), cladded with stainless steel sheet. In the chamber, tray can be slid on the rack support. Volume of the tray was specified as 22 x 22 x 1.2 cm^3. A blower was attached to the drying chamber for hot air supply. To measure the temperature and humidity in the air, thermocouples are mounted at either ends of the drying chamber. To control the temperature and air flow rate, a digital temperature controller, temperature indicator, on/off starter switch for blower, mcb for heater and a fuse were mounted on a control panel which is attached to the tray to the tray dryer. Fig. 1 and 2 show schematic diagram and working of lab scale convective tray dryer respectively.

Minimum and maximum range of parameters were decided based on equipment limitations and requirement of the process. Air velocity was kept low enough so that particles of corn could not be fluidized. The temperature range was set to preserve nutrients in corn kernels. An amount of sample was decided based on the capacity of the tray dryer. Considering all these aspects, single layer corn drying was performed [13,14,15].



1 –Temperature Sensor
2 – Air Blower
3 –U-Tube Manometer
4 – Tray Chamber
5 – Tray
6 – Orifice Meter
7 – Supporting Stand
8 – Heating Coil

Fig. 1. Schematic diagram of convective tray dryer

Fig. 2. Working of convective tray dryer

III. MOISTURE REMOVAL MODELS

A. *Response Surface Methodology (RSM)*

Final graphical representation of behaviour of drying process can be shown by RSM. The permutations and combination of parameters shown in (1) give the final graphical representation

$$Y = f(x_1, x_2, x_3, \ldots, x_n) \quad (1)$$

Where Y is the response and x_1, x_2, x_3, …x_n are the parameters used in design.

A Box-Behnken method with three levels was utilized to evaluate the effect of parameters on drying of corn kernel. The four parameters were coded at three levels that are +1, 0, and -1 with same step size, where +1 represents the maximum value, 0 represents to the centre value and -1 represents the minimum value of each parameter, which is considered for analysis. Within the present research framework, the discussion was focused on the effect of amount of corn kernel (x_1), temperature (x_2), velocity of hot air (x_3) and drying time (x_4). To find the optimum conditions, a quadratic model is used to relate the dryness of corn kernel to parameters. This model can be shown by (2)

$$Y = \alpha_0 + \sum_{j=1}^{n} \alpha_j x_j + \sum_{j=1}^{n} \alpha_{jj} x_j^2 + \sum_{j=1}^{n-1} \sum_{k=2}^{n} \alpha_{jk} x_j x_k + \delta \quad (2)$$

Where Y is the moisture present in the corn kernels with set of parameters experimented, α's are the coefficients and x's are the parameters. Response surface methodology uses the experimental data points of the design matrix to a proposed model and the unknown coefficients. To find the minimum number of experimental runs required for Box-Behnken design, one can use (3)

$$N = 2N_f (N_f - 1) + C_p \quad (3)$$

Where Nf is the number of parameters used to fit the model and Cp is the number of the central points. To evaluate the coefficient values 27 experiments were carried out according to the Box-Behnken design. The set of a regression coefficient 'α' is unknown and estimated by least squares. In a vector matrix, the equation for the least square fit is given by (4)

$$Y = X\alpha + \delta \quad (4)$$

Where, Y is defined as the measured value and X is matrix of parameters. The common equation for Box-Behnken method is given by (5)

$$Y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 + \alpha_5 x_1^2 + \alpha_6 x_2^2 + \alpha_7 x_3^2 + \alpha_8 x_4^2 + \alpha_9 x_1 x_2 + \alpha_{10} x_1 x_3 + \alpha_{11} x_1 x_4 + \alpha_{12} x_2 x_3 + \alpha_{13} x_4 x_2 + \alpha_{14} x_3 x_4 + \delta \quad (5)$$

Where Y is response and x_1, x_2, x_3 and x_4 are the independent parameters. α_0 is the constant coefficient, α_1, α_2, α_3, α_4 are the coefficient for linear effect, α_5, α_6, α_7, α_8 are the coefficient for quadratic effect, α_9, α_{10}, α_{11}, α_{12}, α_{13}, α_{14} are the coefficients for the interaction effect and δ is the error.

B. *Artificial Neural Network*

Artificial neural network (ANN) is a collection of various nodes called artificial neurons. Artificial neurons are organized in one or multiple layers. Each layer performs different modifications on inputs. Signals are passed from input to output after crossing the layers multiple times. The layer having number of neurons is called hidden layer [16,17,18,19].

