
Modelling and optimising the impact of process variables on brown rice quality and overall energy consumption

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Abstract: This study aimed to optimise the impact of process variables on brown rice quality (brown rice recovery and head brown rice) and overall energy consumption. The applicability of predictive polynomial regression analysis (PRA) and artificial neural network (ANN) models were evaluated. Process variables [paddy moisture content (12–16%), soaking time (10–16 h), steaming time (20–30 min) and soaking temperature (65–75°C)] were interacted using response surface methodology and their impact on brown rice quality and overall energy consumption were determined. The influence of process variables differs significantly with brown rice recovery and head brown rice. However, a decrease in soaking temperature and paddy moisture content was observed to increase overall energy consumption. ANN shows better predictive accuracy than the PRA model. Optimum conditions that can guarantee maximum quality and minimum overall energy consumption was established at 80°C soaking temperature, 7 h soaking time, 35 min steaming time and 14% paddy moisture content.

Keywords: artificial neural network; brown rice; overall energy consumption; polynomial regression analysis; PRA.

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1 Introduction

Rice (*Oryza sativa* L.) can be categorised as one of the major staple food consumed by more than half of the world population. Paddy rice can be processed into white rice, brown rice or polished rice. However, due to the increasing number of individuals' preference for nutritional cereal, brown rice has been identified as a promising whole grain cereal (Qi et al., 2019). Brown rice is whole grain rice enclosed with bran layer in the pericarp. It usually has dark colour due to its bran layer and it has been reported to be a rich source of iron, phosphorus, manganese, thiamine, pyridoxine, niacin, etc. (Babu et al., 2009; Upadhyay and Karn, 2018). In Nigeria, rice is an important food security crop, mainly produced by small-scale farmers who commonly sell 80% of total production and consume only 20%. Rice generates more income for Nigerian farmers than any other cash crop in the country. Rice production in Nigeria has observed a tremendous increase in production as paddy rice production rose from 7,200 to 7,778 metric ton while milled rice production rose from 4,536 to 4,900 metric ton from 2016 to 2019 (USDA, 2020).

Most of the rice produced in Nigeria is polished parboiled rice with little or no emphasis on parboiled brown rice. According to Sanusi et al. (2020), production of parboiled brown rice yields better milling quality than non-parboiled brown rice. However, the limited production of parboiled brown rice in Nigeria may be as a result of sparse knowledge on the nutritional benefits of brown rice for health conscious people or the lack of technological know-how for the production of low cost brown rice. Parboiled brown rice processing involves a hydrothermal pre-milling process that incorporates four stages; soaking, steaming, drying and dehiscing. Brown rice recovery and head brown rice are key parameters that could be used to evaluate the physical quality of brown rice during production (Sanusi et al., 2020). Brown rice recovery represents the percentage of the total mass of brown rice (including broken) obtained from the original dried mass of paddy rice. Head brown rice represents the percentage of the mass of brown rice which is usually three-fourths or more in size of the original brown rice obtained after milling. Parboiling is an energy intensive process (Kwofie and Ngadi, 2017). Several researchers

have reported that the quantity of rice being processed, type of rice variety, parboiling approach used and parboiling conditions, influence the overall energy consumption (Islam et al., 2004; Roy et al., 2006; Ahiduzzaman and Islam, 2009; Goyal et al., 2014; Kwofie and Ngadi, 2016; Kwofie and Ngadi, 2017). Overall energy consumption in brown rice processing can simply be defined as the sum of the energy consumption at each unit operation involved in converting paddy rice into brown rice and the unit is expressed in mega joule (MJ). In the food manufacturing sector, effective energy utilisation requires comprehensive knowledge of the energy performance of machines and operations involved in the production. In order to reduce the operating cost and total energy consumption to the minimum, strategic measures must be put in place to monitor the operating processes (Anjorin et al., 2018). However, little emphasis has been paid towards understanding the simultaneous impact of processing variables on brown rice quality (brown rice recovery and head brown rice) and overall energy consumption. More so, the investigation of the impact of different processing variables could be time consuming and expensive. In contrast, modelling and simulation of the impact of various processing variables on the quality attributes can aid in reduction of operation time, cost, and lead to faster and better outcome. (Hossein-zadeh et al., 2020). Bibliographic research showed there is a paucity of information on modelling the impact of process variables especially in relation to brown rice quality and overall energy consumption. Polynomial regression is a statistical technique that uses numerous independent variables to predict the outcome of a dependent variable. Polynomial regression can formulate study and model the effects of different independent variables on dependent ones. However, there are some limitations associated with the use of polynomial regression such as inability to model nonlinear relationship that exists between the dependent and independent variables (Du et al., 2020; Hossein-zadeh et al., 2020). Modelling technique that offers accurate, flexible and fast approach over mathematical modelling is the Artificial Neural Network (ANN). Hossein-zadeh et al. (2018, 2020) reported that ANN has the capability of modelling processes and also, in mastering the linear and nonlinear relationship that exist among the processing parameters. The application of ANN and polynomial regression models have been compared by some researchers (Xu et al., 2014; Hossein-zadeh et al., 2018; Kim et al., 2018; Park et al., 2018; Hoang, 2019; Hossein-zadeh et al., 2020). However, information is sparse regarding the relative impact of different processing variables on brown rice quality and overall energy consumption. Therefore, this study aimed to optimise the impact of process variables on brown rice quality (brown rice recovery and head brown rice) and overall energy consumption. The predictive capability of polynomial regression and ANN models were also examined.

2 Materials and methods

FARO 44, Nigerian most commercially grown rice, which has an extra-long size and slender shape (Sanusi et al., 2017) were obtained from National Cereal Research Institute, grains breeding laboratory, Baddaggi, Niger State, Nigeria and was stored at 30°C prior use for this study.

