Evaluation of energy consumption patterns in rice processing using Taguchi and artificial neural network models

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Abstract: This study was designed to evaluate and model the impact of processing parameters (steaming time, soaking time, paddy moisture content and soaking temperature) on the energy consumption of five rice varieties (NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44). Energy consumption in the cleaning, soaking, steaming, drying, dehusking, polishing and grading operations were estimated by fitting data on labour, fuel and electricity consumption, time and machine efficiency into standard equations to determine total energy consumption. The energy consumptions were separately modelled using Taguchi and Artificial Neural Network (ANN) models for each rice variety. The accuracy of models was determined using the coefficient of determination (R^2) and Mean Square Error (MSE). Total energy consumption among the rice varieties varied significantly, ranging from 2.31 to 2.33 MJ for white rice, and 45.3 to 76.9 MJ for parboiled rice. Paddy moisture content was observed to be the most important process parameter that influenced energy consumption. Taguchi models were more accurate for total energy consumption prediction [R^2 (0.95-0.97); MSE (1.24-1.96)], than ANN [R^2 (0.93-0.94); MSE (3.21-3.52)]. The study established appropriate processing conditions that can guarantee minimum energy consumption for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44.

Keywords: artificial neural network, energy consumption, modelling, rice varieties, Taguchi

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1 Introduction

Energy audit is a systematic approach used in keeping track of total energy consumption and costs through the whole facility (Akinoso et al., 2013). Energy audit can also be referred to as energy survey, energy analysis, or energy evaluation (Akinoso et al., 2013; Sanusi and Akinoso, 2021). Determination of how and where energy is used or converted from one form to another, identification of opportunities to reduce energy usage, evaluation of the economics and technical practicability of implementing these reductions, and formulation of prioritized recommendations for implementing process improvements to save energy are the key objectives of energy audit in a facility (Capehart et al., 2008). In order to achieve this, data analysis and measurement are needed followed by the development of tables of energy consumption, cost and development of precision models for countermeasures in every factory and every process (Capehart et al., 2008). According to Bakari et al. (2010), energy consumption analysis in rice processing is crucial as a result of dire consequence of increasing cost of fuel and deforestation.

Parboiling process as practiced in many rural rice producing communities is energy intensive, laborious and time-consuming (Kwofie et al., 2016). The recent trend of global energy consumption is increasing and is expected to reach 630 quadrillion Btu by 2020 (IEO, 2013). Therefore, it is of great importance to note that

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energy needs to be supplied in a more sustainable manner and efficient way (Kwofie and Ngadi, 2017). Many researchers have reported parboiling to be energy intensive. Bakari et al. (2010) studied the energy usage in small and medium scale rural rice parboiling centres and reported that the optimization of energy used is needed for sustainable rice processing in rural communities. In addition, sources of energy must be carefully considered (Bakari et al., 2010). Islam et al. (2004) reported that having information on energy requirement in rice parboiling can play a vital role in parboiling plants as it aids in plant efficiency and economic viability. Energy required in various parboiling methods was also reported by Bhattacharya (2013). Goyal et al. (2014) reported that the intensity of energy consumption is influenced by the variety of rice, parboiling conditions, parboiling method and quantity of rice being processed. Kwofie and Ngadi (2016) reported that the state of rice has a huge impact on the energy consumed and it is usually estimated based on the amount and heating value of the fuel used. Goyal et al. (2014) critically appraised the energy use pattern in rice milling industries and reported that there is need to improve their energy efficiency. Kwofie and Ngadi (2016), reported the potential use of rice husk as a strategic way of achieving sustainable energy supply for local rice parboiler in West Africa. According to Kwofie and Ngadi (2017), combinations of processing methods have been identified as a ways of improving energy consumption. In spite of the extensive work that had been done in analyzing the energy consumption involved in parboiling, only few have applied Taguchi model and computational model (Artificial Neural Network) to model the impact of processing parameters on energy consumption of parboiled rice.

Taguchi technique is a statistical method developed to improve the efficiency and enhance quality of manufactured goods in the industry (Singh, 2012; Hussein et al., 2019). According to Singh (2012), Taguchi technique have been widely applied successfully in manufacturing, automobile, military and other industries with specific application in engineering, biotechnology, environmental science, agricultural, science, management and business. Conventional experimental design techniques have been found to have limitations when applied to industrial experimentation (Kondapalli et al., 2015). Based on this fact, Taguchi developed a new method that was known as orthogonal array design, which adds a new dimension to conventional experimental design (Sanusi et al., 2020a). Taguchi Orthogonal Array uses a special set of arrays that gives the minimum number of experiments with maximum information (Dash et al., 2016; Sanusi et al., 2020b).

One of the supervised machine learning models is Artificial Neural Network (ANN) and it is known to mimic a biological nervous system (Oluwatoyin and Chen, 2018). ANN can be defined as a computing system that uses the idea of information technology to mimic the processing, learning processes, transmission and abilities of biological neurons (Huang et al., 2016). Artificial Neural Network development is usually done either by using computer programming to develop the neural network or by the use of commercial artificial neural network software (Funes et al., 2015). According to Chen and Li (2007), developing ANN codes that can turn the theory of a particular ANN model into the design for a computer simulation and implementation, can be a herculean task for most engineers and scientists who do not have the programming and related knowledge of artificial neural networks. The use of commercial software has been the most famous method for developing an ANN model (Bhatt et al., 2014; Funes et al., 2015; Hosseinpour et al., 2019). ANN is a computer technology that emerges recently, it can be applied in a large number of ways such as; monitoring, controlling, modelling, recognition, image processing, optimization, predicts on line and signal processing (Funes et al., 2015; Hosseinpour et al., 2019; Sanusi and Akinoso, 2021). Therefore, the aim of this study was to evaluate and model the energy consumption of five Nigerian rice varieties by using Taguchi and Artificial Neural Network models.

2 Materials and method

Five Nigerian paddy rice varieties (NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44) of 18 kg each were obtained from the breeding laboratory of the National Cereals Research Institute, Badeggi, Nigeria.