Sr. No.	Transfer function	Training function
1	Logsig (log sigmoid)	CGP (Polak-Ribiere conjugate gradient back propagation)
2	Purelin (pure linear)	RP (Resilient back propagation)
3	Tansig (tangent sigmoid)	LM (Levenberg-Marquardt back propagation)
4	-	BFG (BFGS quasi-newton back propagation)

Table I. Transfer functions and Training functions used in ANN training

The input details pass through input layer to hidden layer and finally to output layer and appears in the network. Each node in the hidden or output layer will give combine result and modify the input from previous layer [18,19]. Equation (6) can be used to identify the output [24].

$$y_i = \sum_{j=1}^{p} x_i \times w_{ij} + b_j \qquad (6)$$

Where y_i is the net input to node j in hidden or output layer, i is the number of nodes, x_i is the inputs to node j (or the outputs of the previous layer), w_{ij} is the weights representing the strength of the connection between the i^{th} node and j^{th} node and b_j is the bias associated with node j.

In order to train the neural network, all the experiments data obtained from preliminary study and designed experiments using RSM were used. The more input data feed to ANN, better the training of network will be done. All the data points were distributed for training, testing and validation as 80%, 10%, 10% respectively. Input layer consists of four parameters viz., temperature, amount of corn, air velocity and time of drying and output layer consists of percentage of drying. By applying different training function, performance function, number of layers, numbers of neurons, transfer function and learning function, the train network of various sets was analyzed to optimize the model.

IV. Methodology for Development of Optimal ANN Configuration

This iterative method was used to find an appropriate ANN model with minimum error. The performance of ANN model was measured by mean absolute error (MAE), Root mean squared error (MRSE), standard error (SE) and Correlation coefficient (r^2) using (7), (8), (9) and (10) respectively:

$$Mean\ Absolute\ error = \frac{1}{N}\sum_{i=1}^{N}[\bar{T}_{p,exp,i} - \bar{T}_{p,cal,i}] \qquad (7)$$

$$Root\ mean\ square\ error = \left[\frac{1}{N}\sum_{i=1}^{N}(\bar{T}_{p,exp,i} - \bar{T}_{p,cal,i})^2\right]^{1/2} \qquad (8)$$

$$Standard\ error = \frac{\sqrt{\sum_{i=1}^{N}(T_{p,exp,i} - T_{p,cal,i})^2}}{N-1} \qquad (9)$$

$$Correlation\ coefficient\ (R^2) = \sqrt{\frac{\sum_{i=1}^{N}(T_{p,exp,i} - \bar{T}_{p,exp,i})^2 - \sum_{i=1}^{N}(T_{p,exp} - T_{p,cal,i})^2}{\sum_{i=1}^{N}(T_{p,exp,i} - \bar{T}_{p,exp,i})^2}} \qquad (10)$$

In these equations $T_{p,exp,i}$ and $T_{p,cal,i}$ are the average experimental and predicted drying times for the *i*th observation, respectively and N is the number of observations. A list of different transfer function and training function investigated in this work are listed in Table 1.

Transfer functions such as logarithmic sigmoid (logsig), tangent hyperbolic (tansig) and linear transfer function (purelin) are defined by (11), (12) and (13) respectively

$$logsig(x) = \frac{1}{1+e^{-x}} \qquad (11)$$

$$tansig(x) = \frac{2}{1+e^{-2x}} - 1 \qquad (12)$$

$$purelin(x) = x \qquad (13)$$

Initially, ANN model was analyzed with random numbers of neurons and with a randomly chosen training and transfer function. A combination of different training and transfer function at different hidden neurons were investigated. Influence of one parameter on other parameters was studied by keeping other parameters constant. Subsequently, each of a model parameter was varied. This iterative procedure for performance assessment was continued until the most appropriate model that simulates minimum errors defined in (7) to (10) was obtained.

In order to achieve an optimal number of neurons, the ANN was trained with varying numbers of neurons and randomly chosen tansig transfer function and LM as a training function as shown in Table 2. Minimum 1 neuron to maximum 1000 neurons were simulated with the said algorithm. Errors were changed with respect to the number of neurons, and no relation was found with increasing or decreasing number of neurons. Simulation with 10 neurons was found satisfactorily minimum value of errors in comparison to be lower for higher values of neurons. Thus, it is selected for studying the effect of training and transfer function on a model.

For further refinement of model with transfer and training function, ANN model with 10 neurons and randomly chosen training function with different transfer functions was simulated to find optimal transfer function. Sensitivity study of different transfer function (11) to (13) showed minimum errors of measurement (7) to (10). It can be seen from Table 3 that the network with tansig transfer function performs the best in terms of errors.

In order to obtain accuracy in ANN model, there is a requirement to investigate the effect of several training algorithms expressed at 10 neurons and tansig transfer function. Results of errors with different training function with fixed parameters such as the number of neurons and transfer function are shown in Table 4 and LM was provided the best training function in terms of minimum errors of measurement. However, the errors were much higher in other training functions simulation.

