IMPACTS OF PROCESSING PARAMETERS ON THE QUALITY ATTRIBUTES AND ENERGY CONSUMPTION OF RICE (*Oryza sativa* LINNAEUS)

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BY

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172034

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ABSTRACT

Information on food properties and energy requirements for processing is a prerequisite in plant design. Inconsistent quality attributes of rice varieties and energy profile of the unit operations hinder acceptability. However, literature is sparse on impacts of processing parameters on quality attributes and energy consumption in rice processing. This study was designed, therefore, to investigate and model the impacts of processing parameters on the quality attributes of five locally grown rice varieties and the associated energy consumption.

Optimum rice processing conditions [soaking temperature (65-75°C), soaking time (10-16 h), steaming time (20-30 min) and paddy moisture content (12-16%)] were obtained using Response Surface Methodology (RSM). Paddies of NERICA 8, FARO 52, FARO 61, FARO 61 and FARO 44 varieties were processed to white and parboiled rice using standard procedures. The milling recovery, head milled rice, chalkiness, brown rice recovery, head brown rice, colour, lightness, cooking time and water uptake ratio of each variety were determined using IRRI standard methods. Energy consumptions 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 quality attributes and energy consumptions were separately modelled using Taguchi, RSM and Artificial Neural Network (ANN) techniques for each rice variety. Accuracy of models was determined using coefficient of determination (R^2) and Mean Square Error (MSE). Multi-objectives function optimizer was used to optimize desirable quality attributes and energy consumptions. Data were analyzed using ANOVA at $\alpha_{0.05.}$

Milling recovery, head milled rice and chalkiness for white rice were 65.3-68.3%; 12.7-48.1% and 65.2-83.0% respectively. The corresponding results for parboiled rice were 56.5-73.5%; 48.5-72.7% and 0.3-19.2% respectively. Brown rice recovery, head brown rice, colour, lightness, cooking time and water uptake ratio were 75.9-82.7%; 74.6-82.2%; 14.1-32.0; 22.9-46.8, 10.0-51.6 min and 2.2-4.9 for parboiled rice. FARO 52 had the best quality attributes. The highest energy consuming operations in white and parboiled rice processing were polishing (1.2 MJ) and drying (24.1 MJ). Quality attributes of the rice varieties varied significantly with processing parameters. Total energy consumption among the rice varieties varied significantly, ranging from 2.3 to

2.3 MJ for white rice, and 45.3 to 76.9 MJ for parboiled rice. The ANN models were more accurate for quality attributes [R^2 (0.70–0.99); MSE (0.00-10.87)] than Taguchi [R^2 (0.15-0.85); MSE (0.04-15.58)], and RSM [R^2 (0.22-0.99); MSE (0.01-20.19)]. Taguchi models were more accurate for energy consumption [R^2 (0.95-0.97); MSE (1.24-1.96)], than RSM [R^2 (0.90-0.92); MSE (4.31-4.72)], and ANN [R^2 (0.93-0.94); MSE (3.21-3.52)]. Optimum conditions required for processing the five rice varieties varied significantly. Soaking temperature of 79ºC, 14 h soaking time, 23 min steaming time and 16% paddy moisture content were the optimum conditions for processing FARO 52.

The optimum conditions for achieving acceptable quality and minimal energy consumption in the processing of five local rice varieties were established. Artificial neural network performed best for modelling quality attributes of the rice varieties, while Taguchi was the most precise for modelling energy consumption.

Keywords: Rice processing, Rice quality attributes, Energy consumption, Modelling techniques
Word count: 498

CERTIFICATION

This is to certify that this project work was carried out by SANUSI MAYOWA SAHEED (172034) in the Department of Food Technology, University of Ibadan, Nigeria.

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DEDICATION

This work is dedicated to Almighty Allah for his infinite mercy, guidance, protection and bountiful blessings on me.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of the Study

Rice (*Oryza sativa* Linnaeus) belongs to the class of primary staple food consumed by over one-half of the world's population with many cultivars grown and adapted to cooking and consuming styles around the world (Ferrerira, Oliveira, Pathania, Almeida and Brites, 2017). In many developing countries, rice consumption has risen tremendously by 10% per annum due to consumption preference (Ajala and Gana, 2015). According to RIFAN (2017), annual rice production in Nigeria had rose from 5.5 million tonnes in 2015 to 5.8 million tonnes in 2017. Also, the consumption rate is now 7.9 million tonnes and the production rate has increased to 5.8 tonnes per annum (RIFAN, 2017). Rice quality is a multidimensional concept including physical, textural, cooking and nutritional characteristics. Maintaining rice quality during production and post-harvest processing represent a major goal of Nigeria government to improve rice sustainability for both local trade and consumption and also, for export trade.

There is variation in rating rice grain quality among value chain contributors which are; growers or breeders, millers and consumers. Breeders give preference to grain size and shape while millers are more interested in high yield recovery and whole grain. Appearance and cooking quality are priority of consumers (Cruz and Khush, 2002). Plant breeders have concentrated their efforts on breeding improved rice variety with the evidence of success in the development of early maturing varieties having higher grain yield, resistance to pests and diseases much more than the local cultivars (Oluwaseyi, Danbaba and Zuluqurineen, 2016). NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 are among the improved rice varieties that have unique agronomical characteristics and they have become the variety of choice among rice processors in Nigeria (Oluwaseyi *et al.*, 2016).

In spite of this tremendous success by rice breeders in developing improved rice varieties with good agronomical characteristics, there are still huge losses at post-harvest processing of these varieties (Ajala and Gana, 2015; Kwofie and Ngadi, 2017). The processing approach that involved paddy been allowed to absorb water and gelatinization of starch in the endosperm by steaming is known as parboiling. Parboiling can also be referred to as a hydrothermal process which hardens the grain endosperm by changing the starch structure from amorphous form and gives rice grain translucent look (Danbaba, Nkama, Badau, Ukwungwu, Maji, Abo, and Oko, 2014). In rice processing, soaking, steaming and drying are critical processing parameters that can affect rice quality (Danbaba *et al.*, 2014). Improper processing conditions can result in undesirable rice quality. Hence, there is need to understand how the combination of these processing conditions affect rice quality attributes.

Rice industry that utilized parboiling treatment consumes more energy than the non-parboiled due to additional unit operations involved in parboiling process (Goyal Jogdand and Agrawal, 2014). The energy efficiency usage in the food industry requires the in-depth analysis of energy performance as directly associated with each unit operation in production process (Akinoso, Olapade and Akande, 2013). Energy consumed in processing parboiled rice is substantial (Goyal *et al.*, 2014). Hence, effort should be made towards conserving energy and improve rice quality attributes by improving processing efficiency through modelling and optimization of key processing parameters. The conventional method of analysing product quality through the use of One-Factor-at-a-Time (OFAT) experimental approach has its own limitation in that this approach is time consuming, requires a larger number of experiments, costly and frequently fails to project the true optimal condition (Bezerra, Santelli, Oliveira, Villar and Escaleira, 2008).

An experimental approach that can identify and control critical factors by which multivariate data can be handled and fitted to an empirical function offers a better choice over the OFAT approach (Hibbert, 2012). Statistical techniques and soft computing techniques are now widely being used in place of OFAT experimental approach. Response surface methodology (RSM) and Taguchi orthogonal arrays (TOA) are the commonly used statistical techniques, while Artificial neural networks (ANN) is one of the soft computing techniques used in the food industry (Huang, Hung and Yang, 2016). The TOA experimental design uses a special set of arrays, gives the minimum number of experiments with maximum information about the influence of factors involved in the research study (Dash, Mohammed, Humaira, 2016).

The RSM is an efficient technique in the statistical design of experiments, which can be used to evaluate and model the process parameters in a system even in the presence of complex interactions (Huang *et al.,* 2016). It gave the advantage of reducing experimental trials (Velmurugan and Muthukumar, 2012). Artificial Neural Network is a computational technique that tries to mimic the structure and functionalities of biological neural networks (Mourabet, El Rhilassi, Bennani-Ziatni and Taitai, 2014). The ANN technique have a remarkable ability to provide on-line capability to analyze many processing input parameters and provide information to multiple outputs, resulting in alternative provision for manual laboratory monitoring of product quality (Huang *et al.,* 2016; Oluwatoyin and Chen, 2018). It also has the capability to learn, adapt to changes in processing conditions and simplify the performance of any complex and non-linear process, all these makes it a powerful modelling technique (Adielsson, 2005).

1.2 Research Problem

Information on energy consumption and quality attributes are important to rice processors in ensuring sustainable rice production. Manual or laboratory system of monitoring total energy consumption and rice quality attributes during processing requires skilled manpower which is obviously costly, intolerably time consuming, lacking system flexibility. Parboiling has been reported as a way of improving rice quality and several research works have routinely published effects of parboiling on rice quality and energy consumption. These include Islam, Shimizu and Kimura (2004); Ayamdoo *et al.* (2013); Buggenhout, Brijs, Celus and Delcour (2013); Graham-Acquaah, Manful, Ndindeng and Tchatcha (2015); Leethanapanich, Mauromoustakos and Wang (2016). However, little has been reported on the impacts of rice processing parameters on quality attributes and energy consumption. Also, little has been reported on the novel application of Taguchi, Response Surface Methodology and Artificial Neural Network in developing precision models that can predict the impacts of processing parameters on the quality attributes and energy consumption during rice processing.

1.3 Research Justification

Despite the emergence of newly improved rice varieties with good agronomical characteristics, huge quality and energy loss had been associated with the improper processing of these varieties (Kwofie and Ngadi, 2017). Food operations are complex in term of their intrinsic biochemical properties which influences the behaviour of processing parameters, therefore warranting a strategic application of modelling technique in order to obtain a feasible process that can guarantee optimum quality yield and minimize energy consumption. The determination of optimum conditions for processing is the key to ideal industrial processing (Gulati, Chakrabarti, Sing, Duvuuri and Banerjee, 2010). Therefore, there is need to investigate the impacts of rice processing parameters on quality attributes and energy consumption. Also, to develop process models that can predict the inverse behaviour of impacts of processing parameters on quality attributes, and energy consumptions with a view to computing the required optimum processing conditions that can guarantee acceptable quality attributes and minimal energy consumption.

1.4 Aim and Objectives

The aim of this research study was to investigate and model the impacts of processing parameters on the quality attributes and energy consumptions of five improved rice varieties (NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44). The objectives of this study were to:

i. determine the physical properties of paddy and quality attributes of white rice, and energy consumption pattern in processing paddy into white rice and parboiled rice,
ii. determine the impacts of processing parameters (soaking time, soaking temperature, steaming time and paddy moisture content) on the quality attributes (brown rice recovery, head brown rice, milling recovery, head milled rice, chalkiness, lightness, colour, cooking time and water uptake ratio) and total energy consumption of the rice varieties,
iii. develop and compare models that can predict the impacts of processing parameters on the quality attributes and total energy consumption using TOA, RSM and ANN techniques,
iv. optimize and validate the processing conditions that yield acceptable quality attributes and minimal total energy consumption, and
v. determine the sensory attributes of parboiled rice produced at optimized conditions.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Rice

Rice belongs to genus *Oryza* with the most cultivated ones been *Oryza sativa* and *Oryza glaberrima*. *Oryza sativa* originated from Asian while *Oryza glaberrima* was from Africa (Oluwaseyi *et al.,* 2016). According to Villanova, Vanier, de Avila Madruga, Pesek, Matyska-Pesek, Elias and de Oliveira, (2017), more than three billion people around the globe considered rice as the best staple cereal food and also categorised it as energy food for developing countries. Nigeria is a country blessed with an array of staple food crops that are very significant in overcoming food shortage and ensuring food security of the nation. Among the staple food crops are rice, maize, sorghum, millet, cassava, yam, potatoes, cowpea, groundnut and soybeans (Daudu, Yakubu, Sambo, Okworie, Adeosun, and Onyibe, 2014).

From all the staple crops, rice has being in a domineering position as a major staple food that provides calorie for the household. Rain-fed lowland, irrigated lowland, and rain fed upland represents 69.0%, 2.7% and 28.3% rice production environment in Nigeria (Daudu *et al.* 2014). According to Danbaba *et al.* (2014), rice is a staple food of over approximately one-half of the world population. Increase in population growth and rapid urbanization has raised the demand of rice due to the fact that men and women are now preoccupied with work thus, the case and timeless of preparation has made rice a preferred staple food over others. According to FAO (2017), among the developing countries in Africa, Nigeria is the largest producer of paddy rice with an increase in paddy rice production from 4.7 million tonnes in 2014 to 5.3 million tonnes in 2017. However, rice importation declined from 3.3 million tonnes to 2.2 million tonnes in 2017 (FAO, 2017).

Government policies, acts and initiative on rice in the past years have been favourable towards domestic production of rice in Nigeria most especially the Central Bank of Nigeria anchor borrowers programme (FAO 2017; RIFAN, 2017). The programme has twelve million rice producers' four millions hectares of FADAMA cultivated land (RIFAN, 2017). In spite of this increase, the domestic production of rice has never met its demand because rice consumption superseded production (FAO, 2017). Nigerians still craved for already banned imported rice, because it is obvious that Nigerians are used to its quality and are willing to adjust to any price at which it is offered provided the quality is maintained (Danbaba *et al.,* 2014; Daudu *et al.,* 2014; Oluwaseyi *et al.*, 2016). On the other hand, locally produced rice is not well accepted by Nigerians due to their poor quality (Daudu *et al.*, 2014; Oluwaseyi *et al.* 2016). Nigerians will continue to crave for imported rice until our rice processors start producing rice that match the quality of the imported rice (Oluwaseyi *et al.* 2016). FAO (2011, 2016) also reported high loss during processing and which might be as a result of poor technical know-how and diversity of rice varieties. Therefore, it is imperative to develop techniques that can be used to improve the quality of processed rice in order to substitute the imported rice with the locally produced rice so as to achieve the goal of self-sufficiency in rice production.

