EVALUATION OF THIN-LAYER DRYING MODELS FOR DESCRIBING DRYING KINETICS OF SWEET POTATO *(IPOMOEA BATATAS LAM)*.

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ABSTRACT

It was investigated how sweet potato thin-layer drying behaved in an oven dryer. The drying properties of sweet potato were examined utilizing heated ambient air with 60, 70, and 80°C temperatures and 0.5, 1, and 1.5 m/s airspeeds. The research result was inserted into six empirical models. Three statistical measures were used to compare all of the models: R^2, SSE, and RMSE. The proportion of inaccuracy between the desired and predicted data was calculated using a variety of activation functions and criteria. The results demonstrate that a two-term drying model has a higher level of agreement with the experiment. It was also revealed how temperatures and velocities of the drying affected the model constants and coefficients. As a result, the new model estimating capability was evaluated.

1.0 INTRODUCTION

A significant source of carbohydrates for people in Asia is the sweet potato *(Ipomoea batatas Lam)*. Several studies have looked into the possibilities of manufacturing starches from sweet potato and converting them into noodles and several dishes made with wheat (Noda et al., 2006). Noodles, cake, bread, biscuits, juice, and other baked goods can all include sweet potato starch (Zhang & Oates, 1999).

Industries that are mainly for converting raw food materials into finished products depends heavily on the air-drying application on air drying. Food interiors get heat through conduction and at the air-food interaction, convection occurs (Kiranoudis, *et al.,* 1993). Different complexity levels of models have been developed for this phenomenon. The air-drying process cannot be adequately controlled in industrial applications using the models that are currently available. Physical dynamic models typically lead to couple mathematical applications which are particularly time-consuming due to the complexity of the process. Although not accounting for the complexity of the procedure, these equations can be simplified (Hernandez, 2009), however, they continue to contain typical mathematical applications are difficult to describe for control purposes (Trelea *et al.,* 1997). Empirical models that depict the drying kinetics use a number of line segments, high order polynomials, and neural networks (Daulin,1982), but they only need how basic mathematical processes to simulate, making them simple to include into control software.

Since the perceptron identification techniques were published, neural networks have received substantial study and are considered as effective tools for dynamic modeling (Rumelhart *et al.*, 1986). Interest in this model rests in the capacity to consider interdependencies and variables that are not linearly related as well as without assuming anything on the nature of the underlying mechanism (Bishop, 1994). According to recent findings the capability of ANN to infer solutions to issues from a collection of instances and to offer seamless and acceptable interpolations for fresh data is one of its most impressive features. It is also a strong substitute for convection modeling being derived using statistical techniques that depicts values of one variables on the basis of two or more other variables in the field of food process engineering. The application of ANN in food manufacturing industries are constantly expanding (Erenturk and Erenturk, 2007).

Concisely, an attempt has been made to anticipate the dehydration of sweet potatoes. with a wide variety of independent factors and predicating the transport of moisture during food product air drying. Using experimentally dried sweet potato cube data, the model was validated.

2.0 Material and Methods

2.1 The experimental facility

For this work, processing and storage lab in Niger Delta Univsisty hot-air drier on a laboratory scale was employed. The dryer had an automated temperature controller with a 0.1°C variation range of precision. Using air velocity varied from 0.5-1.5m/s widely different of 0.5m/s with an accuracy of 0.1 m/s. Using a manually operated electronic balance with a 0.61 kg accuracy, the dried samples were weighed (GF-600, Japan). Approximately 100g of samples were utilized in the experiment. Experiments were carried out throughout the drying process until the sample moisture content gives no significant different. Poyesh digital instrument type TMC 101 temperature controller set the air chamber temperature at 0.1°C. The dryer system was turned on in order to reach the desired steady-state condition prior to the start of any investigations. Three times of each of the experiment were performed and the median was taken.

2.2 Material preparation and drying conditions

Sweet potato that had just been picked were acquired from neighborhood farms in Ondewari and kept chilled for experiments at around +5°C. Samples were often chosen that were all the same size. Manually, the immature and rotten ones were separated. Using the application of oven drying technique, the sample original moisture content was identified. At least five different experiments were repeated. The incipient systemic moisture capacity of the fresh Sweet Potato employed in this experiment was 15% (w.b.). Within the temperature ranging from 60-80°C. The air velocity at the measuring position was maintained constant during the drying test at each temperature.