TABLE II. SELECTION OF NUMBER OF NEURONS BY TAKING LM AS TRAINING AND TANSIG AS TRANSFER FUNCTION

No. of Neurons	**Measure of Errors**			
	MAE	***RMSE***	***SE***	***R^2***
1	2.32	3.61	4.42	0.78
2	2.82	3.9	6.8	0.84
4	2.1	2.8	5.6	0.89
5	3.2	4.5	8.71	0.17
9	3.5	6.3	6.14	0.42
10	2.42	3.85	6.92	0.86
11	2.28	4.2	4.15	0.83
100	4.54	7.04	8.1	0.44
500	2.5	3.7	4.5	0.8
950	3.3	6.8	6.8	0.65
1000	2.5	2.7	4.7	0.89

TABLE III. SELECTION OF TRANSFER FUNCTION

Measure of Errors	**Transfer functions**		
	tansig	***logsig***	***purelin***
MAE	0.02	2.64	2.1
RMSE	0.5	3.3	3.14
SE	0.001	3.21	3.21
R^2	0.94	0.84	0.85

TABLE IV. SELECTION OF TRAINING FUNCTION

Measure of Error	**Training function**			
	BFG	***CGP***	***RP***	***LM***
MAE	2.13	1.95	2.06	2
RMSE	3.43	3.2	3.3	3.38
SE	3.5	3.08	3.21	3.36
R^2	0.8	0.87	0.83	0.921

Based on iterative simulation of a number of neurons, transfer and training function, it can be concluded that the neural network model with 10 neurons, tansig transfer function, LM training function and cascade forward back propagation algorithm gives the best accuracy in terms of lowest error measurement and considered the most appropriate ANN model. Fig. 3 shows architecture of ANN.

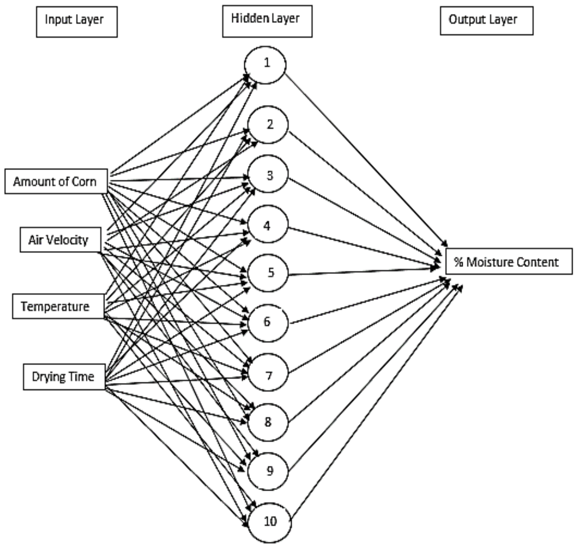


Fig. 3. Architecture of ANN model for input, hidden and output layers

V. RESULT AND DISCUSSION

A. Box-Behnken Design Results

A matrix was obtained using (3). Table 5 shows level of four variables for designing of Box-Behnken design. Table 6 describes the matrix with experimental values according to the coded set. Center value 0 was repeated three times (experiment no 25, 26, 27) to ensure the results and less than 2 % error was obtained. It confirms the reproducibility of the data.

TABLE V. THE LEVEL OF VARIABLES

Parameters	**Low(-1)**	**Centre(0)**	**High(1)**
x_1 (Amount of feed)	50	75	100
x_2 (Temperature)	50	65	80
x_3 (Air Velocity)	2	3.5	5
x_4 (Drying Time)	30	45	60

Each set of parameters for a run was decided based on Box-Behnken design. Lower values are designed as -1, maximum value by +1 and center value as 0.

A relationship between moisture removal and influencing parameters was obtained by correlating experimental results with response functions using the Microsoft Excel 2016 regression program. The quadratic model describing the response function with regression coefficients for moisture removal from corn kernels is given by (14)

$$\%Y_d = -54.051 + 0.1302x_1 + 0.177x_2 + 11.799x_3 + 0.623x_4 + 0.00302x_1^2 + 0.0x_2^2 - 0.803x_3^2 + 0.0003x_4^2 - 0.0009\, x_1*x_2 - 0.0107\, x_1*x_3 - 0.0097\, x_1*x_4 - 0.071\, x_2*x_3 + 0.0072\, x_2*x_4 + 0.0008\, x_3*x_4 \quad (14)$$

Where $\%Y_d$ is percentage moisture removal and it is defined by (15)

$$\%Y_d = \frac{Total\ moisture - moisture\ retained}{Total\ moisture} * 100 \qquad (15)$$

x_1 = Amount of corn (gm); x_2 = Temperature (°C); x_3 = Air velocity (m/sec); x_4 = drying time (min).