2.1 Processing of five Nigerian paddy rice into white rice and parboiled rice

Figure 1 shows the flow chart for processing paddy rice into white rice and parboiled rice. At each stage of unit operation, some energy input is required in form of manual energy, thermal and electrical energy. The type of magnitude of the energy input are functions of the technology and the quantity of paddy rice being processed. In terms of technology for this study, liquefied propane gas powered rice parboiler was used for soaking and steaming the paddy rice of the varieties. The paddy rice were dried at temperature of 38°C to desired paddy moisture content of 12%, 14% and 16%, respectively. Electrical powered rice roll rubber dehusker model (THU 35B, Satake Engineering Corp. Tokyo, Japan) was used for dehusking the dried paddies while electrical powered rice polisher (SE 1009, Satake Engineering Corp. Tokyo, Japan) was used to polish the brown rice obtained from the dehusker. International Rice Research Institute (IRRI) laboratory rice grader was used to grade parboiled rice into head rice and broken rice. The mass of the rice samples were measured using an electronic balance (GF-6000AND, Japan) of ± 0.1g accuracy. To determine the energy consumption, quantitative data of operating conditions for each unit operation, manual, thermal and electrical were measured. In some unit operations, combination of manual and electrical was used. The developed equations for energy consumption evaluation in rice processing are shown in Table 1. The unit operations were cleaning, soaking, steaming, drying, dehusking, first grading, polishing and second grading. The collection was done as a function of operating duration (h), calorific value of fuel, quantity of fuel used (kg), no of person involved, average power of man, power factor and power rating of the machines. Similar approach for energy consumption evaluation were reported by Akinoso et al. (2013); Anjorin et al. (2018) and Sanusi and Akinoso (2020).

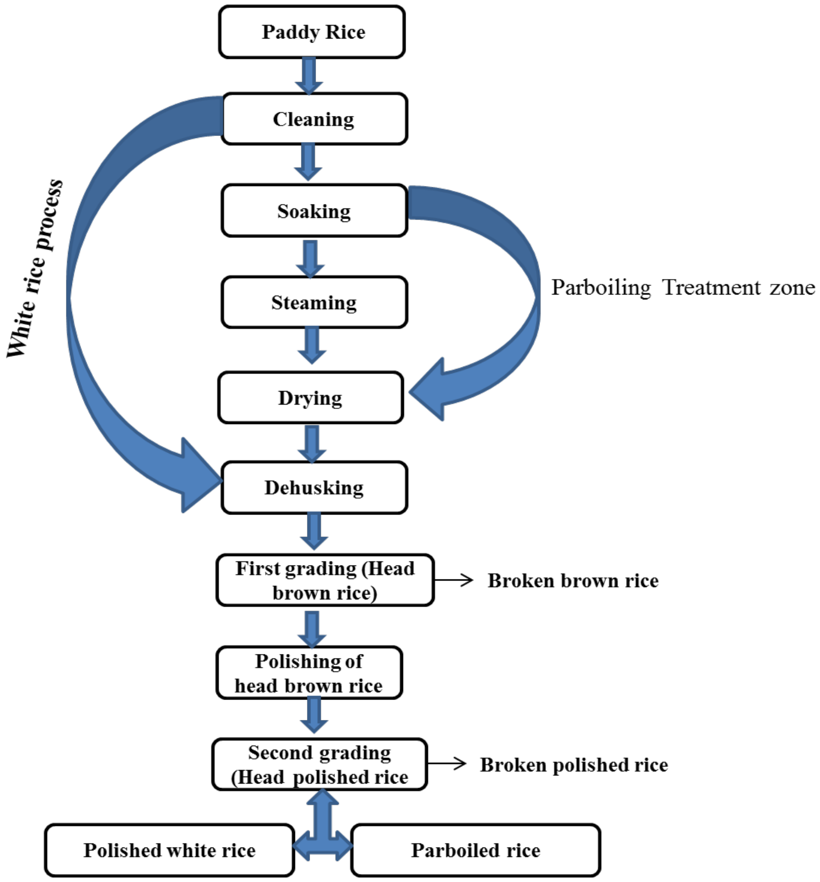


Figure 1 Flow chart for processing paddy rice into white rice and parboiled rice

Table 1 Summary of equations developed for estimating energy consumption in rice processing

S/N	Processing operations	Energy components	Developed equations
1	Cleaning	Manual	$E_c = 0.75N\times0.0167t$
2	Soaking	Manual and Fuel	$E_s = 0.75N\times0.0167t + Q_f\times C_f$
3	Steaming	Manual and Fuel	$E_{st} = 0.75N\times0.0167t + Q_f\times C_f$
4	Drying	Manual	$E_d = 0.75N\times0.0167t$
5	Dehusking	Electricity and Manual	$E_{dh}=3.6\times P\times\varphi+ N\times0.0167t$
6	First grading	Manual	$E_{g1}= 0.75N\times0.0167t$
7	Polishing	Electricity and Manual	$E_p=3.6\times P\times\varphi+0.75\times N\times0.0167t$
8	Second grading	Manual	$E_{g2} = 0.75N\times0.0167t$

where N is the number of male person involved, E is the energy consumption (MJ), t is time taken for a unit operation (h), Q_f is the quantity of liquefied propane gas (kg) used, C_f is the heating value of LPG used for a particular operation, P is the electrical power consumed for a particular operation (MJ), φ is the power factor of the equipment used, 0.75 is the average power of a male in the tropical region (MJ h^{-1}), 3.6 is the conversion factor of 1 kWh to MJ for electrical energy. The total energy consumption in producing a given quantity of paddy rice is the sum of energy components involved in each process operation. Thus, Equations 1 and 2 represent equations for determining the total energy consumption for white rice and parboiled rice.

$$Ecow = E_c + E_{dh} + E_{g1} + E_P + E_{g2} \qquad (1)$$

$$Ecop = E_c + E_s + E_{st} + E_d + E_{dh} + E_{g1} + Ep + E_{g2} \quad (2)$$

2.2 Taguchi experimental design for rice processing

The Taguchi orthogonal array experimental plan was designed using Minitab®version 16 (Minitab, Inc. Coventry, UK) for the rice processing parameters. The experimental design has four factors at three levels given an array of L_9 (3^4). Table 2 summarised the design parameters and their respective levels. In line with the Taguchi design, nine experimental runs were performed to evaluate the impact of processing parameters (steaming time, paddy moisture content soaking temperature and soaking time) on the total energy consumption of the parboiled rice of the five rice varieties.

