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ORIGINAL RESEARCH

Convective drying of unripe plantain: a comparative response surface methodology and genetic algorithm optimization study, certainty, and sensitivity analysis

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Abstract

The requirement for reduction of post-harvest losses increased production, and cost-effectiveness of foods are driving continuous food process investigations. In this study, Response Surface Methodology (RSM) was utilized to understand, model, and optimize the effect of selected process factors on the moisture content (MC) of convectively dried unripe plantain fruit. For technical accuracies, Multi Gene Genetic Programming (MGGP) was also used to model the process and both MGGP and RSM models were statistically compared. Furthermore, Monte Carlo Simulation (MCS) was used to conduct sensitivity analysis of unripe plantain's MC to each selected process factor. Results showed that increased sample thickness increased the MC while increased drying temperature and drying time decreased the MC of unripe plantain. RSM model had Chi-square, MBE, t-value, RMSE and R^2 values of 15.2131, 0.7531, 7.6170, 0.9193 and 0.9674, respectively; while MGGP model had 3.0415, 0.2563, 2.6871, 0.4111 and 0.9956, respectively. Sensitivity analysis showed that sample thickness, drying temperature and drying time had +89.5 %, -10.2 % and -0.3 % contribution to the variances of MC, respectively. These results are useful in unripe plantain drying process prediction, optimization, and product standardization.

Keywords: Unripe Plantain, Sensitivity Analysis, Modelling, Optimization, MGGP, RSM

Introduction

Plantain is an herbaceous plant of the genus *Musa* (Ashaolu and Akinbiyi, 2015) and forms part of human diet. In Africa, plantain provides more than 25% of the carbohydrate requirements for over seventy (70) million people (Oke *et al.*, 1998). Plantain contains 67.30 g of water, 116 kcal of energy, and 31.15 g of carbohydrate (Satimehin *et al.*, 2010); and it is rich in phosphorus, potassium, vitamin C and vitamin A. Plantain also contains traces of lipids, zero cholesterol and low sodium content (Oke *et al.*, 1998; Satimehin *et al.*, 2010). The health benefit of plantain in human diet is an important factor that assist its increased consumption. Plantain is consumed raw or processed in ripe and unripe stages of maturity. In Nigeria for instance, ripe plantains are mostly fried, while unripe ones are converted into flour for making solid foods (Tunde-Akintunde, 2014; Inyang *et al.*, 2018). However, despite the versatility of plantain as food, it is one of the highly perishable fruits and its post harvests losses especially in developing countries are alarming. Therefore, a means of plantain preservation for storage and shelve stability through the application of suitable postharvest technology is important. An easily implemented postharvest technology is drying, giving food products the advantage of low weight, longer shelf life, low transportation cost, smart packaging, and smart market display (Tunde-Akintunde, 2014).

Hot air drying is identified as a simple, easily adoptable, and economic way of drying fruits and vegetables (Johnson *et al.*, 1998) especially in developing countries. Hot air-drying removes moisture content from materials up to acceptable limits that lowers the water activities, inhibits microorganism's growth, and reduces the occurrence rate of enzymic and non-enzymic reactions (Inyang *et al.*, 2018; Johnson *et al.*, 1998). In Nigeria, the abundantly free solar energy enables the practice of sun drying in open spaces, however, the dwindling solar energy radiation, weather fluctuation, susceptibility to poor hygiene through animal and human infestation, non-availability of control mechanism and contamination through sandy breeze amongst others, render open sun drying method unacceptable in today's modern world. Therefore, an easy-to-implement drying technology that overcomes the deficiencies of open sun drying such as hot air oven is desirable. The concept of active drying technologies such as hot air oven as against passive open sun drying ensures quick drying process, product optimization, standardization, and reproducibility.

Drying is a dual process that involves inward penetration of heat energy and outward moisture diffusion of the concerned material (Adeyi *et al.*, 2018). Therefore, when a product undergoes drying, the internal moisture is migrated to the surface and vaporized to the atmosphere by dehumidified hot air that surrounds the product's surface. Amongst the drying indicators (which includes moisture content, moisture ratio, effective moisture diffusivity and activation energy) for analysing the drying characteristics of any product, moisture content remains the fundamental on which other indicators are based and thus remains the most important even in real life drying processes and drying process controller design. Therefore, preliminary investigations can be built around moisture content of a product, which is one of the concepts of this study. The technical requirements in hot air drying are to understand the phenomena involved, prediction of the process, establishment of moisture distribution in the material and understanding the influence of processing variables on drying characteristics (Johnson *et al.*, 1998).

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These backgrounds will assist the optimization and control of the process, which is necessary to avoid unwanted product and destruction of micronutrients (Tunde-Akintunde, 2014; Adeyi *et al.*, 2018). However, scientific investigation leading to the technical understanding should involve sound experimental design for model development (Buxton, 2007). Such model represents the process and can be applied for process and product adjustment and troubleshooting prior to commercialization (Punyapriya, 2012). Optimized process will also ensure process economic in terms of energy usage. To facilitate these technical understanding, this study applied Response Surface Methodology (RSM), Multi Gene Genetic Programming (MGGP) and Monte Carlo Simulation (MCS) tools to investigate the oven drying processing of unripe plantain.