2.1 Experimental design and sample preparation

Process variables (paddy moisture content, soaking time, steaming time and soaking temperature) were selected based on literature review and their influence in the production of parboiled brown rice. These parameters were interacted using central composite rotatable design of response surface methodology (CCRD-RSM) as shown in Table 1. A total of thirty-one (31) runs were generated which consisted of 16 factorial runs, eight axial points and seven replications at the centre point of the domain were performed. Each run used 1.5 kg of FARO 44 and was separately cleaned, soaked, steamed using a locally fabricated rice parboiler and dried at 38°C till desired paddy moisture content in wet basis was achieved. The dried paddy rice from each run was held for 12 h in airtight containers for equilibrium moisture content to set-in and was further dehusked using a rice dehusker (rubber roller brand, Satake Engineering Corp., Model THU 35B, Japan) to get brown rice and graded with their mass measured, using an electronic balance (GF-6000AND, Japan) of ± 0.1 g accuracy. Brown rice recovery and head brown rice were determined using equations (1) and (2) as reported by Sanusi et al. (2020). Response variables (brown rice recovery, head brown rice and overall energy consumption) were determined in triplicate, and the results were analysed using CCRD-RSM analysis to fit in the second order polynomial equation.

$$\text{BRR (\%)} = \frac{\text{MBR}}{\text{MP}} \times 100 \quad (1)$$

$$\text{HBRY (\%)} = \frac{\text{MHBR}}{\text{MP}} \times 100 \quad (2)$$

where BRR is brown rice recovery, MBR is mass of brown rice, MP is mass of paddy rice, HBHY is head brown rice yield, and MHBR is mass of head brown rice yield.

Table 1 Process variables interaction using central composite rotatable design of response surface methodology (CCD-RSM)

Process variables	Unit	Coded levels $-\alpha$ (-2)	Low (-1)	Medium (0)	High (1)	Coded levels $+\alpha$ (+2)
Soaking temperature	°C	60	65	70	75	80
Soaking time	h	7	10	13	16	19
Steaming time	min	15	20	25	30	35
Paddy moisture content	%	10	12	14	16	18

2.2 Determination of overall energy consumption

Energy consumption pattern at cleaning, soaking, steaming, drying, dehussing and grading at each run during the processing of the paddy rice into brown rice were estimated by fitting data on labour, fuel and electricity consumption, time and machine efficiency into standard equations (3)–(9) to determine overall energy consumption. The processing conditions combination derived from the CCRD-RSM design was used for the energy consumption determination. Therefore, the energy consumption at different runs

was estimated. This method of energy consumption determination approach was also reported by Akinoso et al. (2013), Sanusi et al. (2016) and Anjorin et al. (2018).

$$Ec = (0.75N \times 0.016t) \quad (3)$$

$$Es = (0.75N \times 0.0167t) + (Qf \times Cf) \quad (4)$$

$$Est = (0.75N \times 0.0167t) + (Qf \times Cf) \quad (5)$$

$$Ed = (0.75N \times 0.0167t) \quad (6)$$

$$Edh = (3.6 \times P \times \varphi) + (N \times 0.0167t) \quad (7)$$

$$Eg = (.75N \times 0.0167t) \quad (8)$$

$$Ecop = Ec + Es + Est + Ed + Edh + Eg \quad (9)$$

where Ec , Es , Est , Ed , Edh , Eg and $Ecop$ are energy consumption (MJ) for cleaning, soaking, steaming, drying, dehussing, grading and overall energy consumption. N is average power of a normal male labour in the tropical region is 0.75 MJ/h, t is time taken to accomplish a unit operation (h), Cf is the calorific value of liquefied petroleum gas (LPG) (50.35 MJ) and φ is the power factor, P is the power rating of the machines (kW), 3.6 = conversion factor (1 kWh = 3.6 MJ) for electrical energy.

2.3 Polynomial regression analysis (PRA)

Polynomial regression analysis (PRA) is the regression models with dependent variables and two or more independent variables. The PRA was achieved by using the CCRD-RSM in Minitab 16 Software UK. The PRA models were developed using equation (10).

$$Y = \beta_0 + \beta_1x_1 + \beta_2x_2 + \beta_3x_3 + \beta_4x_4 + \beta_{11}x_1^2 + \beta_{22}x_2^2 + \beta_{33}x_3^2 + \beta_{44}x_4^2 + \beta_{12}x_1x_2 + \beta_{13}x_1x_3 + \beta_{14}x_1x_4 + \beta_{23}x_2x_3 + \beta_{24}x_2x_4 + \beta_{34}x_3x_4 + \varepsilon \quad (3)$$

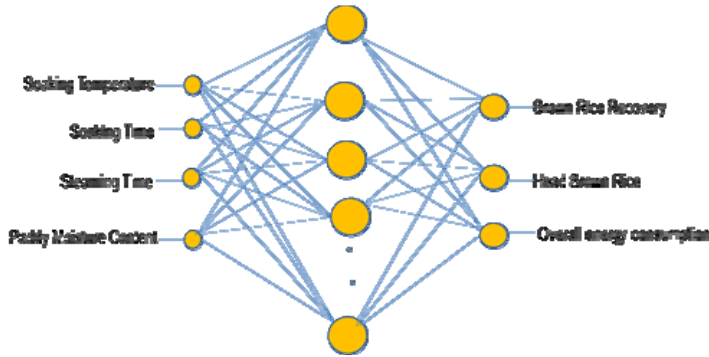
where β_0 is coefficients of the model constant, β_1 , β_2 , β_3 , β_4 are the linear terms, β_{11} , β_{22} , β_{33} , β_{44} are the quadratic terms, and β_{12} , β_{13} , β_{14} , β_{23} , β_{24} , β_{34} are the interaction terms, ε is error, Y is the dependent variables, x_1 , x_2 , x_3 and x_4 are soaking temperature, soaking time, steaming time and paddy moisture content, respectively. The dependent variables are brown rice recovery, head brown rice and overall energy consumption.