Table 2 Taguchi experimental design parameters and levels

Process factors	Code	Unit	Level 1	Level 2	Level 3
Soaking time	A	h	10	13	16
Soaking temperature	B	°C	65	70	75
Steaming time	C	min	20	25	30
Paddy moisture content	D	%	12	14	16

2.3 Modelling of total energy consumption

2.3.1 Taguchi model

The smaller-the-better signal-to-noise (S/N) ratio of Taguchi Orthogonal Array in Equation 3 was used to analyse the experimental result. The 'signal' represents the desirable value and the 'noise' represents the undesirable value, where the signal to noise ratio expresses the scatter around the desired value (Sanusi et al., 2020b). The experimental results of the total energy consumption of the five rice varieties obtained were transformed into linear model using Equation 4.

Smaller is the best characteristic

$$\frac{S}{N} = -10log\frac{1}{n}(\sum y^2) \qquad (3)$$

where $\bar{y}$ the average response data, Sy^2 is the variation of y, n is the number of treatments, and y is the response data.

$$Y=\beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_3+\beta_4x_4 \qquad (4)$$

Y is the total energy consumption, x_1, x_2, x_3 and x_4 are soaking temperature, soaking time, steaming time and paddy moisture content, β_0 is the constant coefficient and β_1, β_2, β_3, β_4 are the linear coefficient terms of the model.

2.3.2 Artificial Neural Network (ANN) model

Neural Network tool box 8.0 in MATLAB software was used for the Artificial Neural Network simulation. The schematic diagram of the Artificial Neural Network (ANN) is shown in Figure 2. The data obtained from Taguchi experimental runs were randomly divided into three groups, 70% in the training set, 15% in the validation set and 15% in the test set. The artificial neural network used was back-propagation (BP), a descent algorithm which attempts to minimize error at each iteration (Turan et al., 2011). A three layer (input: hidden: output) feed-forward back-propagation ANN was used with Levernberg-Marquardt method, four input variables which were soaking temperature, soaking time, steaming time and paddy moisture content and corresponding outputs for the models were the total energy consumption for the five rice varieties. The number of neurons used at hidden layer was varied from 1 to 10 neurons to get the neuron that could give an accurate model. The tangent sigmoid transfer function (tansig) at hidden layer and a tangent sigmoid transfer function (tansig) at output layer were used. Similar approach was also used by Khajeh et al. (2012) and Sanusi and Akinoso (2021). The training function selected for the network was 'Trainlm'. 'Trainlm' is a network training function that updates weight and bias values according to the Lavenberg-Marquardt algorithm. The training set was used to train the weights in the neural network to produce the desired outcome. The validation data set was used to find the best artificial neural-network configuration and training parameters. Validation data was also used to monitor the network error during training. The test set was used only to confirm the actual predictive power of the neural network. The criterion used to stop training were high value of correlation coefficient (R) of regression plot of the training, validation, testing set; low mean square error and also the plot that compares the predicted output of ANN and the actual values. The accuracy of the predicted results of ANN model were analysed by comparing the actual values and predicted values.

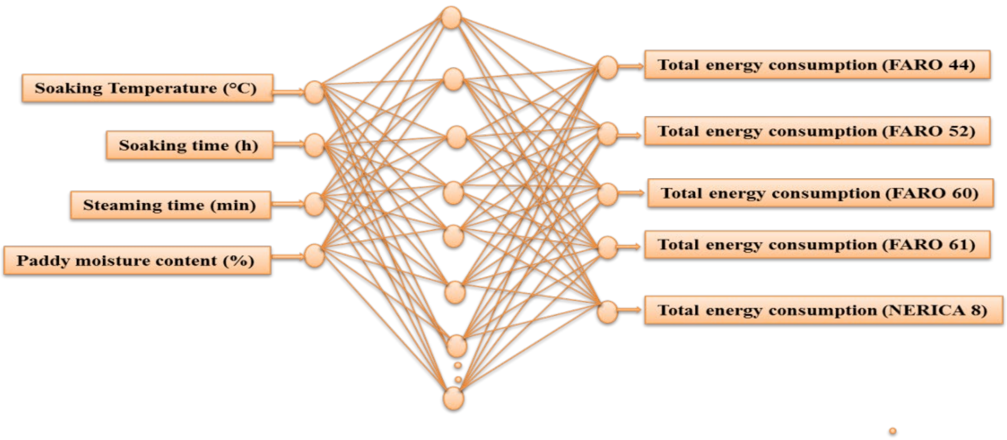


Figure 2 The schematic diagram of the Artificial Neural Network (ANN) for total energy consumption of the five rice varieties

2.3.3 Model validation

The performance and effectiveness of the modelling approach (Taguchi and ANN) were evaluated using mean square error (MSE) and regression coefficient of determination R^2 (Equations 5 and 6). The generated models were then used to predict the total energy consumption. The actual values and predicted values were plotted against each other to determine the R^2 and MSE. The closer the R^2 of the model is to unity the more its reliability and accuracy. Also, lower MSE indicate better and more precise model.

$$MSE = \frac{1}{N}\sum_{i-1}^{n}(y_o - y_e)^2 \qquad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_o - y_e)^2}{\sum_{i=1}^{n}(y_o - y_m)^2} \qquad (6)$$

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 value and y_m is the average of actual values.

2.4 Statistical analysis

All the experimental procedures were duplicated twice and the mean values were estimated using SPSS® version 20 (Statistical Package for Social Sciences, USA) and were recorded. Duncan's multiple-range test was used to compare the difference between means at a probability level < 0.05.

3 Results and discussion

3.1 Energy consumption pattern in white rice and parboiled rice processing

The average energy consumption at each unit operation in processing the rice varieties into white rice is depicted in Figure 3. The total energy consumption for the varieties ranged between 2.31 and 2.33 MJ. The highest average energy consumption was obtained in polishing (1.177 MJ) while the least was found in grading (0.034 ± 0.008 MJ). This result corroborate with Goyal et al. (2014) findings, that the major portion of the total energy consumed in white rice processing was due to polishing operation. The average energy consumptions in dehusking and cleaning operations were 1.040 ± 0.015 MJ and 0.048 ± 0.019 MJ, respectively. The high amount of energy consumed during polishing and dehusking maybe as a result of time required for removing husk and bran from the paddy rice of the varieties. The processing time at each unit operation has a lot of impact on energy consumption (Wang, 2008; Sanusi and Akinoso, 2021). Roy et al. (2003) also reported that the energy consumption for milling rice depends on paddy type, quantity of paddy, process, quality of final product, type/capacity/age or combination of equipment used, power source, efficiency of driver and power transmission. In the white rice processing, electrical energy took the highest energy portion with 96.42% while the human energy consumed 3.58% of the total energy. This implies that white rice production is electrical energy dependent.