It was inferred from (14) and Table 6 that moisture removal ($\%Y_d$) can be fitted with the developed quadratic polynomial equation.

Maximum 3 % error was observed between experimental and predicted values of moisture removal from corn kernels. Positive coefficient indicated a linear effect to increase Y_d and negative coefficient indicated a linear effect to decreased Y_d [21-23].

B. Effect of amount of corn, drying temperature, hot air velocity and drying time on moisture removal

The behavior and extent of interaction of parameters are shown with 3D plots Fig. 4 (a) to 4 (f). Fig. 4 (a) shows the effect of amount of corn and temperature on moisture removal. The moisture removal Y_d can be increased with increasing drying temperature and drying time. The moisture removal increases with the increase in amount of corn [20]. However, a saddle point at 75 gm of corn amount is observed. It can be explained as the amount of corn increases, total moisture present is also increased. In contrast to that the efficiency of moisture removal decreases with increasing amount of corn by keeping other parameters constant. Temperature relatively has a linear effect on an increase in moisture removal.

Fig. 4 (b) and 4 (c) shows the effect of amount of corn with air velocity and drying time with moisture removal, respectively.

TABLE VI. ACTUAL VALUES OF PARAMETERS AND MOISTURE RESPONSE

Run no	Actual values				Experimental Result
	x_1 (g)	x_2 (°C)	x_3 (m/sec)	x_4 (min)	% Moisture removal
1	50	50	3.5	45	9.68
2	50	80	3.5	45	35.48
3	100	50	3.5	45	9.68
4	100	80	3.5	45	34.19
5	75	65	2	30	10.76
6	75	65	2	60	21.45
7	75	65	5	30	15.05
8	75	65	5	60	25.81
9	50	65	3.5	30	9.68
10	50	65	3.5	60	32.26
11	100	65	3.5	30	16.13
12	100	65	3.5	60	24.19
13	75	50	2	45	10.76
14	75	50	5	45	10.76
15	75	80	2	45	27.95
16	75	80	5	45	21.5
17	50	65	2	45	16.13
18	50	65	5	45	22.58
19	100	65	2	45	16.13
20	100	65	5	45	20.97
21	75	50	3.5	30	10.76
22	75	50	3.5	60	17.21
23	75	80	3.5	30	19.35
24	75	80	3.5	60	32.26
25	75	65	3.5	45	19.35
26	75	65	3.5	45	19.35
27	75	65	3.5	45	19.35

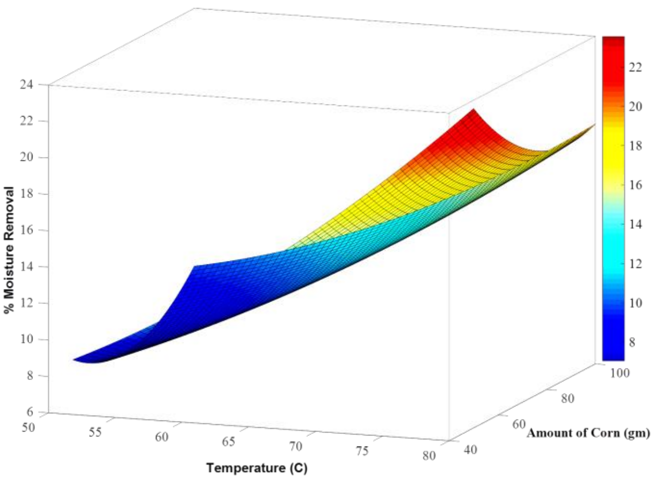


Fig 4.a. Effect of Temperature and Amount of corn on % moisture removal

The behaviour with increasing amount of corn is similar as Fig. 4 (a), increasing amount of corn had increased unbound moisture with constant air velocity and drying time. It depicts that moisture removal is also increased as the unbound moisture increases.

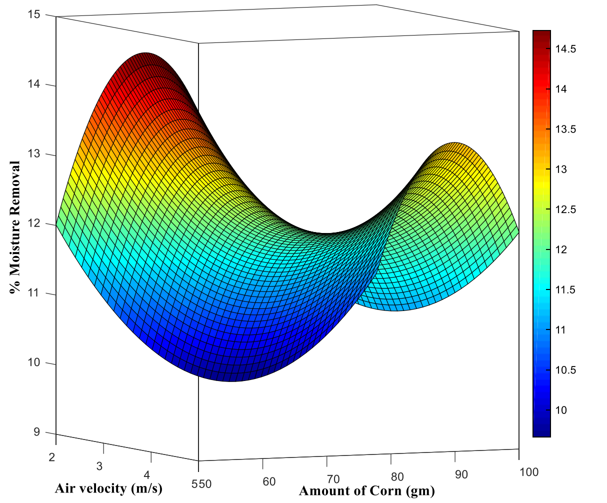


Fig. 4.b. Effect of air velocity and amount of corn on % moisture removal

In Fig. 4 (c), it is revealed that at 100 gm amount of corn, 24.62 % moisture is removed at 20 min of drying time, which shows the minimum value of time and maximum amount of corn.