MGGP is a machine leaning method with the capability for mathematical modelling (data mining) and prediction using historical data. MGGP is a method that mimics the biological evolution through population of computer programs to solve a task of interest (Searson *et al.*, 2010). The individual member of the population has a tree structure representation called gene. The structure and parameters of the empirical mathematical representation of a process data set can be evolved using the intrinsic symbolic regression capabilities of MGGP (Jabeen and Baig, 2010). The mathematical identification of process model by MGGP as against structured network architecture process identification is an important consideration when compared to other artificial intelligent methods such as neural networks, adaptive neuro fuzzy inference system, fuzzy logic, regression tree and support vector machine and others. Apart from the difficulty to unravel technical information in a network structure, specialized programmes are also desirable for its deployment in a typical controller design. On the contrary, availability of mathematical model hastens economic process development and analysis.

More also, it is important to understand the sensitivity of drying indicator to the drying process factors. It is believed that when the degree of sensitivity is determined, improved understanding of the governing mechanism is possible (Adeyi *et al.*, 2018). A method for determining sensitivity and certainty analysis is the MCS. MCS is a risk analysis tool for predictive modelling, forecasting, and optimization (Hoffman and Hammonds, 1994). It gives insight into the critical factors affecting a risk. As against the traditional probabilistic analysis, MCS presents quantitative and qualitative information about the realism of a particular forecast or prediction (Rai *et al.*, 1996).

The requirement for increased production, reduction of postharvest losses, further standardization of products, development of precise, flexible, and cost-effective processes and products are some of the requirements that are driving increased food process research. Amongst researchers of note, Rahmawati *et al.* (2020), Ikrang and Umani (2019) and Pe´rez-Francisco *et al.* (2008) applied RSM to model, predict and optimize drying processes in their respective studies and achieved promising results. It is a fact that a number of researchers (Famurewa and Adejumo, 2015; Ekeke *et al.*, 2019) have investigated the drying kinetics of unripe plantain using statistical, empirical and semi-empirical modelling methods. However, the application of MGGP to investigating the drying process in general and the evaluation of the sensitivity of each drying factor to the MC characteristic of unripe plantain specifically, are scarce in the literature. Therefore, the aim of this study is to fill these vacancies. This will enable better technical insight (that are useful for relevant engineering or physical data useful for equipment design, process design, analysis, control and commercialization) into the drying process of unripe plantain. The specific objectives were to (1) model and optimize the effect of selected drying factors on the MC of unripe plantain using RSM, (2) comparatively model the unripe plantain drying process using MGGP and (3) apply the most effective model between RSM and MGGP to evaluate the sensitivity of the unripe plantain's MC characteristic to drying factors using MCS.

Materials and Methods

Materials

Freshly harvested unripe plantain stalk (*Musa AAB*) was the experimental material and sourced from a farmland in Ogbomoso Oyo State Nigeria. Stangas convective oven equipped with a temperature regulator, 3.0 kW heating element and timer was used for the drying experiment. A digital weighing balance (0.001 g accuracy) was employed for samples weights measurements. A hollow cylindrical ring tool was used to create samples with constant diameters and shape. Vernier calliper was used for sample dimensional confirmation.

Experimental design

The choice of drying factors to be investigated on the drying characteristic of unripe plantain (*Musa AAB*) and their ranges were established through literature survey and preliminary experimental trials. The selected drying factors were the sample thickness *(X_1)*, drying temperature *(X_2)* and drying time *(X_3)*. The percentage moisture content *(Y)* of unripe plantain (*Musa AAB*) in wet basis (% w.b) was selected as the drying characteristic of interest. Using the selected drying factors as the inputs and the selected drying characteristic as the output, Design Expert Software version 8.0.0 (Stat-Ease, Inc., Minneapolis, USA) was used to design the experiment using RSM's D-optimal design. RSM's D-optimal is useful for small and effective experimental runs. The inputs (drying factors) considered were defined as numeric (values that varies at will). The design resulted in eighteen (18) experimental runs coded at three (3) levels of -1, 0 and +1 as shown in Table 1.

Table 1 D-optimal experimental design

Drying Factor	Unit	Factor	Level		
		Representation	-1	0	1
Sample Thickness	mm	X_1	5	7.5	10
Drying Temperature	°C	X_2	60	70	80
Drying Time	min	X_3	100	130	160

Sample preparation and determination of initial moisture content

The unripe plantain fingers were harvested from the stalk, washed with distilled water to remove sand and dirt, and hand peeled. Plantain pulp sample's thicknesses were prepared in accordance with the experimental design earlier described in Table 1. Once the thicknesses are cut out with knife, a hollow cylindrical ring of internal diameter 30 mm was used to give a constant diameter to the samples by pressing the ring against the samples as was done by Inyang *et al.* (2018).