The average energy consumption required in processing paddy rice into parboiled rice varied from one unit operation to another (Figure 4). Drying operation was observed to consume the highest energy with the value of 24.113 ± 1.24 MJ. This maybe as a result of the time required to dry the paddy rice of the varieties to desired paddy moisture content. The steaming and soaking operations were also observed to consume more energy with the values of 21.872 ± 0.209 MJ and 10.757 MJ, respectively. Kwofie et al. (2016) reported similar energy consumption pattern in the unit operations involved in rice parboiling process. The average energy consumption obtained in dehusking, polishing, cleaning, first grading and second grading operations were 1.045 ± 0.015 MJ, 1.177 MJ, 0.0379 ± 0.016 MJ, 0.012 ± 0.003 MJ and 0.032 ± 0.012 MJ respectively. In parboiled rice processing, thermal energy took the highest energy portion with 55.26%, human energy consumed 40.98% while electrical energy consumed 3.76% of the total energy consumption. Therefore, rice parboiling process is thermal energy dependent.

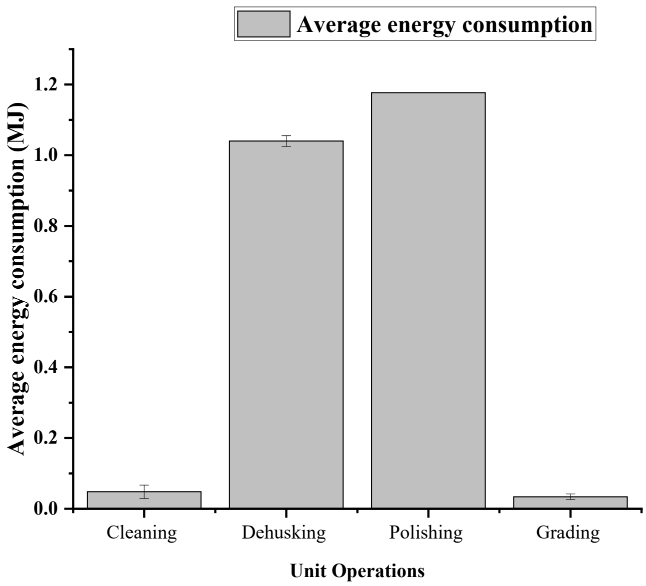


Figure 3 Average energy consumption patterns in processing paddy rice into white rice

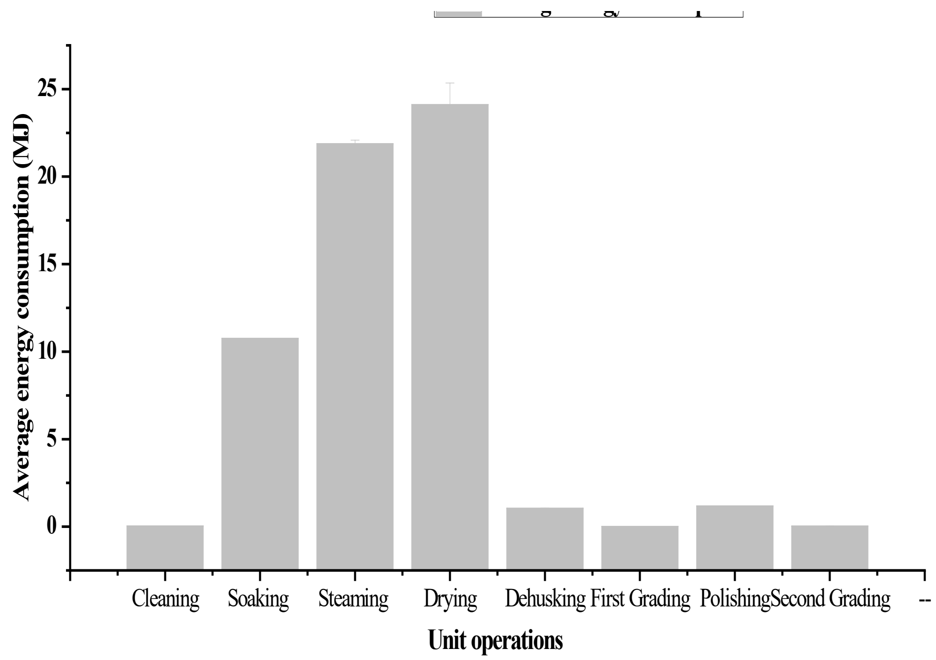


Figure 4 Average energy consumption patterns in processing paddy rice into parboiled rice

3.2 Taguchi modelling of impact of processing parameters on total energy consumption

The impact of processing parameters on total energy consumption was examined to minimize the energy consumption during parboiling as it has been earlier shown in Figure 4 that parboiling is an energy-intensive process. Kwofie et al. (2016) reported that parboiling process has direct implication on production cost due to its energy consumption intensity. Table 3 shows the impact of processing parameters on total energy consumption using Taguchi techniques. The lower the better signal to noise ratio (S/N) of Taguchi indicated that the processing conditions at 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content resulted in high energy consumption for all the rice varieties. However, the least energy consumption differs across the varieties with respect to the processing conditions combination. In FARO 44, the lowest S/N ratio (-33.96) and total energy consumption (49.88 MJ) was observed at 75°C soaking temperature, 13 h soaking time, 20 min steaming time and 16% paddy moisture content.