2.4 Artificial neural network

For the purpose of this study, the toolbox of neural network in MATLAB R2019a was applied to predict the nonlinear relationship between the process variables (soaking temperature, soaking time, steaming time and paddy moisture content) and the responses (brown rice recovery, head brown rice and overall energy consumption). The schematic of the artificial neural network (ANN) model used was presented in Figure 1. The data employed for CCRD-RSM experimental study were randomly divided into three groups, 70% (21 points) in the training set, 15% (5 points) in the validation set and 15% (5 points) in the test set. The ANN model was built using four input variables and three output variables to select the best predictive model. Feed-forward backpropagation and

algorithm of Levenberg-Marquardt (TRAINLM) were used in developing the ANN architecture. Different number of neurons in the hidden layer ranging from 1 to 13 neurons and transfer function (Tansig, Logsig and Purelin) was applied based on trial method to develop the optimum ANN model that can minimise the deviations between the predicted and experimental results. Also, the output signal for accuracy was determined by modifying the number of layers, weights sum of input variables and bias during algorithm iterative until the ANN outputs were closer to the actual values. The best training performance of the developed ANN model was terminated at the lowest MSE and highest correlation coefficient (R) at training, validation, testing and all. Ciric et al. (2020) and Hosseinzadeh et al. (2020) also reported a similar approach while modelling the effect of ultrasound assisted extraction variables on phenolic compounds and modelling different conditions on the nutrient recovery in vermicompost.

Figure 1 The schematic of the artificial neural network (ANN) model (see online version for colours)



2.5 Examination of PRA and ANN models

The experimental and predicted data of the responses (brown rice recovery, head brown rice and overall energy consumption) obtained from PRA and ANN models were employed to determine the coefficient of determination (R^2) and mean square error (MSE) using equation (11) and (12). The R^2 and MSE were used to examine the fitness and prediction accuracy of the models. Generally, model with the lowest MSE and the highest values of R^2 was considered as the best model. Ciric et al. (2020) used similar approach while comparing ANN and second order polynomial regression model.

$$MSE = \frac{1}{N} \sum_{i=1}^n (y_o - y_e)^2 \quad (11)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_o - y_e)^2}{\sum_{i=1}^n (y_o - y_m)^2} \quad (12)$$

where n is the number of experiments used for developing the model, y_o is the predicted value of the model, y_e is the actual or experimental value and y_m is the average of actual values.

2.6 Optimisation of process variables

This study aimed to maximise the brown rice recovery and head brown rice while overall energy consumption is minimised within the ranges of processing conditions applied. The experimental results obtained were used for the numerical optimisation in order to establish the optimum conditions that can guarantee maximum brown rice quality and minimum energy consumption. A modified method of Ciric et al. (2020) was employed for the simultaneous optimisation of the three responses. The predicted responses from the optimisation were transformed into a dimensionless partial desirability function, $d_i(0)$ to a fully desirable function (1). The global desirability function GD, was achieved when the partial desirability functions were merged in a single composite response [equation (13)]. GD is simply the geometric mean of the partial desirability functions of the means of the responses.

$$GD = \left[d_1 \times d_2 \times d_3 \dots d_n \right]^{\frac{1}{n}} \quad (13)$$

The predicted optimum condition was experimented in the laboratory to validate the effectiveness of the optimum conditions using relative error [equation (14)].

$$\text{Relative error} = \frac{\text{Experimental value} - \text{predicted value}}{\text{Experimental value}} \times 100 \quad (14)$$

3 Results and discussion

3.1 Impact of process variables on brown rice quality

Brown rice recovery is among the key quality indices use by brown rice processors. Brown rice with high values of this could signify rice with potential market value. As shown in 3D contour plot [Figures 2(a) and 2(b)] for brown rice recovery, the impact of process conditions on brown rice recovery varied significantly. At holding values of 13 h soaking time and 25 min steaming time, the maximum brown rice recovery could be achieved at high paddy moisture contents ranging from 16 to 18%, and increase in soaking temperature (60–75°C) as presented in Figure 2(a). In Figure 2(b), at holding values of steaming time of 25 min and 14% paddy moisture content, increasing soaking time at low soaking temperature favoured high brown rice recovery while increase in soaking temperature at short soaking duration also favours brown rice recovery. The amount of gelatinised starch during soaking at high temperature and time could be assumed to be correlated with brown rice recovery. Therefore, in-depth understanding of the right processing conditions of the Process variables could guide in achieving an optimum brown rice recovery. This result agrees with the findings of previous research by Nasirahmadi et al. (2014) and Sanusi et al. (2020) which observed that right parboiling conditions can increase rice recovery. The F-value and p-value of analysis of variance as presented in Table 2, shows that soaking time, paddy moisture content and soaking temperature had significant influence on brown rice recovery. The double interactions of soaking time was found not to be significant while interactions of other process variables were observed to be significant in achieving high brown rice recovery.