2.3 Mathematical modelling of the drying curves

Six different moisture ratio models, as describe in table 1 were used to fit drying curves. Utilizing the results of the desiccation experiments, the moisture ratio of the sweet potato fruits was computed using Eq. 1

$$M = \frac{w_i - w_f}{w_f} \quad \ldots \quad 1$$

Table 1. Thin-layer drying model tested for moisture ratio values for Sweet Potato

Model	Equation	Reference
Page	MR = exp(-kt)	Callaghan *et al.*, (1971)
Henderson and Pabis	$MR = \exp(-kt^n)$	Page (194)

Logarithmic	MR = aexp(-kt)+c	Yagcioglu *et al.,* (1999)
Two term	MR = aexp(-k_0t)+bexp(-k_1t)	Henderson (1974)
Approximation of diffusion	MR = aexp(-kt)+(1-a)exp(-kbt)	Yaldz et al., 2001, Bakri and Habari 2000

$$R^2 = 1 - \left[\sum_{i=1}^{n}(MR_{pre,i} - MR_{exp,i})^2\right] \ldots \quad 2$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(MR_{pre,i} - MR_{exp,i})^2}{n}} \quad \ldots \quad 3$$

The optimum combinations for defining the features of desiccation of sample were found to have the greatest (R^2) and lowest RMSE and SSE values.

The highest (R^2) and the lowest RMSE and SSE values were discovered to be the best combinations for describing the characteristics of thin-layer drying of sweet potato fruit. Multiple regression analysis was utilized to regress the constants against the drying air temperature and velocity in order to take the drying factors' effects on the two term model constants into account. All conceivable pairings of the different drying variables were taken into consideration throughout the regression analysis.

3.0 Results and Discussion

Drying curves

It is obvious that the difference in overall drying periods between high and low temperatures is the least. Drying took 2.3–2.6 times longer when air velocity was raised to 70°C. In comparison, trials carried out at 0.5 m/s at constant air temperature took roughly 1.6-2 times longer to dry than those done at 1.5 m/s. In other words, the amount of time it takes for a thin coating of sweet potato to dry depends much more on-air temperature than air velocity. Table 2 to 5 display the experimental data for air flowing at constant speeds of 0.5 to 1.5 m/s varying at 0.5 at 60, 70, and 80°C. The best-fitting curve is additionally depicted in all three pictures (as will be discussed later). While air velocity was maintained constant, the impact of rising air temperature on drying rate is obvious. The drying took place during the phase of falling rate, which has been demonstrated.

Sweet potato drying behavior in a single layer could be predicted using the data from the Two-Term Model, however in an appropriate process did not reveal the impacts of desiccation and fleetness. After using a statistical technique that predicts values of one variable on the bases of more variables to compare the values of coefficients compared to the air-drying parameters T (°C) and V (m/s), the equation is supplied along with the corresponding R^2 values. This was done to take into consideration the effects of the drying expression whose value depends on the constant such as k_0 and k_1 and the coefficients a and b on the two-term model. At a statistical significance level of 1%, regression studies for these variables revealed the following correlation.

$a = -0.053V + 0.007T \quad R^2 = 0.9897 \quad 5$

$b = 0.0119V + 0.007T \quad R^2 = 0.8957 \quad 6$

$k_0 = 0.002V + 5.7 \times 10^{-5}T \quad R^2 = 0.9997 \quad 7$

$K_1 = 0.004V + 0.0002T \quad R^2 = 0.9797 \quad 8$

The results are presented in Figure 1 and show that the model is viable. The data are grouped around a straight line at a 45° angle, illustrating the model suitability for modeling the thin-layer drying behavior of sweet potato.

$MR_{pre} = 0.996MR_{pre} + 0.0018 \quad R^2 = 0.9987 \quad 9$

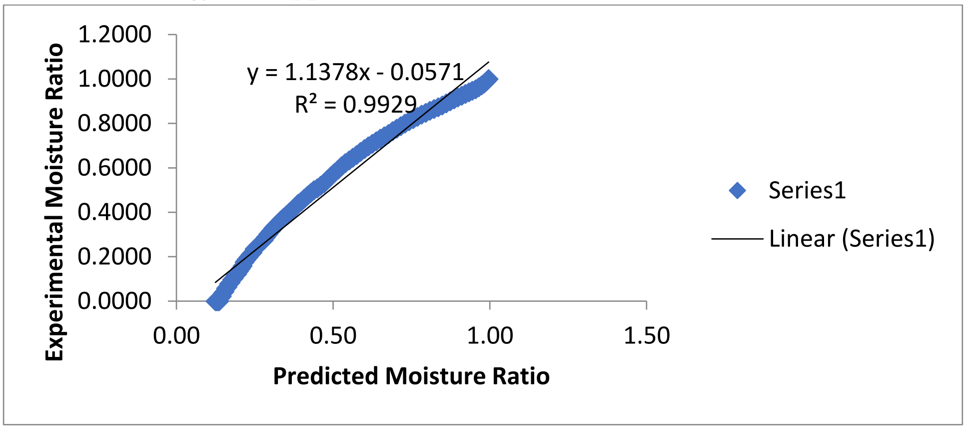

Figure 1: Comparison of experimental and predicted moisture ratio from Two-term exponential mode for sweet potato