2.2 Improved Rice Varieties in Nigeria

Over the past decades, rice varietal improvement has come a long way in Nigeria with evidence of success in the development of early maturing varieties with high yielding potential, resistance to drought and better grain quality (Manful, 2010; Oluwaseyi *et al.*, 2016). Among the improved rice varieties are;

FARO 44: Its original name is SIPI-692033 with national code NGOS-91-44. FARO 44 originated from Taiwan before it was developed by AfricaRice/IITA/NCRI. It has outstanding characteristics of long grain, optimum production under low management and can yield (4-8 t/ha). The agro-ecological zone that favours it was derived savannah and humid forest and it is among the most cultivated variety in Nigeria (Daudu *et al.*, 2014; Oluwaseyi *et al.,* 2016).

FARO 52: Its original name is WITA 4 with national code NGOS-01-52. FARO 52 Originated from AfricaRice and IITA Ibadan and was also developed by them. It has outstanding characteristics of high yielding potential (3-7t/ha) and high tolerant to iron toxicity and drought. It can be categorised under savannah Agro-ecological zones and it is well cultivated (Daudu *et al.*, 2014; Oluwaseyi *et al.*, 2016).

FARO 60: Also known as NERICA–19, WAS 122-IDSA-1-WAS-6-1 with national code NGOS-11-60. It was originated from AfricaRice was developed by both AfricaRice and NCRI. It is characterized as a highly yielding variety (8t/ha), long slender grains and tolerance to iron toxicity. Currently, it is moderately cultivated in savannah agro-ecological zones (Daudu *et al.*, 2014; Oluwaseyi *et al.*, 2016).

FARO 61: Otherwise known as NERICA L-34, WAS 161 -B -6-3-FKR-1 with national code NGOS-11-61. It was originated from AfricaRice and developed by both AfricaRice and NCRI. It has outstanding characteristics of early maturing, submergent tolerant and yielding potential (7t/ha). It can be cultivated in savannah agro-ecological zone and it is moderately cultivated (Daudu *et al.*, 2014; Oluwaseyi *et al.*, 2016).

NERICA 8: This variety can also be called FARO 59 with National code NGOS-11-59. It is an upland rice variety, originated from AfricaRice and developed by AfricaRice and NCRI. It has outstanding characteristics of early maturing, golden grain colour, weed competitiveness and tolerance to lodging (5t/ha). The agro- ecological zones that favoured NERICA 8 were Northern and Southern Guinea Savannah (Daudu *et al.*, 2014; Oluwaseyi *et al.*, 2016).

2.3 Rice Quality

Rice grain quality is very difficult to define with definite precision as quality preference varies from one country to another (Cruz and Khush, 2002; Manful, 2010). According to Futakuchi, Manful and Sakurai (2013), rice grain quality determination is usually influenced by variety type, the production approach and processing facilities. Therefore, it is important to conduct rice quality assessment under standardized cultivation and post-harvest practices. Rice grain quality indicators were distinguished in terms of quality attributes before and after milling process and cooking and eating quality (Manful, 2010; Futakuchi *et al.*, 2013). Also, there are several quality components which are determined by the preparations for which the grains are used for (Manful, 2010). Rice grower, millers and consumers have some desired quality characteristics that they all place emphasis on (Cruz and Khush, 2002). For instance, rice processor also known as millers based their quality upon total brown rice recovery or milling recovery, and the proportion of head brown rice or head milled rice on milling while consumers based their own quality on grain appearance (colour, lightness), grain size and shape, taste, tenderness, behaviour upon cooking and flavour of cooked rice (Cruz and Khush, 2002). According to Cruz and Khush (2002), rice quality indices maybe considered from the viewpoint of milling quality, appearance, grain size and shape and cooking characteristics. Milling yield is one of the most important criteria of rice quality, especially from the marketing point of view (Danaba *et al.,* 2014; Nasirahmadi, Emadi, Abbaspour-Fard and Aghagolzade, 2014). It is expected that a variety should possess a high turnout of head rice and milling recovery in order to have a market value (Nasirahmadi *et al.,* 2014). Brown rice recovery of paddy or rough rice is the estimate of the quantity of head brown rice and total brown rice that can be produced from a unit of rough rice while milling recovery of paddy or rough rice is the amount of head milled rice and total milled rice that can be produced from a unit of paddy rice (Nasirahmadi *et al.*, 2014; Nambi, Manickavasagan and Shahir, 2017).

Thus, the brown rice quality maybe defined as the ability of paddy grains to withstand dehusking pressure without undue breakage so as to yield the greatest amount of brown rice recovery and the highest proportion of head brown rice to broken (Nambi *et al.*, 2017). On the other hands, milling quality of rice can be defined as the ability of paddy grain to withstand dehusking and polishing without undue breakage so as to yield the highest amount of total milling recovery and the highest proportion of head milled rice to broken (Nasirahmadi *et al.,* 2014).

In the milling process, five fundamental unit operations are involved: Paddy or rough rice cleaning to remove leaves, rice stem and other foreign matter, dehusking the cleaned paddy to remove the husks, further cleaning the brown rice to remove the husk that is not totally removed by rice dehusker, polishing the brown rice to obtain milled rice or polished rice and separating the whole (head) grain from broken grains. To customers, the appearance of milled rice in terms of size and shape is a quality indicator because customers generally prefer milled rice with specific size and shape (Cruz and Khush 2002; Manful, 2010). Tables 2.1 and 2.2 shows IRRI (1996) Standard Evaluation System (SES)

Table 2.1. Standard evaluation system for rice size classification

Rank	Type	Size (Length)
One	Extra-long length	Greater than 7.5 mm
Three	Long length	Within 6.6 – 7.5 mm
Five	Medium length	Within 5.51 – 6.6 mm
Seven	Short length	Less than equal to 5.5 mm or less

Source: IRRI, 1996.

Table 2.2. Standard evaluation system for rice shape classification

Rank	Type	Shape (Length/ width ratio)
One	Slender	Greater than 3
Five	Medium	Within 2.1 – 3.0
Nine	Bold	Within 1.1 – 2.0

Source: IRRI, 1996.

for rice classification and is usually applied to determine the paddy or milled rice size and shape. Chalkiness level is another quality indicator that can be used to determine the market value of rice (Cruz and Khush 2002; Manful, 2010).

Chalky appearance denotes grain in which the starch granules are not tightly packed and consequently termed incomplete grain filling (Futakuchi *et al.,* 2013). High chalkiness in grains means the grains are prone to breakage during milling because they are usually softer (Futakuchi *et al.,* 2013). Endosperm opacity of grain is proportional to grain appearance. The amount of chalkiness on the dorsal side of the grain is called chalkiness and on the ventral side is called white back while in the centre is the white centre. According to IRRI (1996), Table 2.3 is used for classifying endosperm chalkiness of milled rice. Grain colour is an important quality attribute in the rice industry. Colour is one of the key attribute customers frequently look at in order to make a decision on the overall appearance of rice (Manful, 2010). Lightness and colour values are two quality indicator of parboiled rice (Islam *et al.,* 2004). Frequently, to produce whiter parboiled rice is the universal goal while discolouration of rice due to parboiling treatment diminishes the quality of rice (Manful, 2010).

Dark coloured rice losses market value and consumer acceptability. According to Cruz and Khush (2002) and Futakuchi *et al.* (2013), amylose content which is proportional to water uptake ratio, cooking time which is also directly related to gelatinization temperature, elongation ratio, aroma, the viscosity of cooked rice flour and protein content are other quality indicators of rice. Futakuchi *et al.* (2001) studied the effects of different harvesting dates on milling and related traits of several varieties and observed interactive effects of harvesting dates and varieties were significant for head rice yield and husking recovery. No significant interactive effects were observed in milling recovery, grain dimensions and chalkiness.

2.4 Rice Parboiling

The main composition of rice grain is polygonal starch granules found in the endosperm (Kwofie and Ngadi, 2017). The endosperm is filled up with air and moisture in its intergranular space. Leethanapanich *et al.* (2016) reported that the cause of breakage during milling could be traced to the fissures and cracks that developed during the maturity of grain.

Table 2.3. Standard evaluation system for rice chalkiness classification

Rank	Chalkiness level
0	No chalkiness
1	less than ten percent chalkiness
5	Ten percent to twenty percent chalkiness, medium
9	More than twenty percent chalkiness, large

Source: IRRI, 1996.

Gelatinization of starch in order to fill the void and cement the fissures and cracks by parboiling has been recommended by many researchers as a way of reducing breakages (Bhattacharaya, 2013; Danbaba *et al.*, 2014; Kwofie, Ngadi and Mainoo, 2016). The origin and large practice of parboiling could be traced to countries like India (Roy *et al.*, 2003), Nigeria (Ndindeng *et al.,* 2015), Ghana (Kwofie and Ngadi, 2016; Kwofie *et al.*, 2016), Benin and Cameroon (Zossou *et al.*, 2010). According to Bhattacharaya (2013); Kwofie and Ngadi (2017), about 130 million tonnes of paddy is parboiled yearly around the globe but unfortunately, about 3 - 4 million tonnes could be categorised as high-value parboiled milled rice being trade at global market.

Parboiling is general understood as a hydrothermal process in pre milling operation and its aids gelatinization of starch component in rice i.e. (conversion of amorphous to translucent form starch) (Bhattacharaya, 2013; Danbaba *et al.*, 2014; Kwofie and Ngadi, 2017). In producing parboiled rice, some certain unit operations are involved; cleaning, soaking, steaming, drying, dehusking, polishing, sorting and packaging. Parboiling hardening the grain and increase its toughness in order to increase its resistance to breakage during milling operation (Igathinathane, Chattopadhyay and Pordesimo, 2005).

Ballogou, Sagbo, Soumanou, Manful, Toukourou and Hounhouigan (2013), reported that parboiling affects the physical, storage, cooking and eating qualities which is as a results of changes in the physical, chemical and organoleptic changes in the grain. According to Danbaba *et al.* (2014), parboiling increases the grain resistance to insect attack and improves its nutritional quality. However, parboiling has been reported to produce some undesirable effects when subjected the paddy to high temperature for a long steaming time, resulting in a dark colour and harder product which reduces its market value (Bhattacharya, 2013). Extensive investigation has been done on the effects of parboiling conditions on the qualities of parboiled rice. According to Islam *et al.,* (2001); Patindol, Siebenmorgen and Duffour (2013); Danbaba *et al.* (2014); Graham-Acquaah *et al.* (2015) parboiling results in an increase in head rice yield and a decrease in overall pasting profile. The severity of the parboiling process, soaking temperature, soaking time, steaming pressure and steaming time affect rice colour (Buggenhout, Brijs, Van Oevelen and Delcour, 2014). Head brown yield was observed to be 89.6 and 62.6% when steamed at 100°C and 120°C for 20 min respectively (Patindol *et al.*, 2013). Also, Buggenhout *et al.*

(2013, 2014) reported that the degree of starch gelatinization which was affected by intensity of parboiling conditions played an important role in breakage susceptibility of parboiled rice. Leethanapanich *et al.* (2016), studied the impacts of parboiling conditions on quality characteristics of parboiled commingled rice. Nasirahmadi *et al.* (2014) studied the influence of moisture content, variety and parboiling on milling of rice quality.

In rural rice producing communities the parboiling process is still energy intensive, time consuming and laborious (Kwofie and Ngadi, 2017). Several researchers through governmental and non-governmental agencies or initiatives such as Africa Rice, Canadian Government, International Rice Research Institute, Philippine, National Cereal Research Institute has been working towards achieving high quality rice products and reduced energy consumption in rice processing in order to achieve a sustainable rice production in Sub-saharan Africa (Daudu *et al.,* 2014; Ndindeng *et al.,* 2015; Kwofie *et al.,* 2016; Kwofie and Ngadi, 2017)

Despite the extensive work that has been done on the effect of different parboiling conditions on rice quality indices, little has been reported on the novel application of Taguchi, Response Surface Methodology and computational techniques (Artificial Neural Network) in designing, studying and modelling the impacts of processing parameters on quality attributes during rice processing.

2.5 Energy

Energy can be defined as the potential for providing useful work or heat. However, it can be changed from one form to another. Analyses of energy consumption and its efficiency in food processing facilities involves the application of scientific and engineering principles such as physics, chemistry, heat transfer, fluid mechanics and thermodynamics (Wang, 2008).

As energy is regarded as the prime mover of any economy and the engine of growth around which all sectors of the economy revolve, the sustenance of the good quality living in any country requires a careful management and utilization of all available energy resources (Azzuni and Breyer, 2018). In this regard, the efficiency and conservation of energy is a major issue in energy usage to ensure proper management and as such prevent wastage. Energy is one of the essential resources in the manufacturing industries.

Sometimes energy cost outweighs the costs of raw material, personnel, depreciation and maintenance. Therefore, in evaluating the overall unit cost of production, energy utilization efficiency plays a major role (Sanusi, Anjorin and Hussein, 2015). In addition, Akinoso *et al.* (2013), stated that energy audit is an important management tool in manufacturing outfit required for economic utilization of energy resources and huge energy losses may result from Inefficient energy audit. Excess energy consumption increase the costs of finished goods produced especially in the energy intensive industries (Akinoso and Olatoye, 2013). In view of this, attempts should be made for higher efficiency of utilization of fuel, electricity, thermal energy and labour, these being the major components of manufacturing cost (Azzuni and Breyer, 2018).