Figure 2 Contour plots describing the impact of process variables interactions on the brown rice recovery, (a) contours between paddy moisture content and soaking temperature (b) contours between soaking time and soaking temperature (see online version for colours)

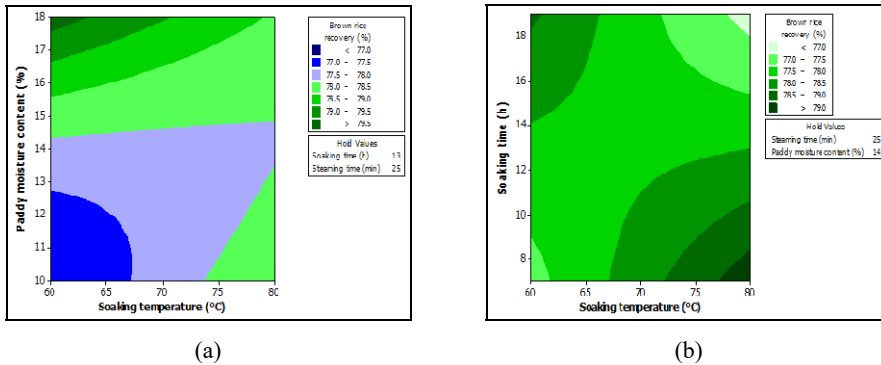
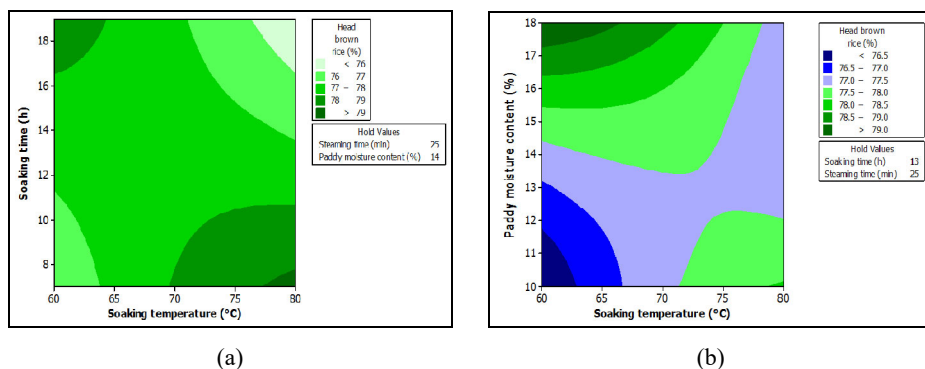


Table 2 Analysis of variance of brown rice quality and overall energy consumption

Polynomial regression	DF	BBR (%)			HRY (%)			Overall energy consumption (MJ)		
		MS	F-value	P	MS	F-value	P	MS	F-value	P
Regression	14	2.04	48.66	0.00	2.04	48.66	0.00	336.66	150.35	0.00
X1	1	3.39	80.95	0.00	3.39	80.95	0.00	78.14	34.89	0.00
X2	1	7.29	173.82	0.00	7.29	173.82	0.00	0.00	0.00	0.99
X3	1	0.04	0.84	0.36	0.04	0.84	0.36	10.79	4.82	0.03
X4	1	0.71	16.91	0.00	0.71	16.91	0.00	9.95	4.44	0.04
X12	1	0.57	13.59	0.00	0.57	13.59	0.00	108.2	48.32	0.00
X22	1	0	0.19	0.67	0.00	0.19	0.67	16.72	7.47	0.01
X32	1	0.39	9.35	0.00	0.39	9.35	0.00	0.59	0.27	0.61
X42	1	1	23.96	0.00	1.01	23.96	0.00	57.39	25.63	0.00
X1X2	1	7.57	180.22	0.00	7.57	180.22	0.00	2.28	1.02	0.32
X1X3	1	0.18	4.17	0.05	0.18	4.17	0.05	0.44	0.19	0.66
X1X4	1	3.41	81.11	0.00	3.41	81.11	0.00	5.05	2.25	0.14
X2X3	1	0.67	16.03	0.00	0.67	16.03	0.00	2.97	1.32	0.25
X2X4	1	1.09	25.84	0.00	1.08	25.84	0.00	6.56	2.93	0.09
X3X4	1	1.59	37.83	0.00	1.59	37.83	0.00	10.66	4.76	0.03
Residual error	78	0.04			0.04			2.24		
Lack of error	10	0.2	10.7	0.00	0.2	10.7	0.00	17.47		
Pure error	68	0.02			0.02			0.00		
Total	92									

Note: X₁, X₂, X₃ and X₄ are soaking time, soaking temperature, steaming time and paddy moisture content; BBR is brown rice recovery; HBY is head brown rice.

Figure 3 Contour plots describing the impact of process variables interactions on the head brown rice, (a) contours between soaking time and soaking temperature (b) contours between paddy moisture content and soaking temperature (see online version for colours)