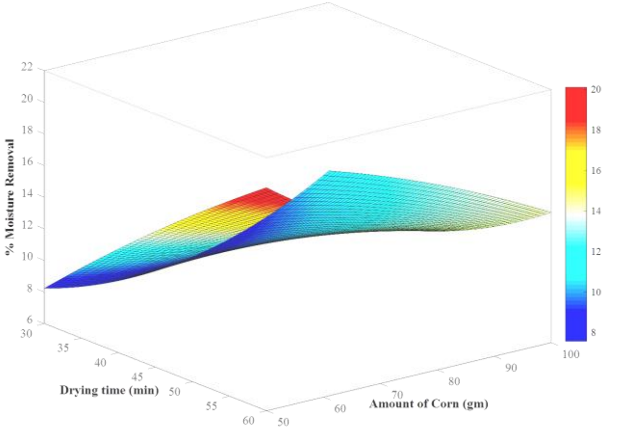


Fig 4.c. Effect of drying time and amount of corn on % moisture removal

It had maximum unbound moisture and sufficient drying time was not available so it showed a minimum point.

Fig. 4 (d) and 4 (e) shows the effect of temperature with air velocity and drying time, respectively. Temperature in both Fig. shows a linear increasing behaviour with moisture removal.

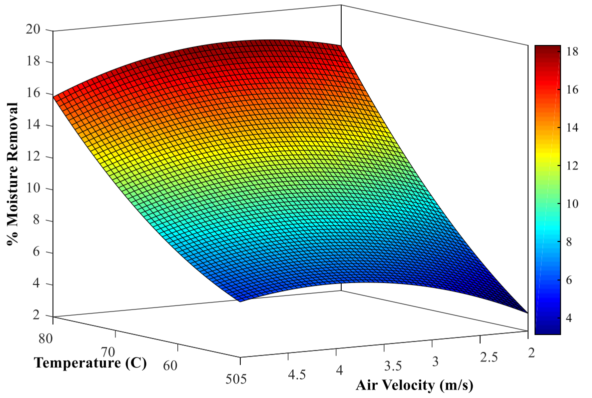


Fig 4.d. Effect of temperature and air velocity on % moisture removal

Moreover, air velocity and drying time are also discerned as linear parameters with moisture removal.

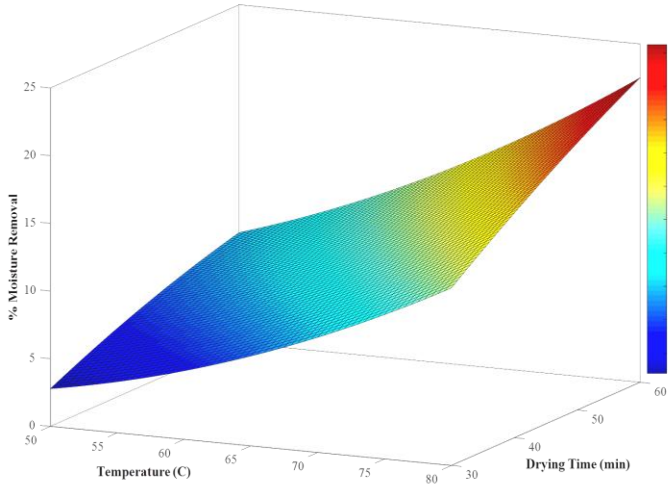


Fig 4.e. Effect of temperature and drying time on % moisture removal

Figure 4 (f) demonstrates the behaviour of drying time and air velocity with moisture removal.

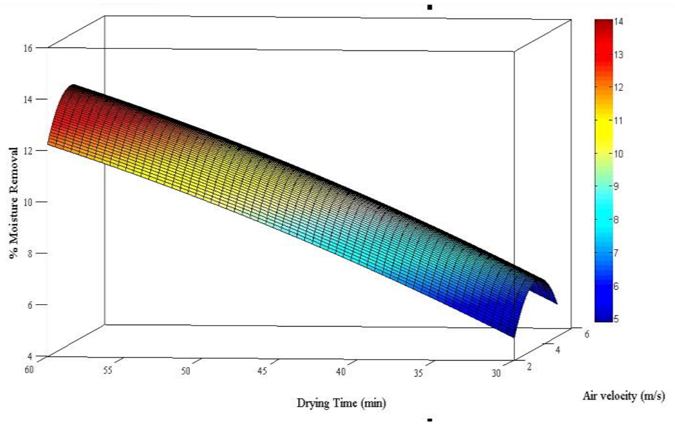


Fig 4.e. Effect of drying time and air velocity on % moisture removal

At air velocity of 2 m/sec with 30 min of drying time, the moisture removal is 12 %, the moisture removal is increased substantially when both the parameters are at their maxima. From the above investigations, it can be concluded that the moisture removal of corn kernels is affected by all parameters: amount of corn kernels, drying time, air velocity and temperature. The optimum conditions for removing moisture were 50 gm of corn kernels, 80^{0}C temperature, 3.5 m/sec air velocity and 60 min drying time.