The samples thicknesses and diameter were confirmed by Vernier calliper. The initial moisture content of unripe plantain (*Musa AAB*) was determined using oven drying method at 105 ^{o}C for 24 h (Fadeyibi *et al.*, 2021).

Drying experimental procedure

The drying experiment was conducted in accordance with the experimental design. Each experimental run was designed to investigate the effect of a peculiar drying process factors combination on the weight loss of the samples. Prior to the commencement of an experimental run, the dryer was allowed to work for twenty (20) min to achieve an equal temperature distribution throughout the oven. Before and after the completion of an experimental run, digital weighing balance was utilized to measure the weight of the sample, followed by recording and determination of percentage moisture content (% w.b). The percentage moisture content (MC) was established using Eqn. (1) (Ekeke *et al.*, 2019).

$$\mathrm{MC} = \frac{\mathrm{M_1} - \mathrm{M_2}}{\mathrm{M_2}} \times 100 \qquad (1)$$

Where M_1 and M_2 are the initial and instantaneous weight of the sample, respectively.

RSM modelling and optimization

Statistical analysis comprising of regression modelling, graphical effects and analysis of variance (ANOVA) were performed in the Design Expert Software. The effectiveness of the model and the significance of the individual model term were established at 5 % significant level in accordance with the work of Singh *et al.* (2018). Thereafter, the optimum combination of drying factors' parameters that best minimizes the moisture content during drying of unripe plantain (*Musa AAB*) slabs was determined.

In the regression model development, a second order quadratic statistical equation was fitted to the experimental observations to investigate the effect of each input drying parameter and their interactions. A typical quadratic model used in this study is represented in Eqn. (2):

$$Y = a + \sum_{i=0}^{k} a_i X_i + \sum_{i=1}^{k} a_{ii} X_i X_i + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} a_{ij} X_i X_j \qquad (2)$$

Where Y is the estimated response parameter; equation coefficients were represented by $\boldsymbol{a}$ (constant term), $\boldsymbol{a_i}$ (linear factor effect), $\boldsymbol{a_{ii}}$ (quadratic factor effect) and $\boldsymbol{a_{ij}}$ (interaction factor effect). $\boldsymbol{X_i}$ and $\boldsymbol{X_j}$ are input factors parameters, and k is the number of parameters investigated in the experimental study.

To achieve unripe plantain drying process optimization, the drying factors (sample thickness, drying temperature and drying time) were set to be within the range of the observed experimental values while drying characteristic (MC) was set to be minimized. The input and output factors were giving the same weight to signify equal importance during optimum solution finding process. Thereafter, solutions with their individual level of desirability were determined.

Experimental validation of the optimum drying condition

The RSM derived optimum unripe plantain drying process condition was experimentally validated by conducting the same drying procedure as previously stated using the RSM specified optimum input factors parameters for the sample thickness, drying temperature and drying time. Three validation experiments were conducted, and their average is reported for statistical significance. The percentage error between the RSM theoretical optimum and its experimental validation was expressed using Eq. (3):

$$\alpha = \frac{Va - Ve}{Ve} \times 100 \qquad (3)$$

Where α is the percentage validation error, *Va* is the MC of the validation experiment and *Ve* is theoretical MC derived from RSM optimization.

MGGP modelling

MGGP works with the evolution of computer programs to solve a particular task. This computer programs are called genes and are composed of tree structures. A typical MGGP gene is represented in Figure 1. The genes are built incrementally to strengthen the model stiffness by minimizing the model sum of square error just like in curve fitting. This result in a model fortified with weights and bias that adequately capture the existing relationship of a data set.

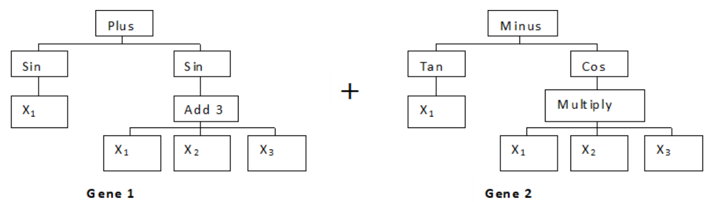


Figure 1 Typical MGGP tree structure

The independent variables of the model structure are represented by X_1, X_2 and X_3 as in Figure 1, and are connected by mathematical node functions that include subtraction, cosine, tan and addition. An MGGP regression model is mathematically represented as in Eqn. (4):

$$y = d_o + d_1 + tree_1 + \cdots + d_m + tree_m \qquad (4)$$

Where d_0 is the model constant or bias term, d_1, …,d_m are the gene coefficient or weights and subscript m is the number of genes presented in the current or ith set of input.