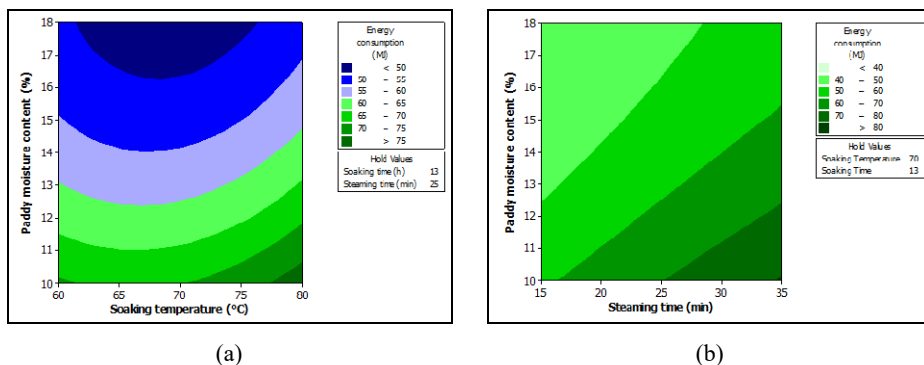
Another quality index that might be used by brown rice processor is head brown rice yield. It is the part of the indices consumers of brown rice considered for acceptability. High head brown rice could be used to judge the nutritive value of the parboiled brown rice to an extent. This is because head brown rice also referred to as whole brown rice yield is as a result of the bran and embryo not taken off during dehushing. Enormous yield of this, invariably have intact bran and embryo hence more nutrients in the rice. Low brown rice yield has lost the bran and embryo (germ) during dehushing process and thus have relatively less nutrient. In addition, high head brown rice could translate to increase in economic value of the product. The impact of process variables on head brown rice was depicted in Figure 3(a) and 3(b). At 25 min steaming time and 14% paddy moisture content holding values, high soaking temperature and minimum soaking time could favour optimum Head brown rice [Figure 3(a)]. At high soaking temperature and minimum soaking time or vis-à-vis, it is expected that the paddy grain starch would have become more gelatinised which further increases the binding effect thus having the capability to withstand dehushing pressure. However, it was observed that at a very high soaking temperature and soaking time, the head brown rice reduces. This might be attributed to severe deformation of the grain as a result of excessive absorption of moisture content which got the husk ruptured and the grain leached out its content, creating holes and became partially cooked. If dried, the hollow grains became weaker and are prone to breakage which gives minimum whole brown rice yield. Parnsakhorn and Noomhorm (2008) reported that longer soaking time was not suitable for parboiled brown rice produced from KDML 105. Bello et al. (2006) also reported on reduced milling yield as a result of soaking at high temperature. Figure 3(b) shows that high paddy moisture content and moderate soaking temperature favours optimum head brown rice yield. This could be ascribed to 12 h holding time given to the paddy after reaching the desired paddy moisture. The holding time resolved the moisture gradient that occurs after drying, thus decreases shear set up during dehushing to yield high whole brown rice yield. This result is in agreement with Bhattacharya and Swamy (1967) findings that stated that holding paddy after drying for some time increase milling quality. Also, Oyedele and Adeoti (2013) reported that 16% paddy moisture content gave maximum head rice yield for Igbemo rice. The F-values and p-values of analysis of variance as depicted in Table 2, shows that the paddy moisture content, soaking time and soaking

temperature had significant influence on head brown rice yield. The double interactions of soaking time was also found not to be significant while interactions of other process variables were observed to be significant $p < 0.05$ in achieving maximum head brown rice yield.

3.2 Impact of process variables on overall energy consumption

Information on the impact of process variables on overall energy consumption could play a vital role in ensuring energy conservation and economic viability of brown rice processing plants. The impact of process variables on overall energy consumption were presented in Figures 4(a) and 4(b). At 25 min steaming time and 13 h soaking time holding values, minimum overall energy consumption could be achieved at high paddy moisture content and moderate soaking temperature [Figure 4(a)]. This is presumable because at high paddy moisture content, lower amount of energy is required to dry the paddy compared to when the paddy is to be dried to low paddy moisture content. In contrast, increase in steaming time, increases the overall energy consumption [Figure 4(b)]. As the steaming progresses, more fuel is been used and this could be ascribed to the increase in overall energy consumption. Therefore, it can be deduced that the processing variables had significant influence on the overall energy consumption. The F-values and p-values of analysis of variance as depicted in Table 2, shows that soaking temperature, steaming time and paddy moisture content had significant influence on overall energy consumption while soaking time was not. This result correlates with Islam et al. (2004) and Kwofie and Ngadi (2017) findings that stated that parboiling conditions could influence energy consumption.

Figure 4 Contour plots describing the impact of process variables interactions on the overall energy consumption, (a) contours between paddy moisture content and soaking temperature (b) contours between paddy moisture content and steaming time (see online version for colours)



3.3 Polynomial regression modelling of brown rice quality and overall energy consumption

The F values of the PRA models for brown rice recovery, head brown rice and overall energy consumption were 48.66, 48.66 and 150.35, respectively as presented in Table 2. The p-values of the responses were less than 0.0001, which clearly state that the models

were significant. This confirmed that the developed polynomial regression models showed the adequacy of the models in the characterisation of the processing parameters. Hosseinzadeh et al. (2020) used multilinear regression model to model TN and TP recovery in vermicompost under different conditions and concluded that the multilinear regression model showed good performance, that correlate with the present study. For brown rice recovery (BRR), twelve coefficients were significant ($p < 0.05$) in the model. The second order polynomial equation (13) was obtained by backward elimination of insignificant ($p > 0.05$) coefficient terms to obtain a realistic model that could predict brown rice recovery. From the equation (13), it can be deduced that increase soaking temperature (x_1), soaking time (x_2) and paddy moisture content (x_4) could increase the brown rice recovery. The ANOVA statistical parameters for BBR show that the good fitness of the model with coefficient of determination R^2 and adjusted R^2 values of 0.901 and 0.884, respectively. The R^2 values were within the acceptable limit $R^2 > 0.80$, which indicated that the experimental results shows good fit with the polynomial equation (13). This agrees with Ciric et al. (2020) that developed second-order polynomial equation which is capable of predicting the effect of process variables on flavonoid content due to high R^2 value.

$$\begin{aligned} \text{BRR} = & 65.531 + 0.365x_1 + 0.990x_2 + 0.043x_4 + 0.001x_1^2 + 0.008x_3^2 \\ & + 0.031x_4^2 - 0.016_{12}x_1x_2 + 0.001x_1x_3 - 0.018\beta_{14}x_1x_4 - 0.003x_2x_3 \\ & + 0.004x_2x_4 + 0.018x_3x_4 \end{aligned} \quad (13)$$