2.6 Energy Consumption in the Food Industry

Energy, an important resource in any nation, is regarded as the prime mover of that nation's economy and the engine growth around which all sectors of the economy resolve (IEA, 2016). In order to ensure sustained economic development, proper understanding of energy utilization and consumption pattern must be predetermined and plan so as to ensure energy management, development and improvement where it is applicable. Food industry adds value and stimulates agricultural production; thereby, contributing to market expansion and generating collateral activities and industrial services to the economy (FAO, 2016).

In food industry operation, the conversion process of edible raw materials obtained from the farm into a higher value added consumer product utilizes significant amount of labour, machinery and energy of which energy utilization is very important. This is due to the fact the cost of energy is a significant part of the total cost of processing foods especially at the unit operations level where various forms of energy may be used. This singular factor determines the economy of the whole process which will in turn affect the overall performance of the product in consumer market (Akinoso *et al.*, 2013).

In addition to this basic factors, the rise in energy requirement together with the finite energy resources, the increasing cost of fossil fuels and the considerable environmental imparts connected with their exploitation necessitate the need to understand the mechanisms which degenerate the quality of energy and energy systems (Kwofie and Ngadi, 2017). Meanwhile, the processes that degenerate the quality of energy resources can only be identified through an in-depth analysis of the whole system in which they are utilized (Waheed, Jekayinfa, Ojediran, and Imeokpariam 2008; Akinoso and Olatoye, 2013; Kwofie and Ngadi, 2017).

Generally, in its operation, the food industry requires energy for a variety of equipment such as gas-fired ovens, dryers, stem boilers, electric motors, refrigeration equipment, heating, ventilation and air conditioning systems (Goyal *et al.,* 2014). For example, heating and cooling are two major unit operations where energy consumption is critical in the food industry. These unit operations employ the use of steam, electric power and water at various stages of production and this makes the use of boilers and refrigeration equipment important processing inputs in any food processing operation. Heating in particular is important due to the requirements of having steam at different temperatures and pressures to achieve acceptable food safety levels (IEA, 2016).

In this regard, boiler fuel represents nearly one-third of end use consumption of energy in the food industry (Goyal *et al.,* 2014). Electricity among others is the principal source of energy use and two thirds of the food industries electric consumption is used in generating mechanical power to operate conveyors, pump, compressors and other machines. In all of the energy usage, approximately half end use consumption is used to change raw materials into products (process use). This includes process heating and cooling, refrigeration, machine drive (mechanical energy) and electrochemical processes. Less than 8 per cent of the energy consumed by the manufacturing operation is for non-process uses including facility heating or cooling, ventilation, refrigeration, lighting, facility support, on site transportation and convectional electricity generation (Goyal *et al.*, 2014). Therefore, the main focus of managers who want to reduce energy costs must be on process related uses.

2.7 Energy Audit

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).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, Spiller and Frazier 2006). In order to achieve this, data analysis and measuring are needed followed by the development of tables of energy consumption and cost and development of precision models for countermeasures in every factory and every process (Capehart *et al.*, 2006).

2.8 Energy Consumption in Rice Parboiling

According to Bakari, Ngadi, Kok, Raghavan, and Diagne (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 energy need to be supply in a more sustainable manner and efficiently way (Kwofie and Ngadi, 2017).

Many scholars 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 optimization of energy use 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 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 is reported to have 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 appraise 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. Parboiling energy consumption of 1680 MJ/tonne equivalent to a specific energy consumption of 1.68 MJ/kg. In spite of the extensive work that had been done in analyzing the energy consumption involved in parboiling, only few has applied statistical simulation model (RSM and Taguchi) and computational model (Artificial Neural Network) to model the effect of parboiling conditions on energy consumption of parboiled rice.

2.9 Design of Experiment (DOE)

In the last decade, DOE has been one of the extensively used methods for experimental study in many manufacturing processes in Engineering (Kondapalli, Llongueras, Capilla-González, Prasad, Hack, Smith, and Rao, 2015). In DOE, mathematical models can be developed through experimental runs of statistical analysis (Bevilacqua, Corbo and Sinigaglia, 2010). Therefore, DOE can simply be defined as an experimental or analytical approach that is commonly used to statistically signify the relationship between input parameter to output responses, systematic way of planning of experiments, collection and analysis of data (Bevilacqua, *et al.,* 2010; Kondapalli *et al.,* 2015). The wide application of DOE has been used in the field of science and engineering, most especially in the area of process optimization and development, process management and validation tests (Bevilacqua, *et al.,* 2010; Kondapalli *et al.,* 2015).

Response Surface Methodology with Central Composite Design (CCD) or Box Benkhen (BBD), Taguchi method and factorial design have been among the most prominently used DOE techniques (Kondapalli *et al.,* 2015; Dash *et al.,* 2016). In order to optimize the quality characteristics under a cost effective process, the synergy between mathematical and statistical techniques of DOE such as Regression, Analysis of Variance (ANOVA), Non-linear optimization and desirability function helps (Yadav, Nikkam, Gajbhiye and Tyeb, 2017). According to Wang, Agrawala and Cohen (2007), ANOVA helps to identify the effect of each factor versus the objective function. Experimental design was first introduced in 1920s by R.A. Fischer and also developed the basic principles of factorial design and the associated data analysis known as ANOVA during research in improving the yield of agricultural crops.

2.10 Modelling in Food Processing

Food processing is recently facing remarkable challenges revolving around satisfying varieties of constraints such as quality of the final product, financial, environmental, safety and human constraints (Enitan and Adeyemo, 2011). Most food industries are in continuous effort to improve their quality, increase their profits and reduce their production costs due to strong competition that exists in the industry (Enitan and Adeyemo, 2011; Noorwali, 2013). In order to overcome the challenges, food industries are trying to improve their process operations by using sophisticated technologies to improve, monitor, optimize and control food processing parameters such as energy consumption, food properties and nutrient composition (Enitan and Adeyemo, 2011; Perrot, Trelea, Baudrit, Trystram and Bourgine 2011). The use of advance technology to improve production efficiency is becoming more increasing (Noorwali, 2013). According to Borkar (2015) modelling techniques are emerging as key technologies to support manufacturing in the 21st century. Due to this, modelling techniques might be expected to be a crucial element of precision in food processing (Enitan and Adeyemo, 2011; Perrot *et al*., 2011).

Modelling is a technique that is used in food engineering to predict the future of food processes and products with good accuracy depending on the purpose of the model (Trystram, 2012). Perrot *et al*. (2011) reported that food process modelling is an important technique to understand, design and control food processes. However, modelling food processes is a complex task due to difficultly in performing experiment that could generate large reliable data, lack of knowledge concerning its working mechanisms and uncertainties involving food properties (Trystram, 2012). In the last decades, model approaches in food science, food technology and food engineering have received great attention (Perrot *et al.* 2011; Trystram, 2012; Ho, Carmeliet, Datta, Defraeye, Delele, Herremans and Van der Sman, 2013) and many academic works have been dedicated to modelling and its application in food processing (Turan, Mesci and Ozgonenel, 2011; Akinoso and Edun, 2013; Borkar, 2015; Dash *et al.,* 2016; Yadav *et al.,* 2017).

The demand for models is clearly established when European food for life platform presents modelling as a key techniques for the development of food industries in Europe (Perrot *et al.,* 2011). In chemical engineering discipline, modelling has been a part of virtually any scientific and technical development, however, food engineering is trying to follow a similar trend with considerable 20 years of delay (Perrot *et al.,* 2011). The delay maybe as a result of increased complexity of food system including physical, biological and chemical phenomena on a wide range of space scales and time (Perrot *et al.,* 2011).

2.11 Building Food Model

Figure 2.1 shows approach for model development in food engineering. In designing a food model, past knowledge from previous scientific or expert background is important (Perrot *et al.,* 2011). This is followed by systemic analysis that comprises of four steps: hypothesis, structure identifiability, known and unknown parameters and uncertainty on the measurements and knowledge (Perrot *et al.,* 2011). The four steps are critical to analysis and development of the model (Perrot *et al.,* 2011).

Based on the systemic analysis, classical experimental or optimal experimental design is usually performed in order to generate model parameters that would be used for the modelling (Perrot *et al.,* 2011). After model development and parameters determination, a range of modelling techniques can be used to study viability, sensibility and uncertainty (Fumes, Silva, Andrade, Nazario and Lanças, 2015). Reconsideration of model hypothesis and structure, design of additional experiments to further allow reliable parameter identification can be used during the validation of the model structure (Perrot *et al.,* 2011; Trystram, 2012). A precision model could serve as sensor, control, decision help and optimization (Enitan and Adeyemo; 2011; Perrot *et al.,* 2011; Goyal, 2013; Fumes *et al*., 2015).

2.12 Taguchi Orthogonal Array (TAO) Techniques

Taguchi techniques are statistical method developed to improve the efficiency and enhance quality of manufactured goods in the industry (Singh, 2012). According to Singh (2012), Taguchi techniques 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).

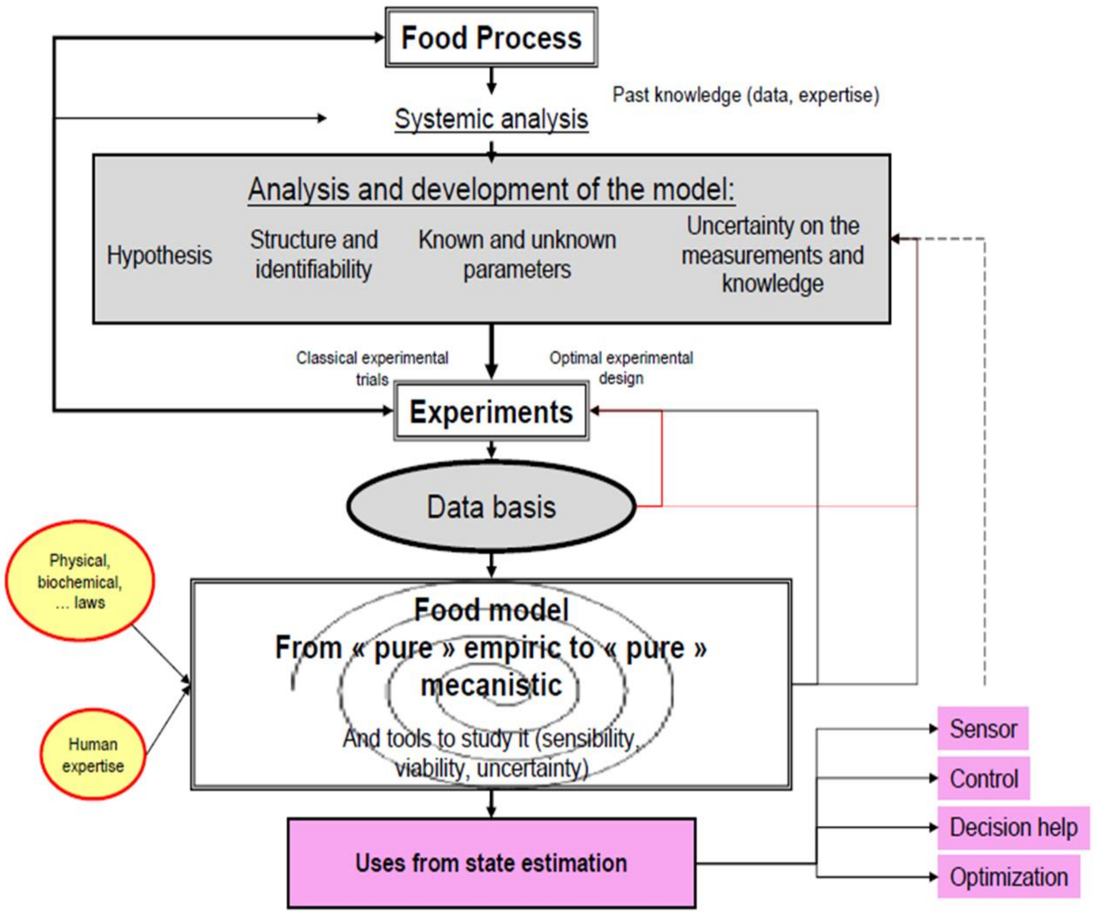


Fig. 2.1. Approach for model development in Food Engineering

Source: Perrot *et al.*, 2011

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 (Dash *et al.*, 2016). Taguchi Orthogonal Array uses a special set of arrays that gives the minimum number of experiments with maximum information (Chen, Chung, Wang and Huang 2011; Dash *et al.,* 2016). According to Dash *et al.* (2016), TAO approach offers recognition of the factors main effect in relatively few experiments and also widely used in the manufacturing section for it robust optimization of process parameters. Dash *et al.* (2016) stated that orthogonal means balanced, separable or not mixed; hence influence of an individual factor was not mixed up with the influence of other factors and was separated as a main effect of the said factor. Montgomery (2013), reported that the effect of single factor in Taguchi can be linear, quadratic or higher order but the model assumes that there are no interactions among the individual factors. Taguchi experimental approach is denoted by $L_a b^c$ where "L_a" means Orthogonal arrays of variables or design matrix, "b" the levels of variables and "c" numbers of variables (Dash *et al.*, 2016). According to Sivarao and Ammar, (2010), Taguchi method was regularly used in automobile, electronics and other processing industries. Its objective was to determine the optimum settings of input parameters, neglecting the variation caused by uncontrollable factors or noise factors (Sivarao and Ammar, 2010).