The workability of genetic programming starts from striving to minimize the fitness function represented by the mean square error of a dataset. This is done by generating set of solutions called population. The fitness metrics is performed on the individual solution within the population to select fitter individuals using a specified type of selection mechanism (reproduction or elitism, crossover, and mutation) for generational progress. The algorithm is organized to supply the simulation process with modelling requirements that enables the determination of optimum solution. The iteration of the genetic programming continues until an optimum solution is derived and or a termination criterion is met. At this point, the genetic programming returns the best individual solution throughout the generations within the simulation process (Orove and Osegi, 2005).

MGGP toolbox was employed using MATLAB R2017b software to model and predict the experimentally derived MC of unripe plantain. The data were partitioned equally into training and testing data set. Both population and generation selection affect the efficiency of MGGP algorithm (Özkan *et al.*, 2019), therefore, in this study, a constant population of 500 and constant generation of 200 were used throughout the MGGP simulation process. Coefficient of determination (R^2) and root mean square error (RMSE) depicted in Eqn. (5) and (6) were used to determine the effectiveness of the MGGP developed model.

$$R^2=1-\left(\sum_{i=1}^{N}\frac{(Pred,i-Exp,i)^2}{(Pred,i-AverageExp)^2}\right) \quad (5)$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(Exp,i-Pred,i)^2}{N}} \quad (6)$$

Where Pred,i is the i^{th} predicted value, Exp,i is the i^{th} experimental value and Averaged Exp is the average of all the experimental values. N represents the number of observations. Table 2 represents the parameter settings of MGGP used in this study.

Table 2 Parameter setting of MGGP

Parameter	Value
Population size	500
Number of generations	200
Tournament size	4
Elitism fraction	0.25
Termination value	0.001
Maximum gene	6
Node Functions	times, minus, plus, rdivide, psqroot, plog, square, tanh, pdivide, iflte, sin, cos, exp

Comparison of the RSM and MGGP

The performance of the models developed by RSM and MGGP methods was established using statistical criteria that included chi-square (χ^2), mean bias error (MBE), t -value, root mean square error (RMSE), and coefficient of determination *(R^2)*. The highest values of R^2 and the lowest values of χ^2, RMSE, MBE and t-values signify a good model performance (Silva *et al.*, 2014). The statistical criteria are defined based on the following mathematical representation (Silva *et al.*, 2014; Adewale *et al.*, 2015).

$$x^2 = \sum_{i=1}^{N}(Pred,i-Exp,i)^2 \quad (7)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(Pred,i-Exp,i) \quad (8)$$

$$t-Value = \sqrt{\left(\frac{(n-1)MBE^2}{RMSE-MBE}\right)} \quad (9)$$

Where Pred,i is the ith predicted value, Exp,i is the ith experimental value and AveragedExp is the average of all the experimental value. N represents the number of observations.

Sensitivity analysis

Sensitivity analysis of the output process response (MC) to input process factors (drying temperature, drying time and sample thickness) was investigated using MCS. The inputs process factors were declared as the assumptions with their respective experimental range of values while output process response was defined as the forecast. Twenty thousand (20,000) iterations were done to ensure accuracy in the result. Table 3 shows the MCS settings used.

Table 3 Input variables used for sensitivity analysis

Input variables	Distribution	Range of variables
Thickness (mm)	Uniform	5 – 10
Temperature (°C)	Uniform	60 – 80
Time (min)	Uniform	100 – 160

Results and Discussion

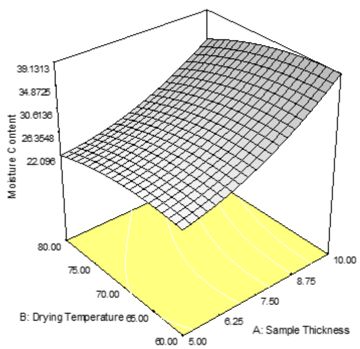
Effect of drying parameters on the moisture content of unripe plantain

The initial moisture content of unripe plantain used in this study was determined to be 58.05 % (w.b). This relatively high initial moisture content shows that unripe plantain is prone to high water activity consequently making it highly perishable. High moisture content also reduces shelf stability of agricultural products. The results of the drying factors effect on the MC of unripe plantain samples are shown in Table 4.