C. Analysis of variance (ANOVA) Results

The significance of each coefficient was determined by Fisher's *F* test and *P* value, the larger *F* value and smaller *P* value suggest the more significance for the corresponding coefficient.

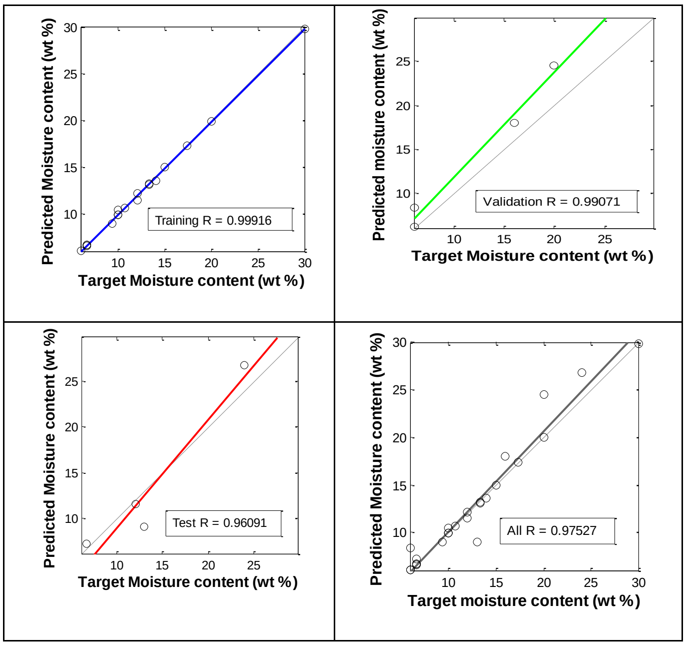
TABLE VII. ANALYSIS OF VARIANCE (QUADRATIC MODEL)

Source	Degree of freedom	Sum of square error	Mean square error	F-Value	P-Value

x_1	1	5.33	5.33	0.05	0.828
x_2	1	456.087	456.087	0.03	0.877
x_3	1	5.824	5.824	1.64	0.224
x_4	1	163.54	163.54	0.41	0.536
x_1* x_1	1	19.051	19.051	0.87	0.51
x_2* x_2	1	9.12	9.12	0.95	0.349
x_3* x_3	1	13.19	13.19	0.16	0.695
x_4* x_4	1	0.875	0.875	1.22	0.291
x_1* x_2	1	9	9	0	0.965
x_2* x_3	1	0.250	0.250	0.87	0.545
x_1* x_4	1	20.25	20.25	0.03	0.867
x_2* x_3	1	4.00	4.00	0.05	0.835
x_2* x_4	1	4.00	4.00	3.68	0.079
x_3* x_4	1	0.00	0.00	0.73	0.411
Residual Error	12	171.81	17.81	-	-
Lack-of-fit	10	171.81	17.181	-	-
Pure error	2	0.00	0.00	-	-

Data in Table 7 showed that, for convective tray drying, all linear components in the experimental model were significant (P < 0.5) with drying time having the strongest effect on the moisture removal.

Mutual interaction effect on process parameters played a dominant role in moisture removal. Coefficients of interaction of drying time with temperature and temperature - velocity was observed positive. However, other interactions with the amount of corn were depicted with a negative coefficient. These observations rationalized drying time has the most significant effect on moisture removal. It is also confirmed with P value.



D. Model validation

The objective of the present study was to optimize the batch drying of corn kernels using RSM to observe the parameters which are affecting most processes of drying for further application of corn kernels. It has been observed that all parameters have a positive effect on drying of the corn kernels. MATLAB has been used to optimize different parameters and to get an optimum response between maximum and minimum limit of parameters.

The parameters 50 gm of corn kernels, 80 °C drying temperature, 3.5 m/sec velocity of air, and 60 min time of drying can remove 42 % of moisture. A confirmation of experiments has been performed in triplicate based on predicted and shows ± 3% error. This indicates that Box Behnken design and ANN in conjunction with ANOVA can be applied efficiently to optimize the design of experiments for drying of corn kernels. Results are mentioned in Table 8.