For Head brown rice (WBRY), twelve coefficient terms were significant ($p < 0.05$) in the model. Polynomial regression equation after deleting coefficients that were not significant ($p > 0.05$) is presented in equation (14). The equation shows that increase in soaking temperature (x_1), soaking time (x_2) and paddy moisture content (x_4) could increase the head brown rice yield. The ANOVA statistical parameters for HRY show that the good fitness of the model with R^2 and $R^2_{(\text{adj})}$ values of 0.897 and 0.879, respectively. These values show the good fitness of the model.

$$\begin{aligned} \text{WBRY} = & 12.243 + 1.228x_1 + 2.298x_2 + 1.138x_4 + 0.027x_4^2 - 0.027_{12}x_1x_2 \\ & - 0.002x_1x_3 - 0.027\beta_{14}x_1x_4 - 0.008x_2x_3 - 0.025x_2x_4 + 0.018x_3x_4 \end{aligned} \quad (14)$$

For overall energy consumption (OEC), seven coefficient terms were significant ($p < 0.05$) in the model. Polynomial regression equation after backward elimination of coefficients that were not significant ($p > 0.05$) was presented in equation (15). From the equation, it can be deduced that decrease in soaking temperature (x_1) and paddy moisture content (x_4) could lead to an increase in overall energy consumption, while increase in steaming time (x_3), increases the overall energy consumption. Increase in double interactions of soaking temperature (x_{12}), soaking time (x_{22}) and paddy moisture content (x_{42}) could lead to increase in overall energy consumption, while increase in the interaction of steaming time (x_3) and paddy moisture content (x_4) would result into decrease in overall energy consumption.

$$OEC = 263.228 - 5.886x_1 + 1.697x_3 - 4.258x_4 + 0.045x_1^2 + 0.049x_2^2 + 0.205x_4^2 - 0.047x_3x_4 \quad (15)$$

The R^2 and $R^2_{(adj)}$ of the OEC were 0.9643 and 0.958. Huang et al. (2011), Pappu et al. (2013) and Tušek et al. (2020) reported that when R^2 of the model was close to unity, the higher the predictive accuracy, the better the model fits the experimental data.

3.4 ANN modelling of brown rice quality and overall energy consumption

Figure 5 shows the optimum architecture of the developed ANN model for simulating brown rice recovery, head brown rice and overall energy consumption. The optimum architecture had four (4) inputs (soaking time, steaming time, soaking temperature and paddy moisture content) and three outputs, respectively. The optimum topology and transfer function for simulating brown rice recovery, head brown rice and overall energy consumption were achieved after repeated trials of different neurons and transfer function. It was observed that neural network architecture with ten neurons at the hidden layer and tangent sigmoid function (tansig) produced the best performance model. According to Yadav et al. (2017), the selection of suitable artificial neural network architecture, its topology, and transfer function is critical for successful application of ANN as a predictive model, as transfer function used influence the ANN learning rate and its performance. Figure 6 represents artificial neural network simulation performance for brown rice recovery. The optimum ANN model for predicting brown rice recovery was terminated when lowest mean square error (MSE) and highest correlation coefficient (R) values were obtained as shown in Figures 6(a) and 6(b). The regression analysis between ANN predicted outputs and experimental data for brown rice recovery indicated a precise and effective prediction capability of ANN model for brown rice recovery with a correlation coefficient (R) of 0.99498, 0.99584, 0.98793 and 0.99386 for training, validation, testing and all data respectively [Figure 6(b)]. The MSE value was found to be 0.056349 at 137 epochs for the optimum architecture of the ANN model.

Figure 5 The optimum architecture of the developed ANN model for simulating brown rice recovery, head brown rice and overall energy consumption (see online version for colours)

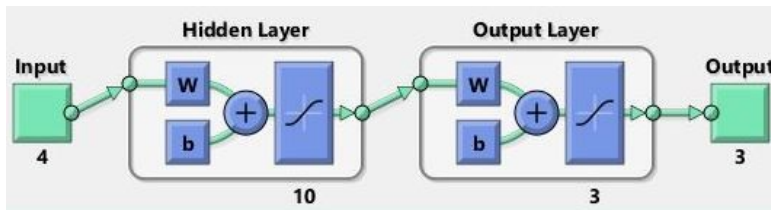


Figure 6 Artificial neural network simulation performance for brown rice recovery (see online version for colours)

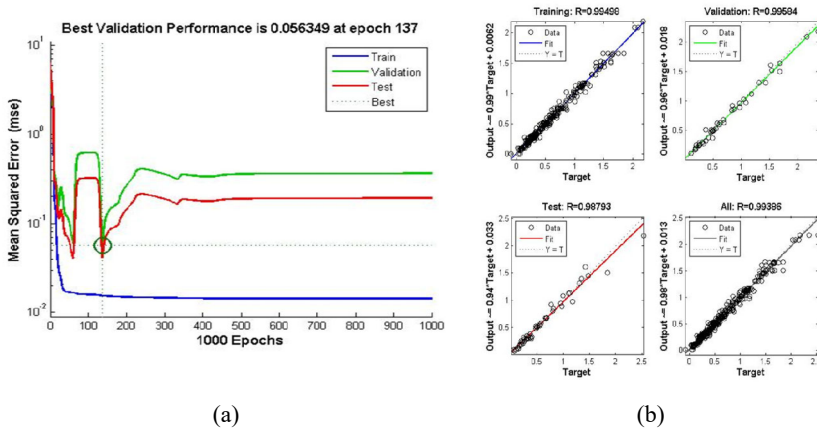
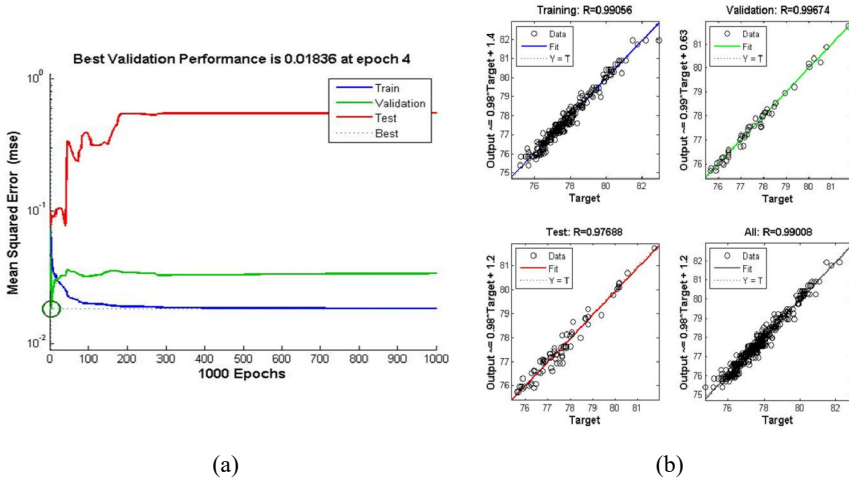