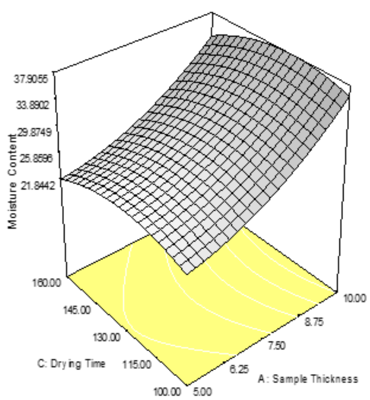
Table 4 Results of drying experiment

S/N	Sample Thickness (mm)	Drying Temperature (°C)	Drying Time (min)	Moisture Content (%w.b)
1	7.50	60.00	130.00	31.0932
2	5.00	80.00	160.00	17.8876
3	10.00	60.00	160.00	37.0009
4	5.00	80.00	100.00	20.6078
5	10.00	80.00	160.00	28.7845
6	7.50	70.00	100.00	27.8975
7	5.00	60.00	100.00	21.9909
8	5.00	60.00	160.00	22.0126
9	10.00	80.00	160.00	28.6754
10	10.00	70.00	130.00	38.5632
11	5.00	80.00	100.00	20.9008
12	5.00	60.00	160.00	22.2346
13	10.00	80.00	100.00	33.9812
14	10.00	60.00	100.00	35.0987
15	7.50	70.00	160.00	25.1114
16	7.50	80.00	130.00	24.0098
17	5.00	70.00	130.00	23.9987
18	5.00	80.00	160.00	20.1209

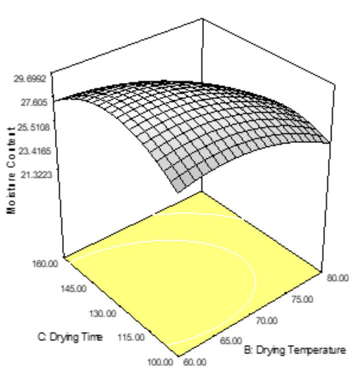
Table 4 showed that the highest MC of 38.5632 % w.b. occurred at drying factors combination of 10 mm sample thickness, 70 ^{o}C drying temperature and 130 min drying time while the least MC of 17.8876% w.b. occurred at 5 mm sample thickness, 80 ^{o}C drying temperature and 160 min drying time. This showed that moisture migrated quicker from sample's core to its surface at higher temperature and lower sample thickness than lower temperature and higher thickness. This can be related to increase in partial pressure of water molecule in fruits at higher temperature and shorter migration distance as samples became thinner. The relatively longer drying time observed at least MC value could be related to casehardening phenomenon, which occurred at extreme temperatures during drying. Buttressing this observation further, the individual and interaction effect of the input drying factors on the MC of unripe plantain samples are represented in Figure 2.



(a)



(b)



(c)

Figure 2 Individual and interaction effect of (a) drying temperature (b) sample thickness and (c) drying time on MC

The essence of drying is to develop a moisture stable product through reduction of the MC to a safe level, therefore, the choice of drying parameters that reduced MC is desirable. Figure 2 (a) showed that increment in drying temperature from 60 to 80 ^{o}C reduced the MC of the samples. This is attributed to decreasing relative humidity of the circulating drying air in the oven as drying temperature increased thereby making air to be more efficient in removing moisture from the samples. Figure 2 (b) showed that increments in sample thickness from 5 to 10 mm increased the samples MC. This is attributed to sample's bulk density, which changed as the sample thickness changed. Figure 2 (c) showed that sample's MC initially increased slightly from 100 min until 115 min, reached a constant period from 115 min until 130 min and then got to a falling period from 130 min until 160 min. The initial increment in the MC is attributed to high relative humidity (at low drying temperature) of the air entering the dryer through the vent. The constant period as time increase is attributed to poor moisture diffusion as a result of collapsed microstructure and casehardening phenomenon in the product's surface. The falling period is attributed to increased temperature that sufficiently reduced the relative humidity of the intake air. In related study on drying of catfish by Ikrang and Umani (2019), the effects of temperature and drying time were reported to be more pronounced on the MC reduction than the sample thickness and salt concentration. Likewise, Ekeke *et al.* (2019) reported that drying temperature and slice thickness decreased the drying rate and MC profile of unripe *Musa paradisiaca* slices.

RSM modelling and analysis

The quadratic equation fitted to the experimental observation in RSM in terms of drying factors effect and drying factors interactions of unripe plantain is presented in Eqn. (10).

$$MC = -121.68472 - 0.073957X_1 + 2.50038X_2 + 0.95878X_3 + 0.36344X_1^2 - 0.014579X_2^2 - 2.78330E - 003X_3^2 - 0.031625X_1X_2 - 4.30240E - 003X_1X_3 - 3.25162E - 003X_2X_3 \quad (10)$$

Where X_1 is sample thickness, X_2 is drying temperature and X_3 is the drying time.

The analysis of Eqn. (10) for its efficiency to investigate the experimental space in terms of individual factor effect and combined factors interaction effect and overall prediction of the experimental data is represented in Table 5.

In Table 5, the 38.39 F-value indicated that the model is significant. This means that there is only 0.01% chance that a model F-value that is this large could be induced by noise (impaired data). Prob > F lesser than 0.0500 means that the model terms are significant. Therefore, model terms X_1, X_2, X_1X_2, etc, are significant as can be seen from Table 5. The Lack of Fit of 4.93 have only 7.58% chance of being noisy. Model's significant lack of fit is not desirable because a fitted model is important for an accurate design, what-if analysis and control of process and equipment.