TABLE VIII. MODEL VALIDATION

Run no	**x_1, gm**	**x_2, °C**	**x_3, m/sec**	**x_4, min**	**Y_d, experimental value**	**Y_d, predicted**	**% error**
28	50	80	3.5	60	42.34	42.06	0.6
29	50	80	3.5	60	42.52	42.06	1.08
30	50	80	3.5	60	42.32	42.06	0.61

E. Artificial Neural Network (ANN) Results

Fig. 5 shows the scatter regression plot of ANN model predicted versus experimental values for the training, validation, testing and all data set with resulting coefficients of 0.99916, 0.99071, 0.96091 and 0.97527 respectively and MSE for the entire data set was 0.0002. An investigated ANN model fits well and the accuracy of the model is high.

F. Comparison of ANN and RSM modeling

Comparison between both the models is done by plotting experimental result versus predicted results. From Fig. 6 shows that ANN is better model and gives reliable results than RSM. Coefficient of regression (R^2) of ANN shows minimum error and maximum curve fitting.

Fig. 5. Scatter plots of ANN model predicted vs. Actual results

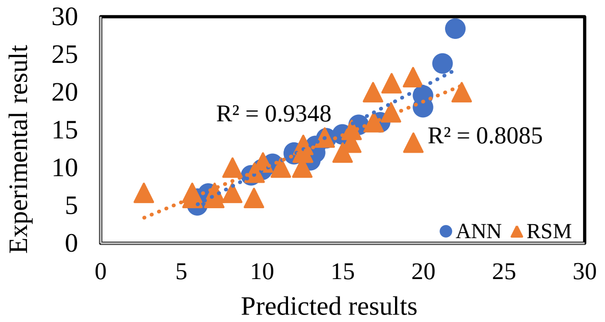


Fig. 6. Comparison of RSM and ANN modelling

VI. Conclusion

In this study, a trainable cascade forward back-proportion network was proposed to correlate the drying of corn kernels in the convective tray dryer for four parameters at different conditions. The proposed ANN model which was consisted of one hidden layer, was trained using LM function. A trial and error approach were used to select *tangent sigmoid* as the best transfer function. The obtained results revealed that the optimum of neurons in the hidden layer was 10 neurons. RSM model validates all parameters and their interaction effect on moisture removal. ANOVA results give *F*-Values and *P*-Values, which indicate feasibility and liability of work.

It can be concluded that all parameters: amount of corn kernels, temperature, air velocity and drying time affect drying of corn kernels in a convective tray dryer. Prediction using RSM model was compared with ANN model. This comparison revealed that the proposed ANN model more accurately correlates the drying of corn kernels compared to RSM. RSM and ANN simulation show coefficient of regression 0.8085, and 0.9348, respectively. The results show ANN gives the better fits for experimental results.

References

[1] R. K. Sahdev, M. Kumar, A.K. Dhingra, "Effect of mass on convective heat transfer coefficient during open sun drying of groundnut", Journal of Food Science and Technology, Vol. 54, No. 13, 2017, 4510–4516.

[2] S. Soponronnarit, A. Pongtornkulpanich, S. Prachayawarakorn, "Drying characteristics of corn in fluidized bed dryer", Drying Technology, Vol. 15, No. 5, 1997, 1603-1615.

[3] L. Momenzadeh, A. Zomorodian, D. Mowla, "Experimental and theoretical investigation of shelled corn drying in a microwave-assisted fluidized bed dryer using Artificial Neural Network", Food and Bioproducts Processing, Vol. 89, No. 1, 2011, 15-21.

[4] S. Roshanak, M. Rahimmalek, S. A. H. Goli, "Evaluation of seven different drying treatments in respect to total flavonoid, phenolic, vitamin C content, chlorophyll, antioxidant activity and color of green tea (Camellia sinensis or C. assamica) leaves". Journal of Food Science and Technology, Vol. 53, No. 1, 2016, 721–729.

[5] W. Shuo, W. Zhenhua, W. Fenghe, W. X. Pengxiao C., Y. Deyong, "Simulation and experimental studies of heat and mass transfer in corn kernel during hot air drying", Food and Bioproducts Processing, Vol. 117, 2019, 360–372.

[6] A. Witek, K. Katarzyna, C. D. Podstawczyk, A.D.K. Pokomeda, "Application of response surface methodology and artificial neural network methods in modelling and optimization of biosorption process", Bioresource Technology, Vol. 160, 2014, 150-160.

[7] A. Kovács, E. Lakatos, G. Milics, M. Neményi, "Finite Element Modeling of Coupled Heat and Mass Transfer of a Single Maize Kernel Based on Water Potential Using COMSOL Multiphysics Simulation", Proceedings of the COMSOL Conference 2010 Paris, 2010.