Taguchi has become a powerful technique for improving productivity during research and development so that high quality products can be produced at reduced costs (Noorwali, 2013). Therefore by using Taguchi techniques, industries are able to greatly reduce product development cycle time for both design and production thus reducing cost and increasing profit. Taguchi method advantage lies in its ability to lay emphasis on a mean performance characteristics value close to the target value rather than a value within certain specific limit, thus improving the product quality.

Also, the method is straight forward and easy to apply to many engineering situations, making it a powerful yet simple technique. Taguchi can be used to quickly narrow the scope of a research project or to identify problems in a manufacturing process from data already in existence. Signal to Noise (S/N) ratio is the term used in TAO to control both the response value and noise factor (Chandrasekar, Kannan, Priyavarshini and Gayathri, 2015; Dash *et al.,* 2016). 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 (Chandrasekar *et al.*, 2015; Dash *et al.*, 2016). According to Chandrasekar *et al.* (2015); Dash *et al.*(2016) three types of S/N ratios are: Nominal is the best, smaller-the-better and larger-the-better as shown in equations 2.1, 2.2 and 2.3 respectively.

Nominal is the best characteristic

$$\frac{S}{N} = 10log\,\frac{\bar{y}}{Sy^2} \qquad 2.1$$

Smaller is the best characteristic

$$\frac{S}{N} = -10log\,\frac{1}{n}\left(\sum y^2\right) \qquad 2.2$$

Larger the better characteristic

$$\frac{S}{N} = -10log\,\frac{1}{n}\left(\sum \frac{1}{y^2}\right) \qquad 2.3$$

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.

The equation in 2.4 represents the experimental data for Taguchi model

$$Y = \beta_O + \sum_{i=1}^{K} \beta_i\, X_1 + \sum_{i=2}^{K} \beta_i\, X_2 + \sum_{i=3}^{K} \beta_i\, X_3 + \sum_{i=n}^{K} \beta_i\, X_n + \varepsilon \qquad 2.4$$

Y is the response or dependent variables, X_i and X_j are the independent variables in the model, K is the number of independent variables, $ß_o$ is the intercept (constants and regression coefficients of the model) and ϵ is the random error term (Dash *et al.,* 2016).

2.12.1. Application of Taguchi in food processing

Due to high competition in food industry, companies have been forced to strategically increase their efficiency and reduce waste and this can be achieved by the introduction of model that can assist in reducing variability level in food processing system (Noorwali, 2013). Taguchi Orthogonal Array (TAO) method has been applied in the areas of food fermentation, food processing, food microbiology, waste water treatment and bioremediation (Rao *et al.*, 2008). According to Singh (2012), Taguchi technique met the current needs of industry due to its shorter design cycle and improved design quality. Asadi and Norouzbeigi (2017) used Taguchi to develop a predictive model and optimize colloidal nanosilica from production of expanded perlite. According to Mohapatra, Dandapat and Thatoi (2017), Taguchi and artificial neural network can be used to model and optimise ultrasonic assisted pretreatment of two *Pennisetum* spp. Chen *et al.* (2011) reported that Taguchi is an effective technique that can be used to optimize factors in food science and engineering. Process factors of ready to eat peanut (*Arachis hypogaea*) was optimized by signal to noise ratio (Chandrasekar *et al.,* 2015). Dash *et al.* (2016) applied an integrated Taguchi and response surface methodological approach for the optimization of an HPLC method to determine glimepiride in a supersaturatable self-nanoemulsifying formulation.

Rao *et al.* (2008), critical appraise the use of Taguchi methodology as a statistical techniques in biotechnology application. They combined Taguchi and regression analysis to define the effectiveness of factors that affect process of drying industrial yeast. Optimization of extracted ginger oil in different drying conditions was reported by Ho-Hsein Chen *et al.* (2011). Optimisation of biodiesel from fish oil using ultrasonic energy was achieved via Taguchi orthogonal approach (Franco *et al.,* 2014). Ghica, Popa, Şaramet, Leca, Lupuliasa and Moisescu (2011) optimize pharmaceutical products and process design using Taguchi engineering principles. Application of Taguchi in studying the impacts of processing parameters, modelling and optimizing total energy consumption and rice quality attributes is few in the literature.

2.13 Response Surface Methodology (RSM)

Regression analysis, statistical analysis and design of experiments are the techniques RSM utilized to establish the relationship between quality characteristics and the dependent variables in order to understand the impact of factorial changes on the response values; determine the optimum processing conditions of the system, or determine the range of factors in order to meet operational needs (Huang *et al.,* 2016). RSM is a collection of statistical techniques meant for experimental designs, developing models, evaluating the effects of variables on response and search for the optimum conditions. Velmurugan and Muthukumar (2012) reported that one of the advantages of RSM is that it could be used to minimize the number of experimental runs. In RSM, the effect of the independent variables alone or in combination on a specific dependent variable is analyzed (Scheuer, Schwartz, Chen, Schulze-Sünninghausen, Carl, Höfer, and Luy, 2016). It can practically be applied to develop and generate approximating model for the true response surface. In RSM, two important models are commonly used. These are the first degree model and second degree model (Bevilacqua, *et al.,* 2010).

For first-degree model (d=1)

$$Y = \beta_O + \sum_{i=1}^{K} \beta_i \; X_1 + \mathcal{E} \qquad 2.5$$

For second-degree model (d=2)

$$Y = \beta_O + \sum_{i=1}^{K} \beta_i \; X_I + \; \sum_{i=1}^{K} \beta_{ii} \; X^2 + \sum_{i=1}^{K} \sum_{i=1} \beta_{ij} \, X_i \, X_j + \varepsilon \qquad 2.6$$

where x_{ij} represents the independent variables, β is a vector of unknown constant coefficients and Ɛ is a random experimental error assumed to have a zero mean and Y is the response or dependable variables (Danbaba *et al.,* 2014; Scheuer *et al.,* 2016).

The first degree model and second degree model are the most frequently used approximating polynomial models in classical RSM (Bevilacqua, *et al.,* 2010). The designs for fitting first degree models are called first order designs and those for fitting second degree models are referred to as second order designs. For first order designs, the most commonly used designs are 2k factorial (K is the number of control variables), placket-Bur-man and simplex designs (Bevilacqua, *et al.,* 2010). In second order design, 3k factorial, central composite and Box-Behnken designs are the most frequently used design. According to Scheuer *et al.* (2016) a good model should be significant at $p \leq 0.05$, i.e high in reliability (data within the 95% confidence interval) and high coefficient of determination (R^2) ($R^2 \geq 70\%$).

2.13.1 Application of Response Surface Methodology

According to Akinoso, Aremu and Akosima (2015), a response surface methodology is a statistical approach that is widely used in food engineering, industrial and biological and clinical sciences. Researchers have applied response surface methodology to develop mathematical models to predict properties of food products during processing and storage (Akinoso *et al.*, 2013). Rosas-Gallo *et al.* (2016), applied RSM to model *Penicillium expansum* growth response to thyme essential oil at selected water activities and pH values. The prediction of hulling efficiency of green gram using response surface methodology was studied by Asare, Sefa-Dedeh, Sakyi-Dawson and Afoakwa (2004). Scheuer *et al.*(2016) used RSM to assess the impact of fat replacer and whole wheat flour at different levels of bread quality.

Models for predicting water absorption and solubility indices of extruded African breadfruit (*Treculia africana*) were developed by Nwabueze (2006). Akinoso, Raji and Igbeka (2009) developed a predictive model using response surface methodology for palm kernel oil. Danbaba, Nkama and Badau (2015) applied response surface methodology to model and optimise mineral composition of rice cowpea flour blend during extrusion process. Lee, Park, Cho, Kim, Choi and Cho (2014) Model and Optimise medium composition for α- galactosidase production by Antarctic bacterial isolate, *Bacillus* sp. LX-1. Nguyen, Le and Le (2013) model and optimise the application of mash treatment under the influence of ultrasound and cellulose preparation of guava in juice production using response surface methodology. The effects of heat treatment on the extraction of Roselle (*Hibiscus sabdariffa L*) seed oil were studied by Akinoso and Suleiman (2011). The application of response surface methodology was adopted by Akinoso *et al.* (2015) in studying the effect of heat treatment on yield and quality of Loofah (*Luffa cylindrical Linn.*) seed oil.

Ravikumar, Renuka, Sindhu and Malarmathi (2013) model and optimise distillery spent wash treatment using Phormidium valderianum through the application of response surface methodology and artificial neural network. Ye, Zhang, Hoffmann, Zeng, Tang, Dresely and Liu (2014), simulate acid activation of bauxsol for phosphorus adsorption by comparing the effectiveness of response surface methodology and artificial neural network models. Danbaba *et al.* (2014) used response surface methodology to model and optimise head rice yield. However, there was no comparison with other novel modelling techniques. Derrien, Badr, Gosselin, Desjardins and Angers (2017) used response surface methodology to model and optimise green process for the extraction of lutein and chlorophyll from spinach. Witek-Krowiak, Chojnacka, Podstawczyk, Dawiec and Pokomeda (2014) adopt response surface methodology and artificial neural network in modelling and optimising biosorption process. Response surface methodology modelling and optimization approach was used in lycopene green ultrasound assisted extraction using edible oil in processing tomato waste (Rahimi and Mikani, 2019). The application of response surface methodology to study the impacts of processing parameters on total energy consumption and quality attributes is few in the literature. Also modelling and optimization of the impacts of processing parameters on total energy consumption and rice quality attributes using response surface methodology is few. Therefore, providing information on the effect, modelling, optimisation will be useful for rice processors as this will serve has a technique for improving the quality parboiled rice.

2.14 Artificial Neural Network (ANN)

One of the supervised machine learning models is Artificial Neural Network 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). According to Bhatt, Pant and Singh, (2014), modelling using artificial neural network are based on brain structure because brain learns from past event so as Artificial Neural Network. Patterns that are too complex to be detected either by statistical models due to high non-linearity in the data to analyse can easily be model using ANN (Oluwatoyin and Chen, 2018). Recently, researches have been tailored towards the use of artificial intelligence (Goyal 2013; Bhatt *et al.,* 2014; Funes *et al.,* 2015; Hosseinpour, Ilkhchi and Aghbashlo, 2019). Artificial Neural Network (ANN) is one of the areas of artificial intelligence (Hosseinpour *et al.* 2019). ANN model tends to mimic the behaviour of biological neurons (Goyal 2013; Bhatt *et al.*, 2014; Funes *et al.*, 2015). Fig. 2.2 shows the structure of a biological neuron.

The outcome of successful training of artificial neural networks can perform tasks such as predicting an output value, recognizing a pattern in multifactorial data and in classifying objects. According to Oluwatoyin and Chen (2018), handwritten recognition, image compression, machine and data prediction are some of the few world application of ANN. ANN is a technique used for predicting the non-linear systems behaviour of a system at various combinations (Bhatt *et al.*, 2014; Funes *et al.*, 2015).

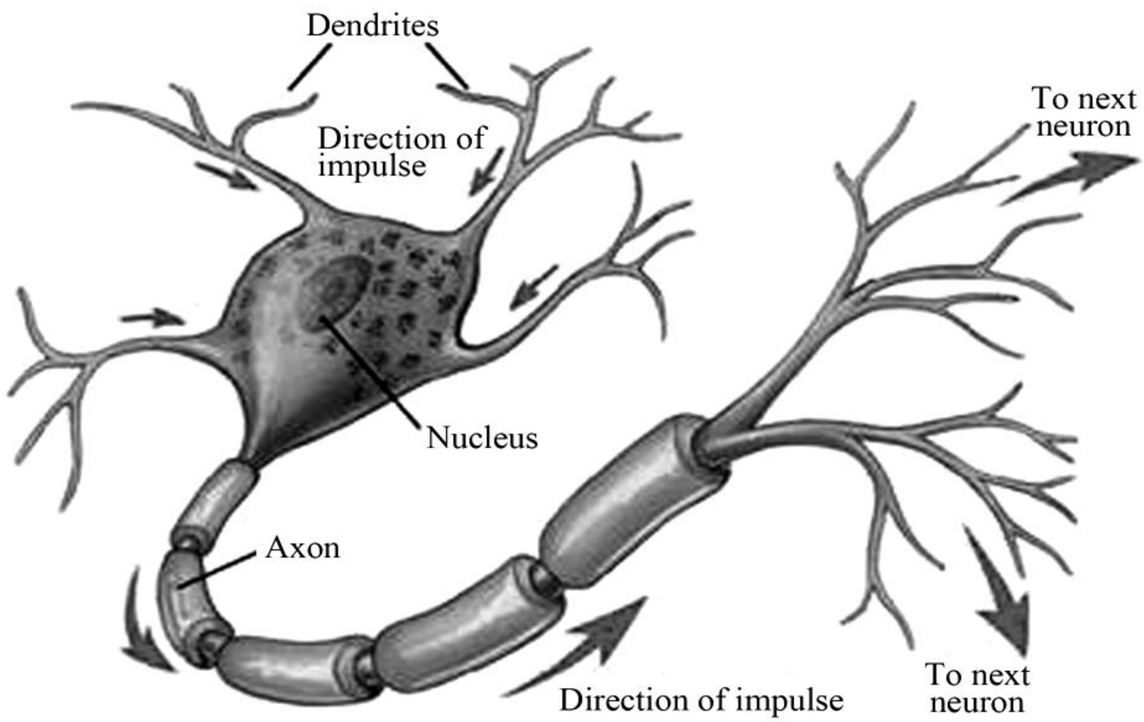


Fig. 2.2. Structure of a biological neuron (Funes *et al.,* 2015)

ANN modelling learns the experimental values of a process, therefore, knowing the system behaviour and using it to predict the output values of the desired set of input variables (Goyal 2013; Bhatt *et al.*, 2014; Funes *et al.*, 2015). ANN can also simply be defined as a biological neural simulation data processing system that learning from data generated through experiment or using validated model (Funes *et al.*, 2015). ANN can also be referred to as a computer programme developed to imitate the human brain neurons or a data processing device or an algorithm inspired by the design of human brains and components (Funes *et al.*, 2015).