Table 5 Analysis of variance (ANOVA) for the developed model

Source		Sum of Squares	DF Square	Mean Val-ue	F Prob > F		
Model		656.98	9	73.00	38.39	< 0.0001	Significant
	X_1	537.09	1	537.09	282.44	<0.0001	
	X_2	50.97	1	50.97	26.80	0.0008	
	X_3	6.99	1	6.99	3.67	0.0916	
	X_1^2	12.98	1	12.98	6.83	0.0310	
	X_2^2	5.35	1	5.35	2.81	0.1321	
	X_3^2	15.79	1	15.79	8.30	0.0205	
	X_1X_2	6.95	1	6.95	3.66	0.0922	
	X_1X_3	1.16	1	1.16	0.61	0.4576	
	X_2X_3	10.58	1	10.58	5.57	0.0460	
Residual		15.21	8	1.90			
Lack of Fit		12.65	4	3.16	4.93	0.0758	Non Significant
Pure Error		2.57	4	0.64			
Cor Total		672.19	17				

RSM optimization and its experimental validation

The optimization procedure was undertaken to identify the optimum drying factors parameter combination that mimimizes the MC of unripe plantain drying. The developed model was used for this purpose. In the optimization setting, all input parameters are set to be within the range of the investigated experimental data and the MC is set to be minimized. The solutions were found and the best out of the array of solutions that minimized the MC of unripe plantain slices is represented in Figure 3.

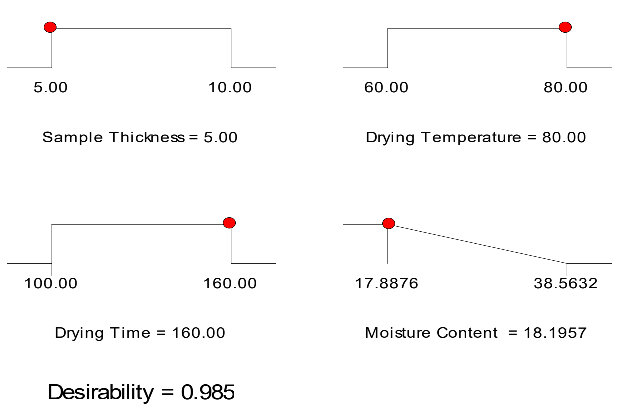


Figure 3 Optimum solution

Figure 3 showed that the optimum MC of 18.1957 % w.b. is achievable at 5.00 mm sample thickness, 80^{O}C drying temperature and 160 min drying time with a desirability of 0.9850. The high desirability implies that the result of the optimization is reliable. The desirability is represented in Figure 4. Figure 4 showed how well each factor satisfies the optimization criteria. Values greater than 0.80 are good and desirable (Oke *et al.*, 2020). In this case, all the variables are greater than 0.90.

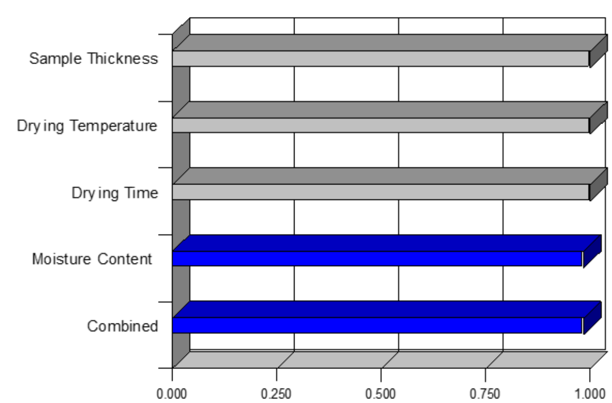


Figure 4 Desirability

The validation experiment was carried out by subjecting a 5 mm thick unripe plantain sample to drying at 80 ^{O}C for 160 mins (being the RSM derived optimum drying condition) in the same Stangas oven used for the previous experimental procedure.

The validation experiment was conducted three times and the mean of the triplicate experiment gave an MC of 18.3003 ± 0.0010 % w.b. Comparing the MC values of the validated and the RSM optimized MC, it can be established that a percentage error of 0.5749 % occurred. This error is low and can be attributed to the uncontrolled laboratory conditions. Therefore the RSM derived optimum drying condition for the unripe plantain is reliable.

MGGP modelling

The MGGP method was comparatively used to develop model for the drying process to investigate possible increased modeling and prediction accuracy. MGGP structure was trained and tested with the experimental dataset in Table 4. In MGGP, models are developed with interested dataset through structure training, testing and validation. The training of MGGP structure in this study is represented in Figure 5 where it is shown that the fitness (root mean square error) significantly decreased, occasionally increased slightly and finally reached minimum towards the end of the training process. This showed that MGGP encountered and overcame local minimums before it finally settled to a global minimum during the course of its solution finding.