Figure 7 Artificial neural network simulation performance for head brown rice (see online version for colours)



The optimum ANN model for predicting head brown rice was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figures 7(a) and 7(b). The regression analysis between ANN predicted outputs and experimental data for Head brown rice indicated a precise and effective prediction capability of ANN model for Head brown rice with a correlation coefficient (R) of 0.99056, 0.99674, 0.97688 and 0.99008 for training, validation, testing and all values, respectively [Figure 7(b)]. The MSE value was found to be 0.01836 at four epochs for the optimum architecture of the ANN model. The optimum ANN model for predicting overall energy consumption was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figures 8(a) and 8(b). The regression analysis between ANN predicted outputs and experimental data for overall energy consumption indicated a precise and effective prediction capability of ANN model for overall energy consumption with a correlation coefficient (R) of 1, 1, 1 and 1

for training, validation, testing and all values, respectively [Figure 8(b)]. The MSE value was found to be 3.6713×10^{-10} at 1,000 epochs for the optimum architecture of the ANN model. The predictive capability of the generated ANN models for brown rice recovery, head brown rice and overall energy consumption were tested using unknown set of inputs data, and the ANN predicted values and experimental values were plotted for BRR, HBR and OEC as shown in Figures 9, 10 and 11. The R^2 between the ANN experimental and predicted data were 0.954, 0.938 and 1.000, respectively. This result showed that the predictive accuracy of the ANN model for BRR, HBR and OEC were high.

Figure 8 Artificial neural network simulation performance for overall energy consumption (see online version for colours)

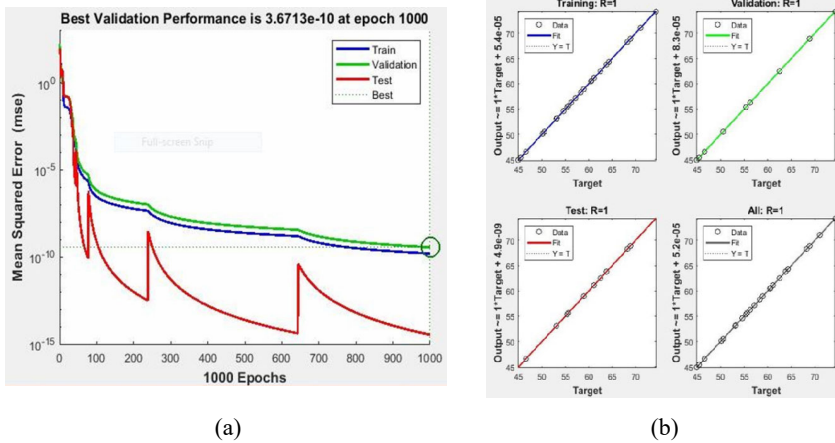


Figure 9 Comparison between the experimental brown rice recovery and predicted brown rice recovery using ANN (see online version for colours)

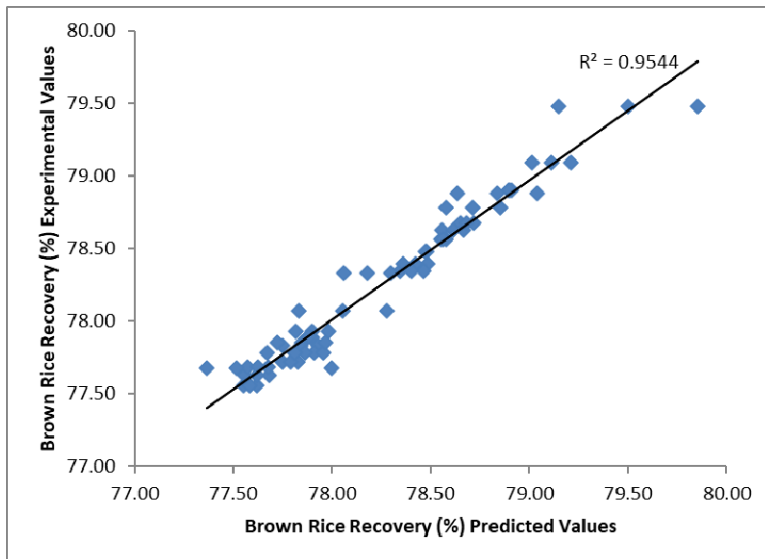


Figure 10 Comparison between the experimental head brown rice and predicted head brown rice using ANN (see online version for colours)