Table 2. Coefficient of determination for v =0.5 m/s, Varying T

TEMPERATURE									
	60°C			70°C			80°C		
Model	R^2	RMSE	SSE	R^2	RMSE	SSE	R^2	RMSE	SSE
Newton	0.8893	0.0657	0.1553	0.9192	0.0564	0.1048	0.9315	0.0544	0.0798
Page	0.9982	0.0085	0.0025	0.9949	0.0144	0.0066	0.9904	0.0208	0.0112
Henderson and Pabis	0.9631	0.0385	0.0517	0.9607	0.0399	0.0509	0.959	0.0429	0.0478
Logarithmic	0.9916	0.0186	0.0128	0.9987	0.0074	0.0017	0.999	0.0067	0.0011
Two term	**0.9981**	**0.0089**	**0.0026**	**0.9999**	**0.0025**	**0.0002**	**0.9997**	**0.0036**	**0.0003**
Approximation of	0.9979	0.0095	0.0032	0.9998	0.0029	0.0003	0.9997	0.0036	0.0003

Table 3. Coefficient of determination for v = 1 m/s, Varying T

Temperature									
	60°C			70°C			80°C		
Model	R_2	RMSE	SSE	R_2	RMSE	SSE	R_2	RMSE	SSE
Two term	**0.9996**	**0.0049**	**0.0009**	**0.9998**	**0.0028**	**0.0004**	**0.9995**	**0.0054**	**0.0007**
Logarithmic	0.9886	0.0083	0.0029	0.9988	0.0077	0.0023	0.996	0.0145	0.0053
Henderson and Pabis	0.9828	0.0170	0.0144	0.9672	0.0378	0.0510	0.9164	0.0684	0.1209
Approximation of diffusion	0.9896	0.0048	0.0009	0.9998	0.0034	0.0006	0.9886	0.0093	0.0035
Page	0.9894	0.0056	0.0013	0.9953	0.0144	0.0075	0.9746	0.0278	0.0199
Newton	0.9727	0.030	0.0346	0.9283	0.0549	0.1111	0.8134	0.0946	0.2412

Table 4. Coefficient of determination for v = 1.5 m/s, Varying T

TEMPERATURE									
	60°C			70°C			70°C		
Model	R^2	RMSE	SSE	R^2	RMSE	SSE	R^2	RMSE	SSE
Two term	**0.9999**	**0.0023**	**0.0004**	**0.9998**	**0.0078**	**0.0026**	**0.9999**	**0.0055**	**0.0008**

Logarithmic	0.9937	0.0283	0.0305	0.9922	0.0185	0.01434	0.9936	0.0178	0.0110
Henderson and Pabis	0.9559	0.0594	0.2516	0.9666	0.0388	0.0609	0.9545	0.0710	0.1959
Approximation of diffusion	0.9998	0.0023	0.0005	0.9988	0.0093	0.0035	0.9994	0.0059	0.0014
Page	0.9851	0.0349	0.238	0.9965	0.0124	0.0066	0.9828	0.0273	0.0270
Newton	0.9618	0.0884	0.4874	0.9185	0.0597	0.1489	0.8588	0.1010	0.4076

Table 5. Coefficients for each experiment two-term model in the regression analysis

v = 0.5 m/s			
Temperature	50°C	60°C	70°C
A	0.3422	0.5181	0.5477
K	0.007663	0.006877	0.008653
B	0.8415	0.6768	0.6543
K_1	0.000676	0.000582	0.000895
v = 1 m/s			
A	0.2512	0.4129	0.6177
K_0	0.0045212	0.004788	0.009877
B	0.9494	0.6843	0.5743
K_1	0.00711	0.000583	0.000833
v = 1.5 m/s			
A	0.4421	0.3618	0.5782
K_0	0.003543	0.005512	0.008239
B	0.7556	0.8343	0.5112
K_1	0.000408	0.000509	0.000597

The data points on a graph comparing experimental and anticipated values should have a tendency to accrue inside a level, parallel to the horizon that is concentrated on or clustered around a central point on the infinite integer line, indicating that there are no observable desensitization procedure toward a particular pattern, according to (Xanthopoulos *et al*., 2007). Plotting the experimented against the predicted values of the dimensionless moisture ratio as a result, no trends were apparent (Fig. 6). The experimented proximity to the zero line serves as evidence that the model that was created is accepted.

Conclusions

The effectiveness of six thin-layer drying models in simulating oven drying of sweet potatoes were analyzed. The experimental data from drying sweet potatoes in a hot-air dryer at a laboratory scale with mean air temperatures of 60 to 80°C were subjected to regression analysis using non-linear regression methods. It was discovered that the drying curves of Sweet Potato showed the period of falling rate. Temperature had a much greater impact on the length of time it took for sweet potatoes to dry than air speed; air speed increased drying times while air temperature stayed constant. We calculated and evaluated the performance of fitting the regression coefficients for each model.

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