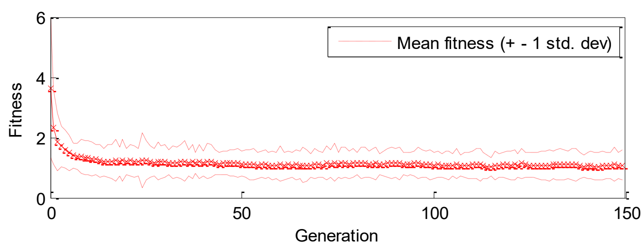


Figure 5 Training process of MGGP

In addition, Figure 6 showed the set of possible model solutions that has capability to represent and predict the drying process. Amongst the possible model solutions, the most efficient one should have the least fitness (i.e., lowest root mean square error and highest coefficient of determination) and least complexity. In the results displayed in Figure 6, the blue coloured model solutions are ones with unacceptable model complexity (measured with number of node in the genetic programming tree) while the green coloured model solutions are ones with acceptable model complexity. The only model solution with red and green coloration is the best model amongst the pareto fronts. This model had the least fitness coupled with acceptable complexity. It is therefore designated as the MGGP model solution for this study.

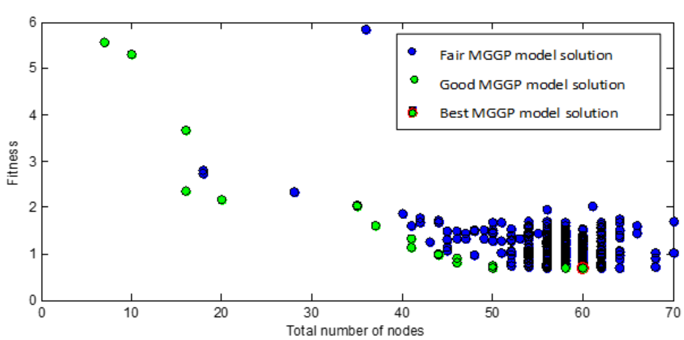


Figure 6 Parent front

The mathematical model of the Pareto front with the green and red coloration is represented in Eqn. (11).

$$MC = 0.1616X_3 - 0.7981X_1 + 0.0002189\,(X_1^2 + X_2 + X_3)(X_2 + X_3 + X_1 * X_2) + \frac{4.072X_2X_3^3}{10^8} - \frac{4.072X_3^4}{10^8} - 7.301X_1X_2^2X_3\frac{X_2 - 8.792}{10^8} - 0.1517 \quad (11)$$

Where X_1 = Sample thickness, X_2 = Drying temperature and X_3 = Drying time

Usually, the structure of artificial intelligent models are composed of weights and bias. Eqn. (11) composed of four genes (weights) and a bias (constant) as shown in Figure 7, which depicts the intrinsic multi gene characteristics of the MGGP.

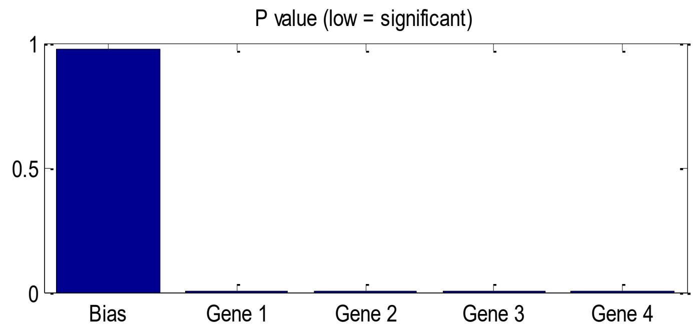


Figure 7 Model structure

The multigene approach is a linear combination of smaller low depth trees and often gives simpler models than single gene approach. Figure 7 also showed that the genes in the MGGP model are of high significance judging from their P-values (see diagram title) and model reduction in terms of unperforming gene elimination is not necessary. The p-value of bias is the highest, implying its low significance to the model effectiveness. The efficiency of Eqn (11) to predict drying process is represented in Figure 8.

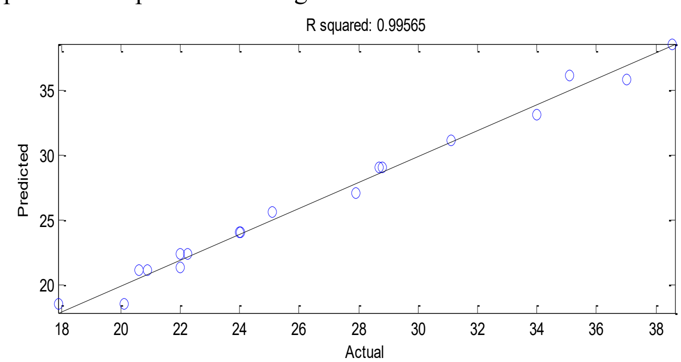


Figure 8 Parity plot

Figure 9 showed that the prediction accuracy of MGGP is close to unity (1). Adewale *et al.*, (2015) remarked that the closer the R^2 value of a model to unity, the better the prediction capability of such model. Oke *et al.* (2020) also remarked that a model is only reliable if the R^2 value is greater than 0.8000. Therefore, this MGGP model is reliable.