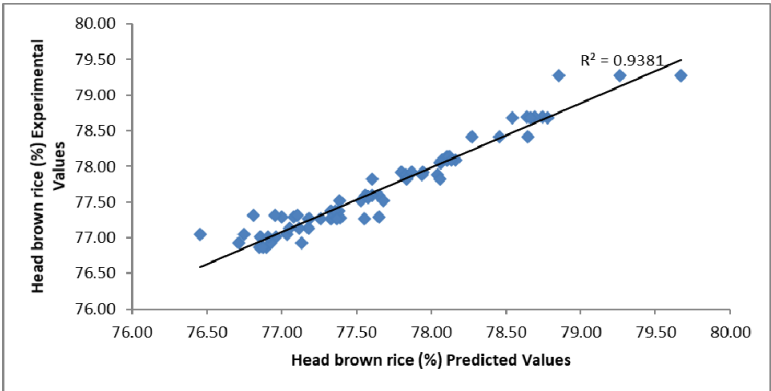
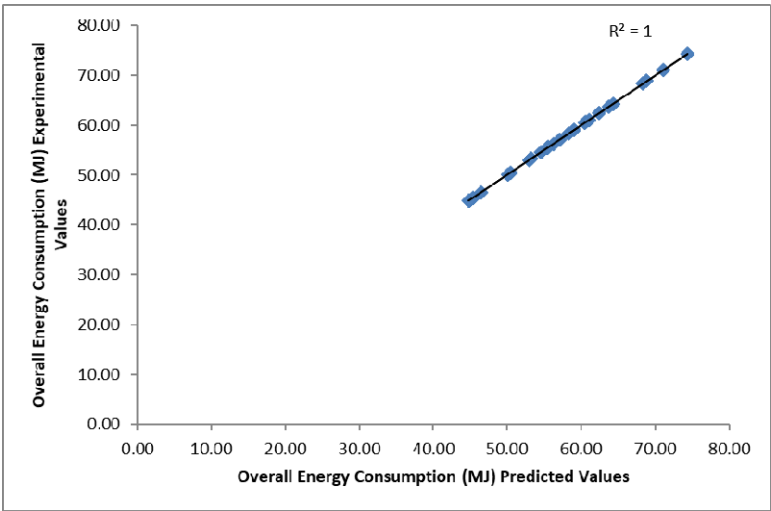


Figure 11 Comparison between the experimental overall energy consumption and predicted overall energy consumption using ANN (see online version for colours)



3.5 Comparison of ANN and PRA models

PRA and ANN models effectiveness and predictive capability were examined by plotting the predicted values against the experimental values of brown rice recovery; head brown rice and overall energy consumption. The results in Table 3 shows that ANN model has more predictive accuracy and capability while fitting the experimental data with predicted date, with the highest R^2 values and lowest MSE values for BRR, WBRY and OEC, as against PRA with lowest R^2 and MSE values for the responses. The deviation observed while plotting the experimental data against predicted was the cause of the low R^2 and MSE observed in PRA. The nonlinearity nature of ANN model in relating the independent variables with dependent variables might be reason for a better predictive

capability of ANN. For PRA, its predictive capability is usually based on the polynomial relationship between the independent variables with dependent variables. Therefore, ANN architecture is more precise in predicting brown rice recovery, head brown rice and overall energy consumption under different processing conditions. Betiku and Taiwo (2015) and Yadav et al. (2017) reported that R² and MSE can be used to compare evaluate the effectiveness of ANN models with RSM model, and reported that ANN shows more predictive capability.

Table 3 Comparison of PRA and ANN models in brown rice quality and overall energy consumption prediction

Index	Brown rice recovery		Head brown rice		Overall energy consumption	
	ANN	PRA	ANN	PRA	ANN	PRA
R ² (%)	0.954	0.901	0.938	0.897	1.000	0.964
MSE	0.019	1.880	0.046	1.220	0.000	0.040

3.6 Optimisation of the process variables

The maximum brown rice recovery and head brown rice and minimum overall energy consumption was actualised using numerical optimisation. Table 4 summarised the optimum condition of the process variables with maximum global desirability value. For all the responses, one optimum condition was obtained at 80°C soaking temperature, 7 h soaking time, 35 min steaming time and 14% paddy moisture content. The optimum condition was established when the desirability values of the predicted responses and global desirability value (GD = 0.99) were closer to unity. The optimum predicted process variables were experimented to confirm the result. The result validate that the predicted and experimented values for the responses closely matches with small relative error less than 1.5%. Thus, the optimum condition can be used to achieve brown rice with maximum brown rice recovery and head brown rice and minimum overall energy consumption.

Table 4 Optimum conditions of the process variables with maximum global desirability value

Parameters	Predicted value	Experimental value	Relative error (%)	Desirability	Global desirability
Soaking temperature (x ₁)	80	80	0		0.997
Soaking time (x ₂)	7	7	0		
Steaming time (x ₃)	35	35	0		
Paddy moisture content (x ₄)	14.12	14	0.857		
Brown rice recovery (Y ₁)	80.5	80.3	0.249	1.000	
Head brown rice (Y ₂)	80	79.5	0.629	1.000	
Overall energy consumption (Y ₃)	66.9	66	1.363	0.991	

4 Conclusions

This study established an optimum process conditions that gives maximum brown rice recovery, head brown rice and minimum overall energy consumption. The most significant process variables that influence brown rice recovery, head brown rice and overall energy consumption were highlighted. The experimental results obtained while studying the impact of process variables were used to build PRA and ANN models capable of predicting BRR, HBR and OEC changes, under different processing conditions. The models were compared statistically using R^2 and MSE, with ANN having accurate predictive capability than PRA model.

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