2.14.1 Artificial Neural Network architecture

A typical multi-layer artificial neural network was shown in Fig. 2.3. The multi-layer is formed by an interconnection of nodes (Chen *et al.,* 2007). The artificial neural network is made up of an input layers, two hidden layers and an output layer (Chen *et al.,* 2007). The three layers are very essential to the operation of the artificial neural network (Chen *et al.*, 2007). Fumes *et al.* 2015 stated that ANN is more or less works as a black box to which some set of input data are sent to the input node. The network processed the input information or data through the interconnections between the nodes (Funes *et al.,* 2015). The entire processing occurred in the hidden layer (Funes *et al.*, 2015). After processing, the network gives an output results through an output nodes. Other important terms in developing ANN architecture are: Processing element/Neurons which is referred to as biological neurons in ANN (Fumes *et al.* 2015). Each neuron has many inputs and outputs. The neurons have connections which carry numeric data; connection weight is what is used to connect the output path of neurons to the inputs path. It is similar to the synaptic strength of neural connections; training of network is key in developing neural network, some set of training rules must be followed, the weight of joints are shifted on the basis of presented patterns (Fumes *et al.,* 2015).

Training helps the neural network to learn from existing data; Error is the total difference between the desired output and output produced by the network from the set of inputs; learning rate or algorithm is used to change the connection weights of the network in response to the inputs and desired outputs of those inputs (Fumes *et al.*, 2015).

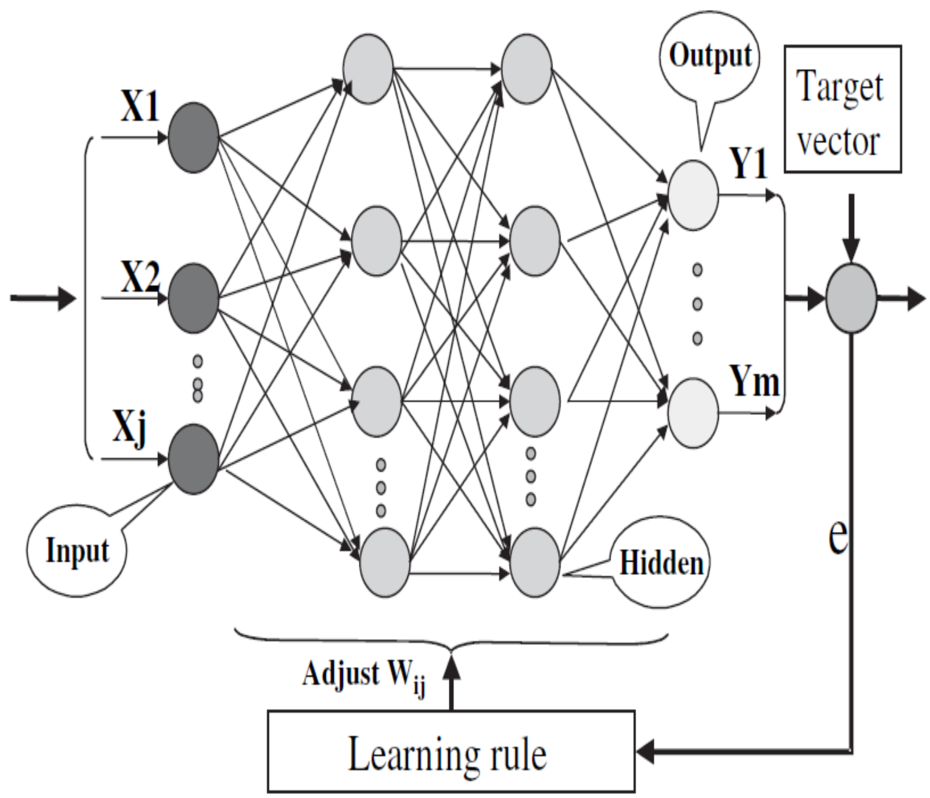


Fig. 2.3. Atypical multi-layer Artificial Neural Network (Chen *et al.* 2007)

The reinforcement technique used in training humans is similar to the training of neural network model, where specific synapses that connect the neurons selectively get strengthened as the training proceed leading to increase in the accuracy (Fumes *et al.* 2015). The most commonly used learning rate is Levenberg-Marquardt while others are the moment, conjugate and gradient; recall is how the network processes a data set presented at it input layer and produces a response at the output layer (Mourabet *et al.*, 2014; Fumes *et al.,* 2015). During the recall process, the weights are not changed (Fumes *et al.*, 2015).

2.14.2 Artificial Neural Network development

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 (Fumes *et al.,* 2015). According to Chen *et al.* (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).

Rapid development of computer software has pave way for development of several ANN software's which can be used for developing ANN models for various specific purposes such as prediction, optimization, classification and control. Among the commonly commercial softwares are: Matlab Neural network techniques box (MathWorks, Inc., Natick, MA), Statistica Neural Networks (StatSoft, Inc., Tulsa, OK), Neural-Ware Professional, Neural-Shell, Neuro-solution (Neuro-Dimension, Inc., Gainesville, FL) and Neuro-Genetic Optimizer (BioComp Systems, Inc, Bloomington, MN) (Fumes *et al.*, 2015).

In developing an artificial neural network model by using commercial ANN software, selection of inputs and outputs, data collection, optimization of configuration, training or learning and testing or generation are important steps that are usually followed (Goyal, 2013; Fumes *et al*., 2015). In order to develop an artificial neural networks model with the best performance for specific problem, the configuration parameters of the ANN must be established by trials and errors. Transfer functions, learning rules, learning rate, momentum coefficient, number of hidden layers, number of neurons in each hidden layer and learning runs are key configuration parameters needed (Enitan and Adeyemo, 2011; Goyal, 2013; Goyal *et al.*, 2013; Fumes *et al*., 2015).

A set of known input and output data is presented to the network to train it and it is done repeatedly. This step is referred to as training or learning step. During the training process, the weight factors between nodes are adjusted until the specified input produce the desired output. The adjustments process makes the artificial neural network learns the correct input and output response behaviour. In ANN model development, this phase of training is basically the longest and most time consuming. This phase is also critical to the success of ANN the network (Enitan and Adeyemo, 2011; Fumes *et al*., 2015). Recall and generalization step is the step that usually followed training step. In the recall step, the ANN model will be subjected to different array of input data used in training, and adjustments are introduced to make the system more reliable and robust (Fumes *et al*., 2015).

The generalization step involved the subjection of the network to input data which it has not seen before, but whose outputs data are known (Fumes *et al*., 2015). This will aid in evaluating and monitoring the system performance. The performance of artificial neural networks can be evaluated visually by graphs (Plotting the experimental data against predicted data) (Chen *et al.*, 2007).

2.14.3 Types of Artificial Neural Network

Back propagation network: This is the most successively used network after it has been extensively studied theoretically. In designing back propagation network, three- layered system is usually used; input, hidden and output layers. According to Mourabet *et al.* (2014), an equation in the hidden layers (transfer function) determines whether inputs are sufficient to produce an output. Among the most commonly used transfer functions are: sigmoid function, hyperbolic function, linear threshold and Gaussian transfer function (Mourabet *et al.*, 2014). In ANN training using back propagation network, the values predicted by the network are compared to experimental values using delta rule, equation

2.7, which minimizes error between experimental values and network predicted values (Mourabet *et al.*, 2014),.

$$\mathcal{Y}n = \frac{\mathcal{Y}a - \mathcal{Y}min}{\mathcal{Y}max - \mathcal{Y}min} \qquad 2.7$$

where $\mathcal{Y}n$, $\mathcal{Y}a$, $\mathcal{Y}m$in and $\mathcal{Y}m$ax are normalized value, actual value, minimum value, and maximum value, respectively.

The obtained errors are the back propagated to hidden and input layers to adjust weights. This process is repeated many times until errors between predicted and experimental values are minimized (Mourabet *et al.,* 2014). General regression neural network: This is memory based on feed forward networks which imply that all the training samples are stored in the network. General regression neural network possesses a special property that does not require iterative training (Fumes *et al*., 2015).

2.14.4 Application of Artificial Neural Network (ANN)

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 (Goyal, 2013; Bhatt *et al.*, 2014; Funes *et al.*, 2015; Hosseinpour *et al.*, 2019). For instance, Hosseinpour *et al.* (2019) Artificial Neural Network in developing an intelligent machine vision for beef quality using a smart phone app while Ozkaya and Seyfi (2015) used artificial neural network to optimize microstrip patch antenna and its simulation resulted into a prototype microstrip with the best antenna parameter. Artificial neural network has been frequently and successfully used in fields of food processing, energy, agriculture, medicine, transports etc (Fumes *et al.,* 2015). However, this research only looks at its application in the food industry. The food industry has a number of objectives among which are; improving quality of products, waste reduction, elimination of toxins, and above all, having an efficient process (Fumes *et al*. 2015). Based on the usefulness of ANN, it can be incorporated into controlling, modelling and monitoring industrial processes using their data, therefore, paving way for reduction in process costs and increase in products outputs. For instance, Gokmen, Açar, Serpen and Süğüt, (2009) used ANN to model dead-end ultrafiltration of apple juice while Lamrini, Della Valle, Trelea, Perrot and Trystram,

(2012) used ANN to predict the bread dough temperature through dynamics modelling of the kneading process.

Abakarov, Teixeira, Simpson, Pinto and Almonacid (2011), delivered power modelling of squid protein hydrolysis using ANN. The food industry is also using ANNs for overall prediction food storage temperature, characteristics of food using on-line quality check and parameters for the elaboration process. Topuz (2010) used neural network approach to predict the drying characteristics of Chickpea and Bea. Bahramparvar, Salehi and Razavi (2014), predict total acceptance of ice cream using ANN. The permeate flux of red plum juice was predicted by ANN during membrane clarification as reported by Nourbakhsh, Emam-Djomeh, Omid, Mirsaeedghazi and Moini (2014). ANN has been used to determine the sugar content in fruits (Funes *et al*., 2015). Bhatt and Pant (2015) used back propagation ANN to develop a model for automatic apple grading. In spite of the numerous application of ANN in the food industry, little has been reported about its application in rice processing, most especially in the area of modelling the impacts of processing parameters on energy consumption and also in modelling the impacts of processing parameters on quality attributes of parboiled rice.

CHAPTER THREE

3.0 MATERIALS AND METHODS

Five paddy grains varieties (NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44) were obtained from the breeding laboratory of the National Cereals Research Institute, Badeggi, Niger State, Nigeria. This research study was conducted at the grain quality laboratory of National Cereal Research Institute from August, 2016 to January, 2017.

3.1 Determination of Physical Properties of Paddy Rice

The following physical properties of the paddy rice of each variety were determined using standard methods as follows:

3.1.1 Axial dimension

The major axial dimensions; length (L), width (W) and thickness (T) of 200 randomly selected paddy for each variety were measured using a vernier caliper (digital) with 0.01 mm resolution (Model AD-5765-100) (Sanusi, Akinoso and Danbaba, 2017). Plate 3.1 shows the axial dimensions of paddy grain, white rice and parboiled polished rice. The length to width ratio of the paddy grains were determined using the length and width values obtained for paddy grains, polished white rice and polished parboiled rice with a view of assessing the overall rice shape. Length to Width Ratio was calculated using equation 3.1.

$$\text{LWR} = \frac{L}{W} \qquad 3.1$$

where, LWR denotes length to width ratio of paddy grain, polished white rice and polished parboiled rice, L is the length (mm) and W is the width (mm)