For FARO 52, the lowest S/N ratio (-34.28) and total energy consumption (52.08) was observed at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content. FARO 60 observed the lowest S/N ratio (-33.79) and total energy consumption (48.91 MJ) at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content. For FARO 61, the lowest signal to noise ratio (-34.28) and total energy consumption (51.37 MJ) was observed at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content. The lowest total energy consumption (52.27 MJ) and S/N ratio (-34.36) that occurred in NERICA 8 at 75°C soaking temperature, 13 h soaking time, 20 min steaming time and 16% moisture content. Although there was no significant difference ($p>0.05$) in the total energy consumption of NERICA 8 at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture. It can be deduced that the right combination of processing conditions is significant in identifying energy conservation approach. The variation in the intensity of energy consumption could be as a result of the parboiling method used, variety of rice and processing parameters.

Roy et al. (2003), also observed that energy consumption varied from process to process while according to Kwofie and Ngadi (2017), energy consumption are influenced by the quantity of rice being processed, state of rice (rough or dehusked), parboiling method used, variety of rice, and processing factors such as the soaking temperature and time etc. Table 4 shows the ranks of processing parameters on the total energy consumption, which represent the S/N ratio, mean values, delta values, and ranks of each processing parameters. The ranks of processing parameters based on their influence on total energy consumption of the five rice varieties were paddy moisture content, steaming time, soaking time and soaking temperature respectively. The ranking trend corroborates with Goyal et al. (2014) findings which stated that the drying operation was the highest consuming operation in rice parboiling. Therefore, the time required to dehydrate the paddy rice varieties to desired paddy moisture content could be the reason why paddy moisture content was ranked first. Also, Islam et al. (2004) reported that steaming and drying operations consumed more than 90% of total energy required in a rice milling system. The generated Taguchi models to predict the total energy consumption were expressed in Table 5.

The generated models have R^2 that ranged between 0.945 and 0.966 while R^2_{adj} ranged between 0.880 and 0.930. The R^2 and R^2_{adj} values obtained were closer to unity. Zaibunnisa et al. (2009) reported that when R^2 is close to unity, the better the empirical model fit the experimental data. According to Koocheki et al. (2009) for a well-fitted model, R^2 should not be less than 0.80, while Chauhan and Gupta (2004) reported R^2 greater than 0.75 as acceptable for fitting a model. Therefore, the developed models indicated their appropriateness to predict total energy consumption. The generated models were fit to predict the total energy consumption while processing different rice varieties into parboiled rice. The generated mean square error (MSE) between the actual values and predicted values obtained from the developed models were 1.814, 1.959, 1.240, 1.838, and 1.555 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The high and low values obtained for R^2 and MSE values from the developed models showed that the models were fit to predict the total energy consumption of the varieties during rice processing.

Table 3 Impact of processing parameters on total energy consumption using Taguchi model

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	EC 44 (MJ)	S/N	EC 52 (MJ)	S/N	EC 60 (MJ)	S/N	EC 61 (MJ)	S/N	EC 8 (MJ)	S/N
65.00	10.00	20.00	12.00	54.28^{e}	-34.69	55.81^{e}	-34.93	53.40^{d}	-34.55	55.69^{c}	-34.92	57.84^{d}	-35.25
65.00	13.00	25.00	14.00	58.44^{d}	-35.33	59.85^{d}	-35.54	57.02^{c}	-35.12	59.42^{b}	-35.48	60.98^{c}	-35.70
65.00	16.00	30.00	16.00	59.63^{c}	-35.51	60.93^{c}	-35.70	57.67^{c}	-35.22	60.15^{b}	-35.58	61.02^{c}	-35.71
70.00	10.00	25.00	16.00	50.78^{f}	-34.11	51.74^{f}	-34.28	49.46^{e}	-33.88	53.05^{d}	-34.49	52.51^{f}	-34.41
70.00	13.00	30.00	12.00	66.96^{b}	-36.52	67.84^{b}	-36.63	65.71^{b}	-36.35	68.64^{a}	-36.73	67.49^{b}	-36.58
70.00	16.00	20.00	14.00	53.81^{e}	-34.62	55.46^{e}	-34.88	53.51^{d}	-34.57	55.29^{c}	-34.85	56.18^{e}	-34.99
75.00	10.00	30.00	14.00	59.10^{cd}	-35.43	59.71^{d}	-35.52	57.16^{c}	-35.14	59.59^{b}	-35.50	60.53^{c}	-35.64
75.00	13.00	20.00	16.00	49.88^{f}	-33.96	52.08^{f}	-34.33	48.91^{e}	-33.79	51.37^{e}	-34.21	52.27^{f}	-34.36
75.00	16.00	25.00	12.00	68.41^{a}	-36.70	70.22^{a}	-36.93	67.05^{a}	-36.53	69.40^{a}	-36.83	70.11^{a}	-36.92

Note: The values of mean in the same columns with the same superscript do not differ significantly (p<0.05)

EC 8, EC 52, EC 61, EC 60 and EC 44 represent Total Energy Consumption for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44

Table 4 Ranks of processing parameters on total energy consumption

	Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)
Levels	S/N ratio	S/N ratio	S/N ratio	S/N ratio
FARO 44				
1	-35.18	-34.75	-34.42	-35.97
2	-35.08	-35.27	-35.38	-35.13
3	-35.36	-35.61	-35.82	-34.53
Delta	0.28	0.86	1.4	1.44
Rank	4	3	2	1
FARO 52				
1	-35.39	-34.91	-34.72	-36.16
2	-35.26	-35.5	-35.58	-35.31
3	-35.59	-35.84	-35.95	-34.77
Delta	0.33	0.92	1.23	1.4
Rank	4	3	2	1
FARO 60				
1	-34.96	-34.53	-34.3	-35.81
2	-34.94	-35.09	-35.18	-34.94
3	-35.15	-35.44	-35.57	-34.3
Delta	0.22	0.91	1.27	1.51
Rank	4	3	2	1
FARO 61				
1	-35.33	-34.97	-34.66	-36.16
2	-35.36	-35.47	-35.6	-35.28
3	-35.51	-35.76	-35.94	-34.76
Delta	0.19	0.78	1.28	1.39
Rank	4	3	2	1
NERICA 8				
1	-35.55	-35.1	-34.87	-36.25
2	-35.33	-35.55	-35.68	-35.45
3	-35.64	-35.87	-35.98	-34.83
Delta	0.31	0.78	1.11	1.42
Rank	4	3	2	1