[8] M. Kaveh, A. Jahanbakhshi, Y. Abbaspour-Gilandeh, E. Taghinezhad, M.B.F. Moghimi, "The effect of ultrasound pre-treatment on quality, drying, and thermodynamic attributes of almond kernel under convective dryer using ANNs and ANFIS network", Journal of Food Process Engineering, 12868, 2018.

[9] P. Khawas, K.K. Dash, A.J. Das, S.C. Deka, "Modeling and optimization of the process parameters in vacuum drying of culinary banana (Musa ABB) slices by application of artificial neural networkand genetic algorithm", Drying Technology, Vol. 34, No. 4, 2016, 491–503.

[10] M.S.H. Kalathingal, S. Basak, J. Mitra, "Artificial neural network modeling and genetic algorithm optimization of process parameters in fluidized bed drying of green tea leaves", Journal of Food Process Engineering, 13128, 2019.

[11] F. Karimi, S. Rafiee, A. Taheri-Garavand, M. Karimi, "Optimization of an air drying process for Artemisia absinthium leaves using response surface and artificial neural network models", Journal of the Taiwan Institute of Chemical Engineers, Vol. 43, No.1, 2012, 29–39.

[12] M. Aramide, S.O. Akintunde, E.B. Ajala, "Optimization of Bauhinia monandra seed oil extraction via artificial neural network and response surface methodology: A Potential biofuel candidate", Industrial Crops and Products, Vol. 67, 2015, 387-394.

[13] I. Doymaz, "Thin-layer drying of spinach leaves in a convective dryer", Journal of Food Process Engineering, Vol. 32, 2009, 112–125.

[14] M. Gur & M. Gur, "Comparing Corn Drying in Fluidized Bed Dryer and Convective Tray Dryer. In: Dincer I., Midilli A., Kucuk H. (eds)", Progress in Exergy, Energy, and the Environment, Springer, Cham, 2014.

[15] R.S. Pohndorf, G.H. Lang, C.D. Ferreira, V. Ziegler, J.T. Goebel, M. De Oliveira, "Kinetic evaluation and optimization of red popcorn grain drying: Influence of the temperature and air velocity on the expansion properties and β-carotene content", Journal of Food Process Engineering, 13204, 2019.

[16] M. Beigi, M. Torki-Harchegani, M. Tohidi, "Experimental and ANN modeling investigations of energy traits for rough rice drying", Energy, Vol. 141, 2196–2205.

[17] C.R. Chen, H.S. Ramaswamy, I. Alli, "Prediction of quality changes during osmo-convective drying of blueberries using neural network models for process optimization", Drying Technology, Vol. 19, No. 3-4, 2001, 507–523.

[18] P. P. Tripathy, S. Kumar, "Neural network approach for food temperature prediction during solar drying", International Journal of Thermal Sciences, Vol. 48, No. 7, 2009, pp. 1452-1459.

[19] A. Omari, N. Behroozi-Khazaei, F. Sharifian, "Drying kinetic and artificial neural network modeling of mushroom drying process in microwave-hot air dryer", Journal of Food Process Engineering, 12849, 2018.

[20] S. Acharya, S.K. Sharma, G. Chauhan, D. Shree, "Statistical Optimization of Electrocoagulation Process for Removal of Nitrates Using Response Surface Methodology", Indian Chemical Engineer, Vol. 60, No. 3, 2018, 269-284.

[21] A.M. Tayeb, M. A. Tony, S. A. Mansour, "Application of Box–Behnken factorial design for parameters optimization of basic dye removal using nano-hematite photo-Fenton tool", Applied Water Science, Vol. 8, 2018, 138

[22] T. Aktas, S. Fujii, Y. Kawano, S. Yamamoto, "Effects of pretreatments of sliced vegetables with trehalose on drying characteristics and quality of dried products", Food and Bioproducts Processing, Vol. 85, No. 3, 2007, pp. 178–183.

[23] G. Cuccurullo, L. Giordano, A. Metallo, L. Cinquanta, "Drying rate control in microwave assisted processing of sliced apples", Biosystems Engineering, 170, 2018, pp. 24–30.

[24] T. Menlik, V. Krmac, H. Usta, "Modeling of freeze drying behaviors of strawberries by using artificial neural network", Journal of Thermal Science and Technology, Vol. 29, No. 2, 2009, pp. 11–21.

AUTHOR PROFILE

Shraddha Pandya obtained her B.E. degree in Chemical Engineering from Shroff S.R. Rotary Institute of Chemical Technology, Gujarat Technological University and M. Tech degree in Petrochemical Engineering from M.S. University, Vadodara. Currently she has been working as Assistant Professor in the department of Petroleum Engineering, Parul University, Gujarat. Her research interest includes Modeling and simulation of unit operations and extraction of heavy metals from waste water.