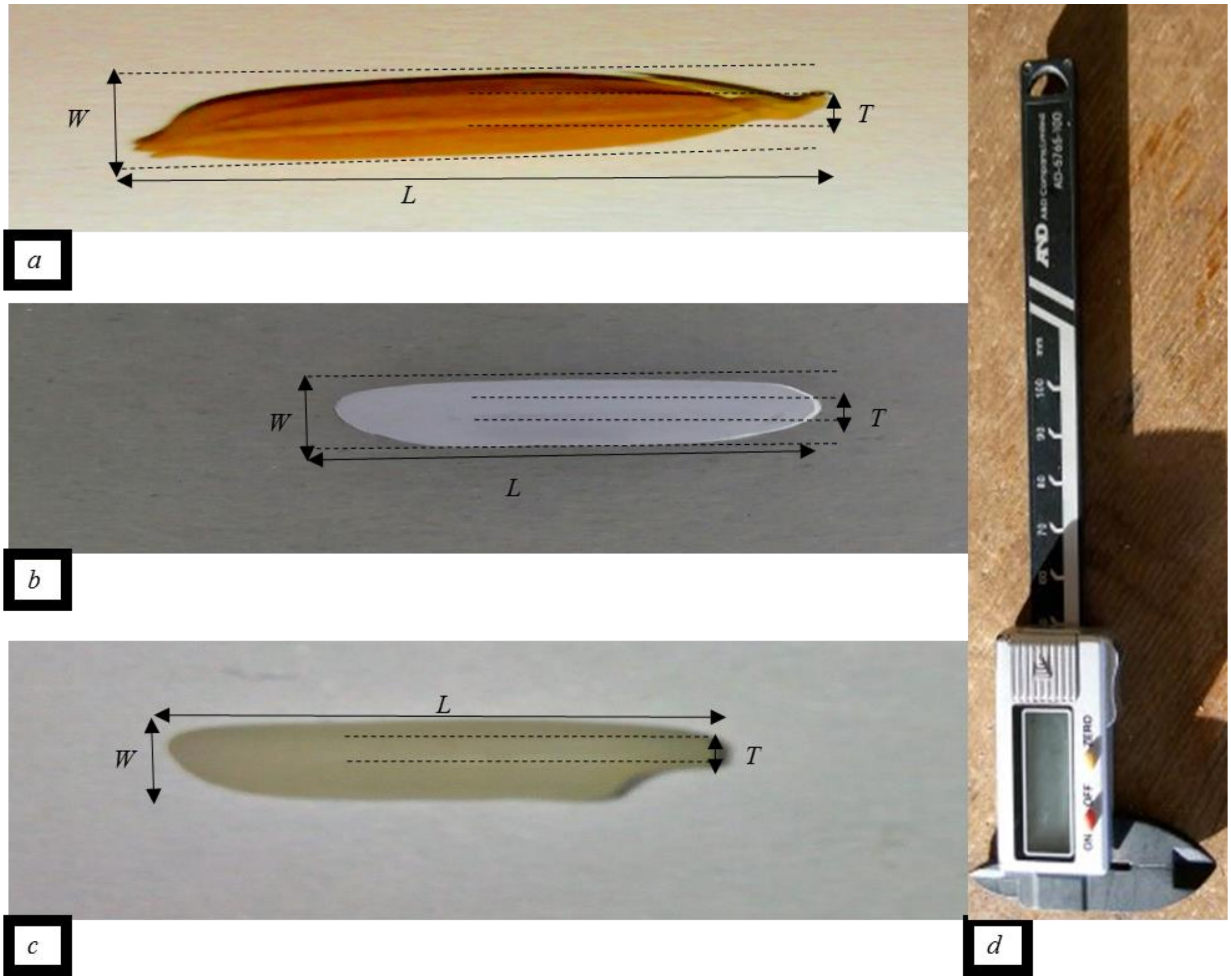


Plate 3.1. Paddy grain (a), White rice (b) and Parboiled polished rice (c) axial dimensions and digital vernier caliper (d)

3.1.2 Equivalent diameter (De)

The equivalent diameter (mm) was determined using the axial dimensions of paddy grains using the expression as described in equation 3.2 (Adebowale, Sanni, Owo and Karim 2011).

$$De = (\frac{(L(W+T)^2}{4})^{1/2} \qquad 3.2$$

where, L is the length, W is the width and T is the thickness

3.1.3 Sphericity (Sh)

The sphericity (Sh) which is defined as the ratio of the surface area of the sphere having the same volume as that of paddy grains to the surface area of the paddy grain was determined using the expression as described in equation 3.3 (Adebowale *et al.*, 2011).

$$Sh = \frac{(LWT)^{1/3}}{(L)} \qquad 3.3$$

where, S_h is Sphericity

3.1.4 Grain volume (GV)

The grain volume of paddy grains was calculated by using equation 3.4 (Adebowale *et al.*, 2011).

$$GV = 0.25\left[\frac{\pi}{6}\ L\ (W+T)^2\right] \qquad 3.4$$

where, GV is grain volume

3.1.5 Surface area (Sa)

For the paddy grains, the surface area for each variety was calculated by using equation 3.5 as used by Bashar, Wayayok and Soom Mohd (2014);

$$Sa = \frac{\pi L\sqrt{WT}}{(2L-\sqrt{WT})} \qquad 3.5$$

where Sa is the surface area

3.1.6 Aspect ratio (AR)

Varnamkhasti, Mobli, Jafari, Keyhani, Soltanabadi, Rafiee and Kheiralipour (2008) approach was used to determine the aspect ratio (AR) using equation 3.6.

$$AR = \frac{W}{L} \qquad 3.6$$

where AR, is the aspect ratio

3.1.7 Thousand grain weight

Thousand grain mass of paddy varieties were determined by selecting 100 grains randomly and weighed using a digital electronic weighting scale (GF-6000AND, Japan) of ±0.001g accuracy. The measurements were repeated ten times for each variety and reading was multiplied by 10 in order to obtain the mass of 1000 grains for each variety (Sadeghi, Araghi and Hemmat, 2010).

3.1.8 Bulk density (ρb)

The bulk density (ρb), which is defined as the ratio of the mass of paddy grains to its total volume, was determined by using equation 3.7. Bulk density was determined as described by Adebowale *et al.* (2011). Fifty grams (50 g) of the paddy grains were weighed into 100 ml graduated cylinder and tapped 50 times against the palm of the hand. The bulk density was calculated as the ratio of paddy grains weight to the volume occupied in the cylinder.

$$\rho b = \frac{Mp}{V} \qquad 3.7$$

where, ρb, v, m_p denotes bulk density, volume occupied (cm^3) and mass of paddy grains (g).

3.2 Processing Paddy Rice into White Rice

All the varieties were processed into white rice in order to know their inherent quality attributes as shown in Figure 3.1. Each variety of paddy grains (1500g) were separately conditioned to 12%±1% paddy moisture content, dehusked using a rice roll rubber dehusker laboratory model (THU 35B, Satake Engineering Corp. Tokyo, Japan) and polished for two minutes using SATAKE grain testing mill (SE 1009, Satake Engineering Corp. Tokyo, Japan). Polished rice was cooled at temperature condition of 29 ± 2°C before separating the whole rice (head rice) from the broken rice, using International Rice Research Institute (IRRI) laboratory rice grader and the mass was measured using an electronic balance (GF-6000AND, Japan) of ± 0.1g accuracy. The following quality attributes of white rice: axial dimensions of white rice (as earlier shown in plate 3.1), head milled rice, milling recovery, chalkiness, broken milled rice, cooking time, water uptake ratio and colour in terms of L*,a*,b* of the white rice were determined using standard method reported by IRRI (2002, 2009).

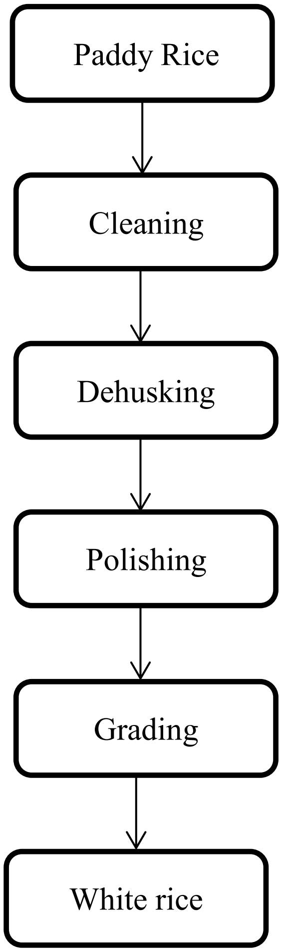


Fig. 3.1. Processing of varieties of paddy into white rice (IRRI, 2010)

3.3 Experimental Design for Rice Parboiling

In order to define the experimental range for the rice parboiling, factors and levels considered were based on information from literature and preliminary laboratory investigations (Danbaba *et al.*, 2014; Nasirahmadi *et al.*, 2014). A preliminary experiment was carried out using laboratory rice milling setup. Important parboiling factors including: soaking temperature (65-75°C), soaking time (10-16 h), steaming time (20-30 min) and paddy moisture content (12-16%) were varied and interacted. The average of the maximum and minimum values obtained from the experiment was used to design the main experiment using Taguchi design and Central Composite Design of RSM.

3.3.1 Taguchi experimental design for rice processing parameters

The Taguchi orthogonal array experimental plan was designed using Minitab®version 16 (Minitab, Inc. Coventry, UK) for rice processing parameters. The experimental design has four factors at three levels given an array of L_9 (3^4). Table 3.1 summarized the design parameters and their respective levels, while the scheme of Taguchi experimental design was presented in Table 3.2. In line with the Taguchi design, nine experimental runs were performed to evaluate the impacts of processing parameters (steaming time, paddy moisture content, soaking temperature and soaking time) on quality attributes of polished parboiled rice and total energy consumption.

3.3.2 Response Surface Methodology experimental design for rice processing parameters

Central Composite Rotatable Design of Response Surface Methodology was designed using Minitab®version 16 (Minitab, Inc. Coventry, UK) for rice processing parameters. The second order CCD consisting of four independent variables; soaking time (A), soaking temperature (B), steaming time (C) and paddy moisture content (D) and five level combination coded value -2,-1, 0, +1 and +2 was used to evaluate the impacts of processing parameters on quality attributes of parboiled rice and total energy consumption as shown in Table 3.3, while Table 3.4 shows the outline of the experimental design with coded and un-coded using CCD-RSM.

Table 3.1. 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

Table 3.2. Scheme of Taguchi experimental design $L_9\,(3^4)$

Experimental Runs	Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture content (%)
1	65	10	20	12
2	65	13	25	14
3	65	16	30	16
4	70	10	25	16
5	70	13	30	12
6	70	16	20	14
7	75	10	30	14
8	75	13	20	16
9	75	16	25	12

Table 3.3. Response Surface Methodology experimental design (Central Composite Design) of independent variables and their levels

Independent Variables	Code	Unit	Coded levels –α (-2)	Low (-1)	Medium 0	High (+1)	Coded levels +α (+2)
Soaking time	A	h	7	10	13	16	19
Soaking temperature	B	°C	60	65	70	75	80
Steaming time	C	min	15	20	25	30	35
Paddy moisture content	D	%	10	12	14	16	18

Table 3.4. Outline of the experimental design with coded and un-coded using RSM-CCD

Experimental runs	A	B	C	D	Soaking temperature (°C)	Soaking time (h)	Steaming time (min)	Paddy Moisture content (%)
	Independent Coded unit							
1	-1	-1	-1	-1	65	10	20	12
2	1	-1	-1	-1	75	10	20	12
3	-1	1	-1	-1	65	16	20	12
4	1	1	-1	-1	75	16	20	12
5	-1	-1	1	-1	65	10	30	12
6	1	-1	1	-1	75	10	30	12
7	-1	1	1	-1	65	16	30	12
8	1	1	1	-1	75	16	30	12
9	-1	-1	-1	1	65	10	20	16
10	1	-1	-1	1	75	10	20	16
11	-1	1	-1	1	65	16	20	16
12	1	1	-1	1	75	16	20	16
13	-1	-1	1	1	65	10	30	16
14	1	-1	1	1	75	10	30	16
15	-1	1	1	1	65	16	30	16
16	1	1	1	1	75	16	30	16
17	-2	0	0	0	60	13	25	14
18	2	0	0	0	80	13	25	14
19	0	-2	0	0	70	7	25	14
20	0	2	0	0	70	19	25	14
21	0	0	-2	0	70	13	15	14
22	0	0	2	0	70	13	35	14
23	0	0	0	-2	70	13	25	10
24	0	0	0	2	70	13	25	18
25	0	0	0	0	70	13	25	14
26	0	0	0	0	70	13	25	14
27	0	0	0	0	70	13	25	14
28	0	0	0	0	70	13	25	14
29	0	0	0	0	70	13	25	14
30	0	0	0	0	70	13	25	14
31	0	0	0	0	70	13	25	14

3.3.3 Artificial Neural Network design for rice processing parameters

The same experimental data, which was used for the CCD-RSM design, were employed in designing the Artificial Neural Network that would model the impacts of processing parameters on quality attributes of parboiled rice and total energy consumption.

3.4 Processing Paddy Rice into Polished Parboiled Rice

One hundred and twenty (120) samples of 1500 g cleaned paddy grains of each variety were loosely tied in cloth bags. Samples were soaked by immersing in hot water at 60°C, 65°C, 70°C, 75°C and 80°C for 7 h, 10 h, 13 h, 16 h and 19 h based on experimental design from Taguchi Orthogonal Array design (Table 3.2) and Central composite rotatable design of response surface methodology (Table 3.4). The desired temperature was monitored with the use of an infra-red thermometer. Soaked samples were drained after each conditions were met. Steaming was done using a locally fabricated rice parboiler for 15, 20, 25, 30 and 35 min. Steamed paddy grains with initial moisture content that ranged from 28 to 30% were shed dried at temperature (36±4°C).

Moisture content was measured at intervals using a grain moisture meter (Model Riceter F506, Taiwan) till desired moisture content of 10±1%, 12±1%, 14±1%, 16±1% and 18±1% (wb) were achieved respectively. Dried samples were packed in airtight plastic for moisture equilibration and hardness stabilization before subjecting to dehusking using a rice dehusker (rubber roller brand) (Satake Engineering Corp., Model THU 35B, Tokyo, Japan), the resulting brown rice samples were graded into head rice and broken rice using IRRI rice grader and their mass measured using an electronic balance (GF-6000AND, Japan) of ± 0.1g accuracy. The whole brown rice obtained were polished for two minutes in a Satake grading testing mill (SE 1009, Satake Engineering Corp. Tokyo, Japan) and the polished rice was allowed to cool to room temperature (29 ± 2°C) and relative humidity (61.5 ± 5%) before separating into head milled rice and broken milled rice using IRRI rice grader. After the experiment, polished samples were packed in paper bags and stored in a cupboard until further required for analysis. Figure 3.2 shows the processing of varieties of paddy into polished parboiled rice.