Table 5 The generated Taguchi models to predict total energy consumption

S/N	Taguchi Models	R^2	R^2(adj)
1	$\boldsymbol{TEC\ (A) = 44.52 + 0.1682S_{temp} + 0.9829S_{time} + 0.9248ST - 2.4474MC}$	0.959	0.920
2	$\boldsymbol{TEC(B) = 45.73 + 0.1804S_{temp} + 1.0752S_{time} + 0.8371ST - 2.4261MC}$	0.947	0.890
3	$\mathrm{T}\boldsymbol{EC(C) = 46.28 + 0.1679S_{temp} + 1.0120S_{time} + 0.8242ST - 2.5098MC}$	0.966	0.930
4	$\boldsymbol{TEC(D) = 47.69 + 0.1699S_{temp} + 0.9175S_{time} + 0.8676ST - 2.4301MC}$	0.949	0.890
5	$\boldsymbol{TEC(E) = 56.49 + 0.1022S_{temp} + 0.9123S_{time} + 0.7583ST - 2.4698MC}$	0.945	0.880

Note: S_{temp}, S_{time}, *ST, MC, TEC, E, B, D, C*, and *A* represent soaking temperature, soaking time, steaming time, paddy moisture content, total energy consumption, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively.

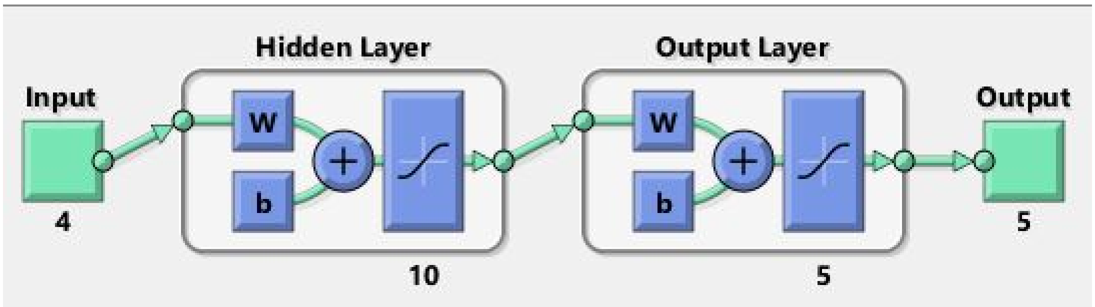
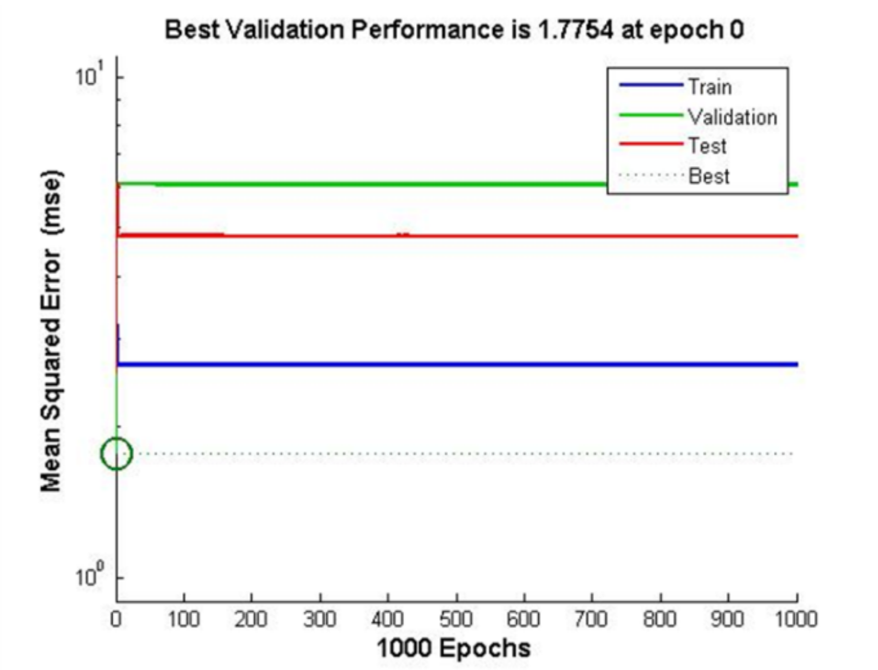


Figure 5 The optimum architecture of the developed ANN model for simulating total energy consumption of the five rice varieties during processing

3.3 Total energy consumption simulation using artificial neural network (ANN)

The data obtained from Taguchi experimental runs were randomly divided into three groups, 70% in the training set, 15% in the validation set and 15% in the test set. The optimum architecture had four (4) inputs (soaking temperature, soaking time, steaming time and paddy moisture content), one hidden layer with 10 neurons and tangent sigmoid function (tansig) at both hidden layer as the training function and output layer with five outputs which are the total energy consumption obtained while processing NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 into parboiled rice. Back-propagation (BP) with Levernberg-Marquardt method of the artificial neural network was used to minimize error at the iterations. Figure 5 shows the optimum architecture of the developed ANN model for simulating total energy consumption of the five rice varieties during processing. It was observed that neural network architecture with 10 neurons at the hidden layer and one layer at the hidden layer produced the best performance model. Also, tangent sigmoid transfer function (tansig) at hidden layer and a tangent sigmoid transfer function (tansig) at output layer gave the optimum topology. Figure 6 represent artificial neural network simulation performance for total energy consumption of the five rice varieties during processing. The optimum ANN model for predicting total energy consumption was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 6 (a) and (b).