Comparison of RSM and MGGP models

The prediction performance of RSM and MGGP used in this study is represented in Figure 8 and the statistical performance criteria for each of the two developed model is also listed in Table. 6.

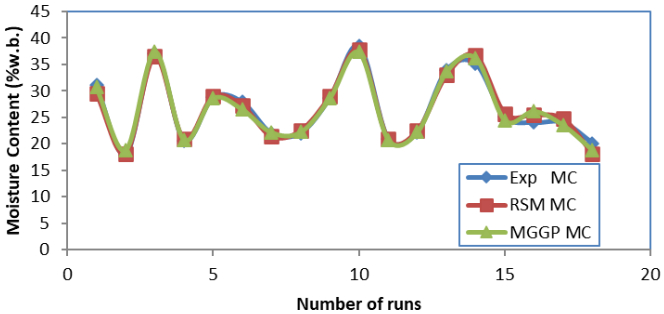


Figure 8 Performance of RSM and MGGP modeling methods

Table 6 Efficiency of RSM and MGGP modeling methods

Statistics	RSM	MGGP
Chi-square	15.2131	3.0415
MBE	0.7531	0.2563
t-value	7.6170	2.6871
RMSE	0.9193	0.4111
R^2	0.9674	0.9956

The comparatively lower Chi-square, MBE, t – value and RMSE and comparatively higher R^2 shows a better predictive model performance (Adewale *et al.*, 2015). It can therefore be established that MGGP model performed better than RSM model for the representation and prediction of the drying process of unripe plantain in this study. Therefore, the next analysis (sensitivity analysis) was conducted using the MGGP model representation depicted in Eqn. (11).

Sensitivity analysis of the unripe plantain drying process factors

The degree of importance of each drying factor to the variances in the MC of unripe plantain during drying process is represented in Figure 9.

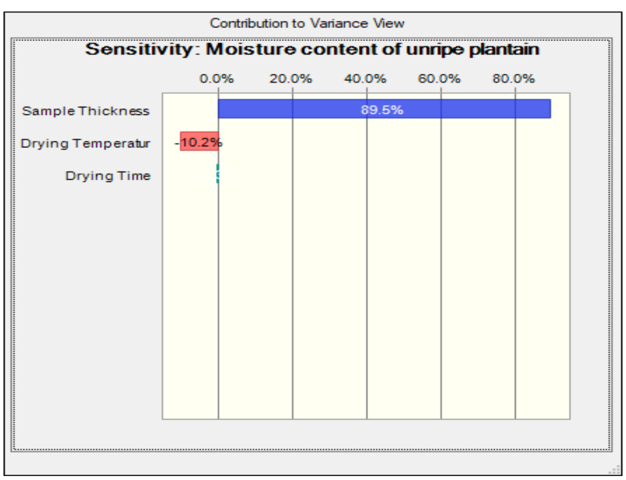


Figure 9 Sensitivity analysis of the drying factors to the changes in MC of unripe plantain

Figure 9 showed that sample thickness had a positive contribution (+89.5 %) to the MC while drying temperature and drying time had negative contributions (-10.2 and -0.3 %) to the MC of unripe plantain. Since MC minimization is the target of drying processing, it negative contribution to variance of MC is desirable. This result shows that relatively lower sample thickness with relatively higher drying temperature and drying time will facilitate the drying process of unripe plantain. This result is in agreement with the result obtained under the optimization study section and can be used as a guide for process monitoring and decision making.

Conclusion

Improved technical understanding of unripe plantain drying process was investigated using Response Surface Methodology (RSM), Multi Gene Genetic Programming (MGGP) and Monte Carlo Simulation (MCS). Results from the RSM study showed that the selected drying factors including sample thickness, drying temperature and drying time had significant effect on the moisture content (MC) of unripe plantain. RSM theoretical optimization also showed that minimum moisture content of 18.19 % w.b. is achievable with 5 mm thick sample, 80 ^{O}C drying temperature and 160 min drying time. The experimentally validated optimum gave MC of 18.30 % w.b. The Chi-square, MBE, t-Value, RMSE and R^2 value of RSM and MGGP models were 15.21, 0.75, 7.61, 0.91 and 0.96; and 3.04, 0.25, 2.68, 0.41 and 0.99, respectively; showing that MGGP model performed better in this study. Sample thickness, drying temperature and drying time had +89.5 %, -10.2 % and -0.3 % contributions to the changes in MC, respectively. It can be concluded that the methods used in this study enhanced a better technical understanding of the drying process and the developed mathematical model can be utilized for process design, troubleshooting and control while the optimum drying factor parameters could be useful for economic drying processing and product standardization.

Conflict of Interest Declarations

Authors declare no conflict of interest

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