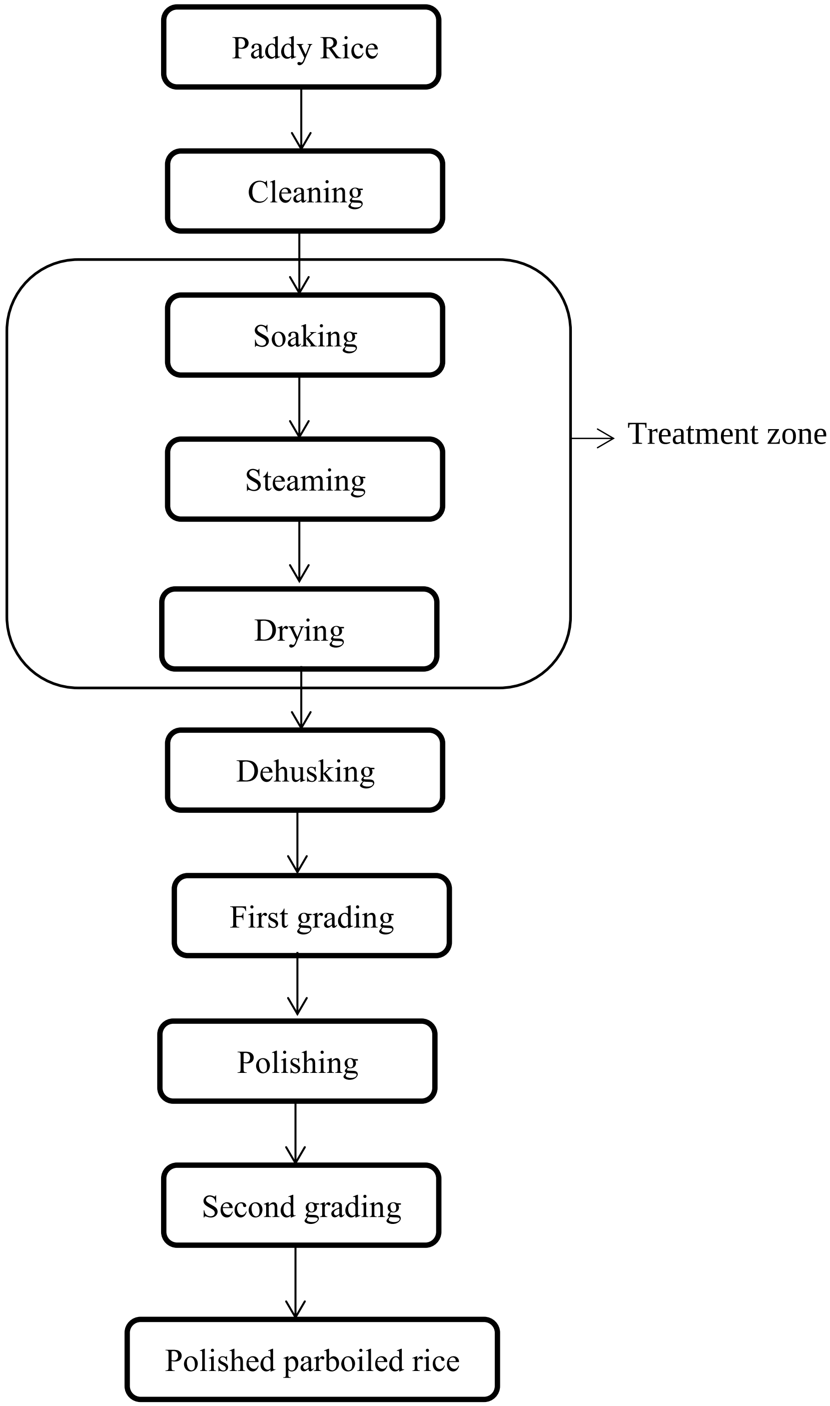


Fig. 3.2. Processing of varieties of paddy rice into polished parboiled rice

3.5 Determination of Quality Attributes of Polished Parboiled Rice

The important quality attributes that are used as rice quality indicators in rice industry including brown rice recovery, brown head rice, milling recovery, head milled rice, chalkiness, lightness, colour value, cooking time and water uptake ratio were determined using standard methods as follows:

3.5.1 Brown rice recovery (BRR)

Brown rice recovery was calculated according to IRRI (2002) method using equation 3.8

$$BRR = \frac{MBR}{MPG} \times 100 \qquad 3.8$$

where BRR is brown rice recovery (%), MBR is mass of brown rice (g) and MPG is the mass of paddy grains (g)

3.5.2 Head brown rice (HBR)

Head brown rice was estimated by separating broken brown rice from brown rice recovery. The head brown rice was calculated using equation 3.9 (IRRI, 2002).

$$HBR = \frac{MHBR}{MPG} \times 100 \qquad 3.9$$

where HBR, MHBR, PG denotes head brown rice (%), mass of head brown rice (g) and mass of paddy grains (g)

3.5.3 Milling recovery (MR)

Milling recovery was calculated according to IRRI (2002) standard using equation 3.10.

$$MR = \frac{MHBR}{MPG} \times 100 \qquad 3.10$$

where MR, MHBR, MPG denotes milling recovery (%), mass of head brown rice (g) and mass of paddy grains (g)

3.5.4 Head milled rice (HMR)

Head milled rice is the percentage weight of those kernels whose length is more than ¾ of the kernel. The percentage of head milled rice was calculated using (IRRI, 2002) equation 3.11.

$$HMR = \frac{MHMR}{MPG} \times 100 \qquad 3.11$$

where HMR, MHMR, MPG denotes head milled rice (%), mass of head milled rice (g) and mass of paddy grains (g)

3.5.5 Chalkiness

Whole grains (10 g) were measured and visualized using IRRI magnifier lens to assess the chalkiness. According to standard evaluation systems of the IRRI (2009) for chalkiness, chalkiness grains can be calculated using equation 3.12

$$WB = \frac{WBM}{MMR} \qquad 3.12$$

where WB is the chalkiness grains (%), WBM is chalkiness mass (g) and MMR is the mass of milled or polished rice (g)

3.5.6 Determination of colour and lightness

Whole milled or polished rice lightness and colour values were measured by utilizing L*, a*, b* uniform colour space produce using a colour meter. A colour meter (Model CR-10, Konica Minolta optics, Tokyo Japan) was used to measure the lightness and colour value. The lightness value is expressed as L* value which gives a measure of sample lightness, a chromatic colour which varied from 0-100 (fully black to fully white); mixed red-green colour of samples was determined by a* values. Red on the negative side and green to the positive side while mixed blue-yellow colour of samples was known by b* and it ranges from blue on the negative side to yellow on the positive value. The standard white plate was used to calibrate the instrument with values of L* 95.82, a* +1.2 and b* -2.98 respectively. Ten replicate was done for the measurement of each sample and the average was considered. The colour value (C) was calculated for the parboiled milled rice samples using the equation 3.13.

$$C = \sqrt{(a*)^2 + (b*)^2} \qquad 3.13$$

3.5.7 Cooking time

According to Parnsakhorn and Noomhom (2008) method, two lots of 10 g of polished white and parboiled rice of each variety were cooked in 100 ml of water at 96°C using an electric cooker (Model RC-18R, Toshiba, China). After 10 min of cooking, the cooked rice were checked at every two minutes intervals for testing by randomly taken ten cooked grains and pressed between two clean glass plates. This is done until the end of the cooking cycle. The time at which at least 90% of the grains were translucent was considered to be cooking time. Cooking time was recorded for each treatment meant for each variety.

3.5.8 Water uptake ratio (WUR)

Whole rice grain (10 g) from each treatments were cooked in distilled water (100 ml) for a cooking time at which at least 90% of the grains were translucent using an electric cooker (Model RC-18R, Toshiba, China).

The water uptake ratio of the cooked samples was determined using equation 3.14.

$$\text{WUR} = \frac{\text{WCR}}{\text{WUCR}} \qquad 3.14$$

where WUR, WCR, WUCR denotes water uptake ratio, mass of cooked rice (g) and mass of uncooked rice sample (g)

3.6 Estimation of Energy Consumption

Energy consumption pattern at each unit operation during the processing of varieties of paddy into white rice and polished parboiled rice were estimated. Also, the energy consumption at different processing conditions was estimated. The processing conditions combination derived from the CCD-RSM design and Taguchi design as earlier stated in Tables 3.2 and 3.4 respectively were used for the energy estimation. The data for energy consumption pattern were collected by determining the energy consumption at each unit operation involved in production of white rice and parboiled rice as shown in Table 3.5 and Table 3.6. The 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 (0.75 MJ/h) and woman (0.68 MJ/h), power factor and power rating of the machines (Akinoso *et al.*, 2013; Anjorin, Akinoso and Sanusi, 2018). The collected data were fitted into equations 3.15 to 3.25 to determine energy consumptions.

The equations below were used to estimate the energy consumption at each unit operation.

$$E_c = (0.75N \times 0.0167t) \qquad 3.15$$

$$E_s = (0.75N \times 0.0167t) + (Qf \times Cf) \qquad 3.16$$

$$E_{st} = (0.75N \times 0.0167t) + (Qf \times Cf) \qquad 3.17$$

$$E_d = (0.75N \times 0.0167t) \qquad 3.18$$

$$E_{dh} = (3.6 \times P \times \omega) + (N \times 0.0167t) \qquad 3.19$$

Table 3.5. Measured parameters during estimation of energy consumption in processing the varieties of paddy rice into white rice

Unit operation	Required parameters
Cleaning	Person involved in cleaning
	Duration taken required for cleaning (min)
Dehusking	Person involved in dehusking
	Duration taken required for dehusking (min)
	The power factor of the dehusking machine
	The power rating of dehusker (kW)
Polishing	Person involved in polishing
	Duration taken for polishing (min)
	The power factor of the milling machine
	Power rating of the milling machine (kW)
Grading	Person involved in grading
	Duration taken required for grading (min)

Table 3.6. Measured parameters during estimation of energy consumption in processing the varieties of paddy rice into parboiled rice

Unit operation	Required parameters
Cleaning	Person involved in cleaning
	Duration taken required for cleaning (min)
Soaking	Person involved in soaking
	Duration taken required for soaking (h)
	The quantity of fuel used (LPG) (kg)
	The Calorific value of fuel
Steaming	Person involved in steaming
	Duration taken required for steaming (min)
	The quantity of fuel used (LPG) (kg)
	The calorific value of fuel
Drying	Person involved in drying
	Duration taken for drying (min)
Dehusking	Person involved in dehusking
	Duration taken required for dehusking (min)
	The power factor of the dehusking machine
	The power rating of dehusker (kWh)
First grading	Person involved in grading
	Duration taken for grading (min)
Polishing	Person involved in polishing
	Duration taken for required for polishing (min)
	The power factor of the polishing machine
	Power rating of the milling machine (kWh)
Second grading	Person involved in grading
	Duration taken required for grading (min)

$$E_{g1} = (0.75N \times 0.0167t) \quad 3.20$$

$$Ep = (3.6 \times P \times \omega) + (0.75 \times N \times 0.0167t) \quad 3.21$$

$$E_{g2} = (0.75N \times 0.0167t) \quad 3.22$$

$$Ecow = E_c + E_{dh} + E_P + E_g \quad 3.23$$

$$Ecop = E_c + E_s + E_{st} + E_d + E_{dh} + E_{g1} + Em + E_{g2} \quad 3.24$$

$$E_i = \frac{E_{co}}{Pm} \quad 3.25$$

where, E_c is energy for cleaning (MJ), Es is energy for soaking (MJ), Est is energy for steaming (MJ), Ed is energy for drying (MJ), E_{dh} is energy for dehusking (MJ), E_{g1} is energy for first grading (MJ), E_p is energy for polishing (MJ), E_{g2} is energy for second grading (MJ), E_{cow} is total energy consumption for white rice (MJ), E_{cop} is total energy consumption for parboiled rice (MJ), N is average power of a normal male and female labour are 0.75 MJ/h and 0.68 MJ/h, t is time taken to complete unit operation (h), C_f is the calorific value of LPG (Liquefied Petroleum Gas) (50.35MJ) and ω is the power factor, P is the power rating of the machines (kW), 3.6 = Conversion factor (1kWh = 3.6MJ) for electrical energy, $E_i$is Energy intensity and P_m is the paddy mass.

3.7 Modelling Quality Attributes and Total Energy Consumption during Processing of Polished Parboiled Rice

Taguchi orthogonal array, central composite rotatable design of response surface methodology and artificial neural network was used to develop models that can predict brown rice recovery, head brown rice, milling recovery, head milled rice, chalkiness, lightness value, colour value, cooking time and water uptake ratio. Also, Taguchi, RSM and ANN were used to develop models that can predict total energy consumption with precision.

3.8 Modelling Quality Attributes and Total Energy Consumption using Taguchi

The Taguchi Orthogonal Array is a unique statistical experimental design approach that greatly improves the food processing productivity (Vermam, *et al.,* 2012). Taguchi suggests the production process that needed to be applied at optimum levels with minimum variation in its functional attributes. Therefore, the signal-to-noise (S/N) ratio

(η, dB) represents quality characteristics for the observed data in the Taguchi method. The signal-to-noise ratio is an index to evaluate the quality of production process. 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. The experimental results obtained from Table 3.1 were transformed into model using equation 3.26 and two types of S/N ratios namely: smaller-the-better (equation 3.27) was used to analyze total energy consumption, chalkiness, colour value and cooking time while the larger-the-better (equation 3.28) was used to analyze brown rice recovery, milling recovery, head brown rice, head milled rice, water uptake ratio and lightness value.

$$Y=\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\beta_4 x_4 \qquad 3.26$$

Y is the response, 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.