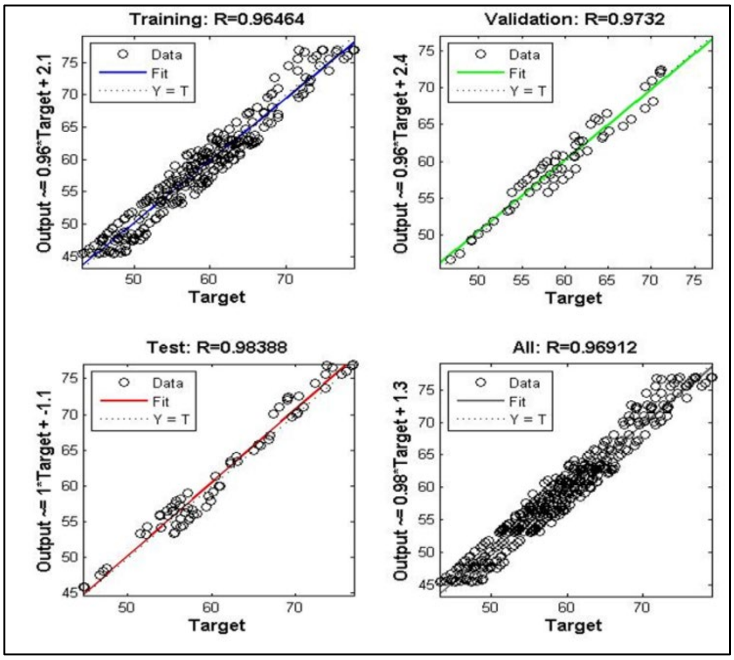


Figure 6 Artificial neural network simulation performance for total energy consumption

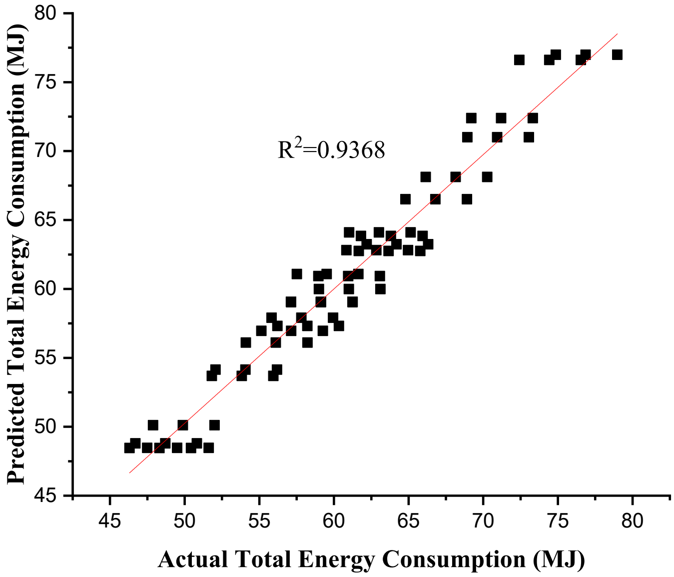


Figure 7 The actual total energy consumption values and predicted total energy consumption values using ANN for processing NERICA 8 into parboiled rice

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. The regression analysis between ANN predicted outputs and experimental data for total energy consumption indicated a precise and effective prediction capability of ANN model for total energy consumption with a correlation coefficient (R) of 0.964, 0.973, 0.9838 and 0.9691 for training, validation, testing and all data respectively (Figure 6b). The MSE value was found to be 1.7754 at 0 epochs for the optimal architecture of the ANN model. The predictive capability of the generated ANN model for total energy consumption was tested using unknown set of inputs data and the ANN predicted values versus actual values was plotted for each rice variety that was processed into parboiled rice as depicted in Figures 7, 8, 9, 10 and 11. The coefficient of determination (R^2) between the ANN actual and predicted data were 0.9368, 0.9347, 0.9376, 0.9379, and 0.9413 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively while the mean square error between the predicted values and actual values were 3.305, 3.522, 3.327, 3.212 and 3.345 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. This result showed that the predictive accuracy of the ANN model for total energy consumption was high.

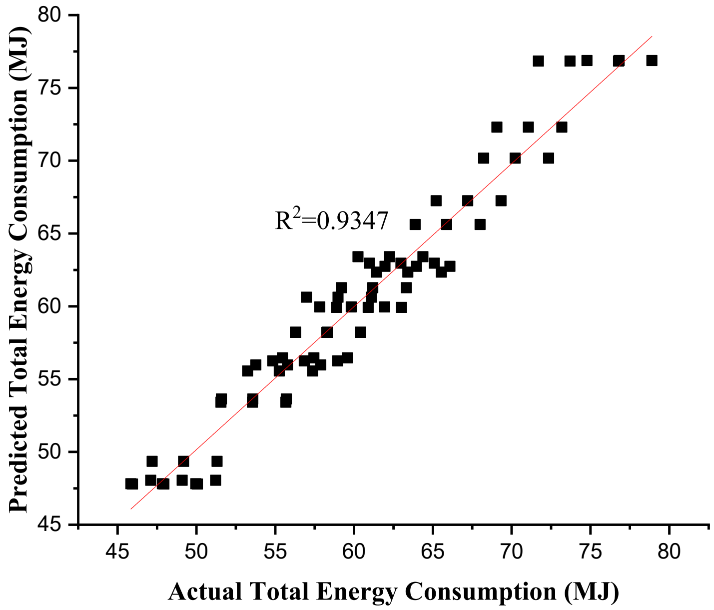


Figure 8 The actual total energy consumption values and predicted total energy consumption values using ANN for processing FARO 52 into parboiled rice

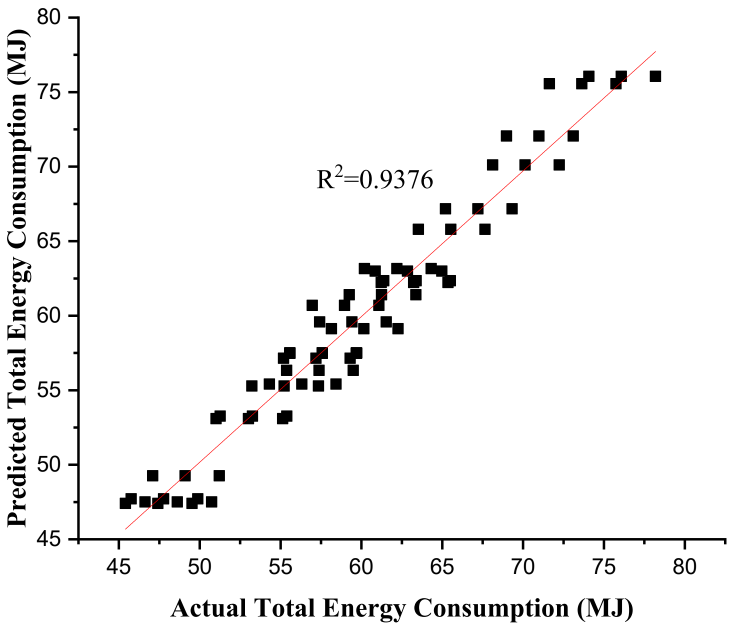


Figure 9 The actual total energy consumption values and predicted total energy consumption values using ANN for processing FARO 61 into parboiled rice

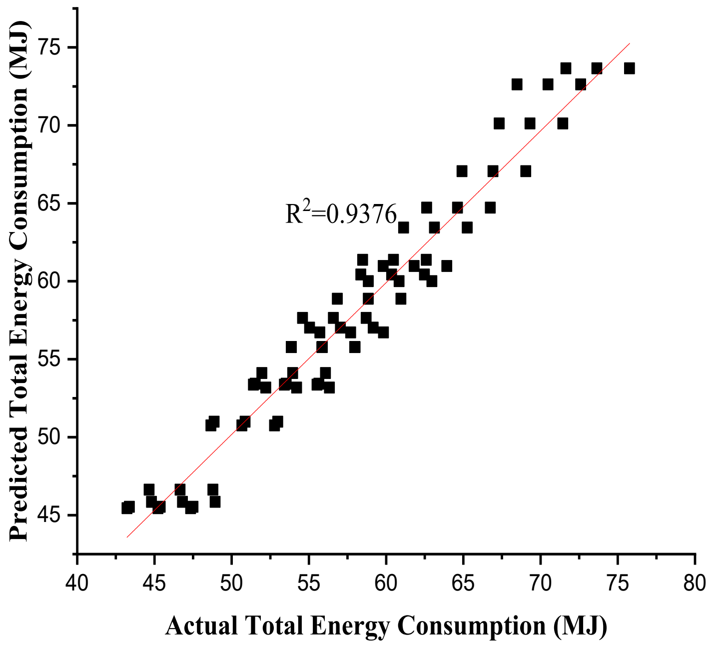


Figure 10 The actual total energy consumption values and predicted total energy consumption values using ANN for processing FARO 60 into parboiled rice

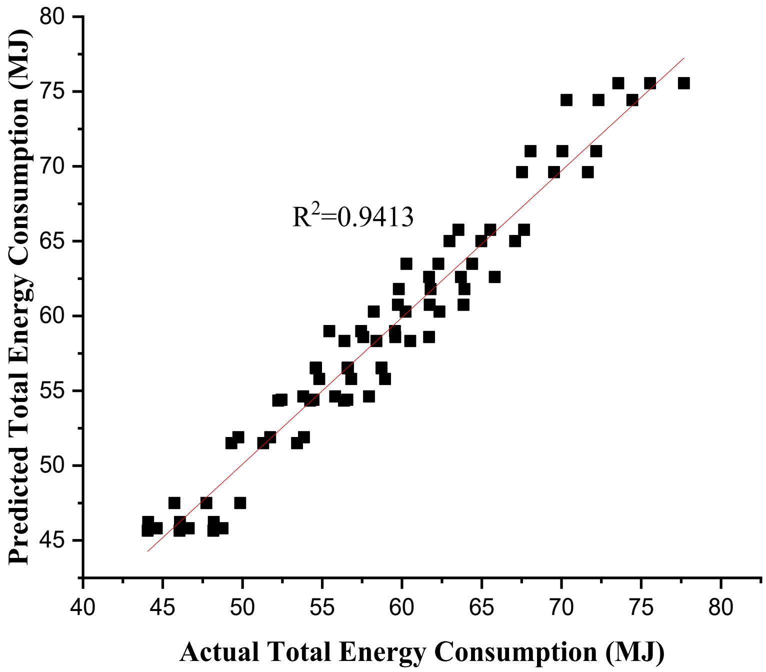


Figure 11 The actual total energy consumption values and predicted total energy consumption values using ANN for processing FARO 44 into parboiled rice

3.4 Comparison of Taguchi and ANN models

The effectiveness of Taguchi and ANN models in predicting the total energy consumption of the five rice varieties into parboiled rice were compared using coefficient of regression (R^2) and mean square error (MSE) were presented in Table 6. Betiku and Taiwo (2015) reported that R^2 and MSE can be used to evaluate the effectiveness of modelling techniques. Table 6 shows the comparative results of the obtained coefficient of determination (R^2) and MSE for Taguchi, and ANN models in fitting the actual data of total energy consumption. Taguchi model was observed to have highest R^2 values and lowest MSE for total energy consumption than and ANN models. This might be due to the linear relationship that exists between the processing parameters and total energy consumption. Dash et al. (2016) reported that Taguchi techniques have capability of predicting linear or homogenous relationship that exists in a process.

Table 6 Comparison of Taguchi, RSM and ANN coefficient of determination (R^2)

RICE VARIETY	TAGUCHI MODEL (R^2)	ANN MODEL (R^2)	TAGUCHI MODEL (MSE)	ANN MODEL (MSE)
FARO 44	0.959	0.941	1.555	3.345
FARO 52	0.947	0.935	1.959	3.522
FARO 60	0.966	0.937	1.240	3.212
FARO 61	0.949	0.938	1.838	3.327
NERICA 8	0.945	0.937	1.814	3.305

4 Conclusions

The polishing operation was the highest energy consuming unit operation while processing paddy rice into white rice and electrical energy accounted for 96.42% of total energy consumption. The paddy moisture, steaming and soaking operations consumed 24.11 MJ, 21.87 MJ and 10.76 MJ of the total energy involved in processing paddy to parboiled rice with thermal energy accounting for 55.26%, human energy 40.98%, and electrical energy 3.76% of the total energy consumption. The paddy moisture content and steaming time were the most significant processing parameter that affected the total energy consumption. Taguchi model showed most predictive accuracy for total energy consumption with coefficient of determination (R^2) that ranged between 0.947 and 0.966, and mean square error (MSE) from 1.240 – 1.959 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 than ANN that had R^2 and MSE that ranged between 0.935 and 0.941 and 3.212 and 3.522 respectively. Therefore, Taguchi model is more accurate for predicting total energy consumption during the production of parboiled rice of different rice varieties. This study will guide in establishing the optimum processing conditions that can guarantee minimum energy consumption during the processing of the rice varieties to parboiled rice and also minimize the manual or laboratory system of monitoring total energy consumption during processing.

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