Smaller is the best characteristic

$$\frac{S}{N} = -10log\frac{1}{n}(\sum y^2) \qquad 3.27$$

Larger the better characteristic

$$\frac{S}{N} = -10log\frac{1}{n}\left(\sum\frac{1}{y^2}\right) \qquad 3.28$$

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.

3.9 Modelling Quality Attributes and Total Energy Consumption using Response Surface Methodology

Response surface methodology combined with central composite design (RSM-CCD) was adopted for modelling the quality attributes and total energy consumption during the processing of polished parboiled rice. The RSM models were developed using equation 3.29.

$$Y=\beta_0+\beta_1m_1+\beta_2m_2+\beta_3m_3+\beta_4m_4+\beta_{11}m_1^2+\beta_{22}m_2^2+\beta_{33}m_3^2+\beta_{44}m_4^2+\beta_{12}m_1m_2+\beta_{13}m_1m_3+\beta_{14}m_1m_4+\beta_{23}m_2m_3+\beta_{24}m_2m_4+\beta_{34}m_3m_4 \qquad 3.29$$

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, Y is the response or dependent variables, m_1,m_2,m_3 and m_4 are soaking time, soaking temperature, steaming time and paddy moisture content respectively. Polynomial model equation for quality attributes and total energy consumption during processing of polished parboiled rice was carried out using Minitab®version 16 (Minitab, Inc. Coventry, USA). The response variables: total energy consumption, brown rice recovery, head brown rice, milling recovery, head milled rice, lightness value, colour value, chalkiness, cooking time and water uptake ratio were all modelled.

3.10 Quality Attributes and Total Energy Consumption Simulation using Artificial Neural Network

Neural Network tool box 8.0 in MATLAB (Mathwork, 2013) software was used for the Artificial Neural Network simulation. The schematic diagram of the Artificial Neural Network (ANN) is shown in Fig. 3.3. The data obtained from CCD-RSM experimental work were randomly divided into three groups, 70% in the training set, 15% in the validation set and 15% in the test set. 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 correlation coefficient (R) of regression plot of the training, validation, testing set, low mean square error and also the plot that compares the output of the ANN and experimental values. The artificial neural network used 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, brown rice recovery, head brown rice, milling recovery, head milled rice, chalkiness, lightness value, colour value, cooking time and water uptake ratio for the five 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 transfer function was also used by Khajeh, Moghaddam and Shakeri (2012).

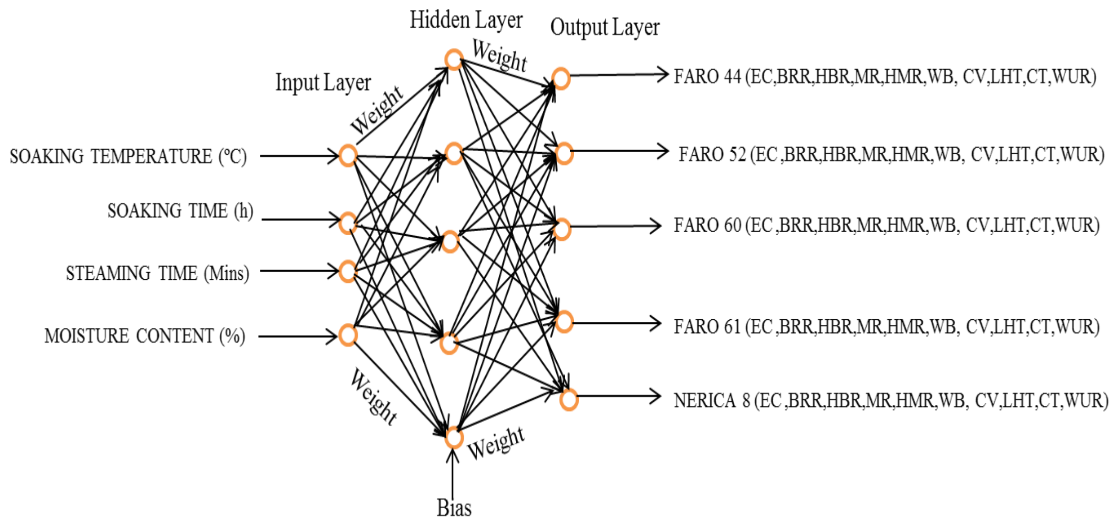


Fig. 3.3. Schematic diagram of the developed feedforward multi-layer ANN

where EC is total energy consumption, BRR is brown rice recovery, HBR is head brown rice, MR milling recovery, HMR is head milled rice, WB is chalkiness, CV is colour value, LHT is lightness value, CT is cooking time and WUR is water uptake ratio

The training function selected for the network was 'trainlm'. The Trainlm' is a network training function that updates weight and bias values according to the Lavenberg-Marquardt algorithm. The accuracy of the predicted results of ANN models were analyzed by comparing the experimental values and predicted values.

3.11 Validation of Modelling Techniques

The performance and effectiveness of the modelling techniques (Taguchi, RSM and ANN) were evaluated using mean square error (MSE) and regression coefficient of determination R^2 (equations 3.30 and 3.31). The experimental values of the quality attributes and total energy consumption obtained from Taguchi, RSM and ANN were used to develop models from each technique. The generated models were then used to predict the responses (quality attributes and total energy consumption) under the same treatments as earlier used in the main experiment. The experimental 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.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_o - y_e)^2}{\sum_{i=1}^{n}(y_o - y_m)^2} \qquad 3.30$$

$$MSE = \frac{1}{N}\sum_{i-1}^{n}(y_o - y_e)^2 \qquad 3.31$$

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.

3.12 Multi-Objectives Optimization of the Processing Conditions for the Varieties

The multi-objectives function optimiser in MINITAB 16 was used to determine the optimum processing conditions for the varieties. The optimum processing conditions that yield minimum total energy consumption, high brown rice recovery, high head brown rice yield, high milling recovery, high head rice yield, low chalkiness, high lightness value, low colour value, short cooking time and high water uptake ratio for each variety was established. For this purpose, the use of desirability functions is one of the useful approaches for optimisation of multiple responses. In this technique, the general approach is to first convert each response y_i into an individual desirability function d_i that varies over the range of 0≤ di≤ 1, where if response y_i is at its target value T, then di = 1, and if it is outside an acceptable region, then di = 0. The individual desirability, di, is calculated using equation 3.32.

$$d_i = \begin{bmatrix} 0\ if\ y_i < 1 \\ \left(\frac{y_i - L}{T - L} \atop 0\ if\ y_i < T \right)^s \end{bmatrix} \quad \text{if L} \le \ y_i \le T \qquad 3.32$$

where T is the target value of the response (total energy consumption and quality attributes), L is the lower acceptable value of the response and s is the mass. Therefore, when s = 1, the desirability function is linear. When s > 1 was chosen, a major importance is given to the points near the target value. When s < 1 was chosen, this last demand is of low importance. Desirability function of variation rate was controlled by s. By varying the value of s, one can attribute different desirability to the responses and can increase and decrease the range of acceptable values in the optimization process. The design variables were chosen to maximize the overall desirability of equation 3.33.

$$D = (d_1 \times d_2 \times \dots \dots d_i \dots \dots .. \times d_n)^{1/N} \qquad 3.33$$

where D is the overall desirability value, di is the individual desirability value of the response variables and N is the number of responses. The desirability of several responses was generated using the MINITAB 16®.

3.13 Validation of the Optimum Processing Conditions

In order to validate the optimal processing conditions obtained from the multi-objectives optimiser, the optimum conditions for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were experimented in laboratory to determine their impacts on total energy consumption, brown rice recovery, head brown rice, milling recovery, head milled rice, lightness value, colour value, chalkiness, cooking time, and water uptake ratio. The experimental values from the laboratory and predicted values from the response optimiser were compared. The percentage errors were then determined by the validity of the optimisation as shown in Equation 3.34 as described by Skara, Novotni, Čukelj, Smerdel, and Ćurić (2013).

$$Percentage\ Deviation = \frac{(Experimental\ value - Predicted\ value)}{Predicted\ value} \times 100 \qquad 3.34$$

3.14 Sensory Evaluation using Quantitative Descriptive Analysis

Sensory evaluation was carried out on cooked samples for each rice variety using the polished parboiled rice from the optimum processing conditions. The cooked samples sensory attributes were scored by fifteen trained panelist using a Quantitative Descriptive Analysis (QDA) as described by Tomlins *et al.* (2005) with little modification by change the unsaturated structure to mm instead of cm. The sensory evaluation was conducted at National Cereal Research Institute (NCRI), Baddeggi, Nigeria. The sensory panel comprised of staff of rice research programme and food value addition programme of NCRI. The sensory panel was screened on the basis of availability, perception on the basic taste of rice in terms of saltiness, bitterness, sweetness and sourness, familiarity with cooked product and ability to determine differences between rice samples. After successful screening, fifteen panels were selected for the sensory evaluation. The fifteen panels had a training session for a period of one week on different sensory attributes of cooked rice. Sensory attributes for cooked rice in terms of visual, odour, taste and texture were developed during the training session that was guided by the panel leader (Head, food value addition programme).

A total of eleven cooked sensory attributes were developed and defined for which the sensory panels agreed upon. The sensory attributes developed for the cooked rice was shown in Table 3.7. Gayin *et al.* (2009) used similar approach to determine the sensory properties of rice varieties from improvement programme in Ghana. Approximately 300 g of each rice variety was cooked in 400 ml of salt water. The five rice samples were tasted in triplicate by the trained panels over a five day period and the order in which the rice were cooked was random. Fifty grams (50 g) of cooked rice samples each were served at room temperature. Each sample was coded with four random letters and served in random order to each panelist. The intensity of cooked rice samples were rated on a scale of 100 mm unsaturated. The unsaturated scale is designated with the terms “not very” at the left end and “very” at the right end. Bottled water was used by the panelists to rinse their mouth before tasting each sample.

Table 3.7. Quantitative descriptive analysis for sensory evaluation

Sensory Attribute	**Description of Attributes**
Uniform appearance	Uniformity in the colour of the cooked rice
Black specks	Blackened ends of cooked rice
Whitish appearance	Pale appearance
Yellow colour	Cooked rice with yellow colour
Brown colour	Brown colour of the Cooked rice
Creamy flavor	Freshly cooked rice with creamy taste
Typical rice odour	Freshly cooked rice with odour characteristic
Sweet taste	Cooked rice with typical delightful taste of the
Sticky texture	Gluey property of cooked rice
Grainy texture	Coarse/gritty texture
Hard texture	Inflexible texture

Source: Gayin *et al.*, 2009.

3.15 Principal Component Analysis (PCA) of Varieties of Cooked Rice

Principal component analysis (PCA) was conducted to determine the overall relationship between the quantitative descriptive attributes of the cooked rice and the rice varieties. The PCA was applied to panellist QDA data to determine overall attributes ratings to identify panelist preference patterns toward the cooked rice samples. The data of cooked rice attributes from QDA were arranged and analysed using using SPSS® version 20 in data view mode. The Bartlett test of sphericity, a statistical test for the presence of correlation among the sensory attributes, and the measurement of sampling adequacy of Kaiser-Meyer-Olkin (KMO) which must exceed 0.5 was determined. The data were reduced by SPSS data analysis and two main components were selected and a two dimensional component figure of the analysed samples was obtained.

3.16 Statistical Analysis

All the experimental procedures were replicated thrice 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. Microsoft Excel spreadsheet software version 2013 was used to do all the experimental calculations. Neural Network tool box in MATLAB (Mathwork, 2013) for ANN simulation, Data were analyzed using Minitab software®version 16 ((Minitab, Inc. Coventry, USA) to generate regression equations and Analysis of Variance (ANOVA) which were determined at 5% level of significant.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Physical Properties of Paddy Rice

Table 4.1 presented the physical properties of the paddy at 12±1% wet basis. The result indicated that the longest paddy length (size) was observed in NERICA 8 (9.51 mm) and least in FARO 52 (8.88 mm). Paddy length of NERICA 8, FÁRO 60 and FÁRO 61 were not statistically significant ($p \geq 0.05$) as shown in Table 4.1. Based on International Rice Research Institute (IRRI) classification, it was observed that the paddy length for the varieties could be classified as extra-long paddy length. Mir *et al.* (2013), reported that different rice varieties had wide range of paddy length. Length to width ratio (shape) of the varieties ranged from 4.03 mm in NERICA 8 to 4.72 mm in FARO 61 and these varieties falls under slender paddy based on IRRI classification.

According to Danbaba *et al.* (2014), when developing new rice varieties for commercial production, physical appearance of paddy is an important quality criterion for rice breeders. Varnamkhasti *et al*. (2008) also reported that principal axial dimensions including length (size), width, thickness and length to width ratio (shape) are essential physical appearance of paddy and are necessary in calculating power during the rice milling operations and designing and selecting sieve separators. The paddy grains equivalent diameter and sphericity were significantly differed among the varieties. The mean equivalent diameters of paddy were observed to vary from 3.19 (FARO 52) to 3.52 mm (NERICA 8). For sphericity, the smallest sphericity value was observed in FARO 61 (33.93%) and highest in NERICA (36.78%). The variation in the sphericity might be due to the length axis which has pointed tips thus, increasing the characteristic length of the paddy length to width ratio.

Table 4.1. Physical properties of paddy rice

Physical properties	NERICA 8	FARO 52	FARO 61	FARO 60	FARO 44
Paddy length (mm)	9.51±0.44^{a}	8.88±0.38^{b}	9.50±0.51^{a}	9.50±0.49^{a}	9.28±0.51^{ab}
Paddy length to width ratio	4.03±0.29^{c}	4.31±0.46^{cb}	4.72±0.37^{a}	4.55±0.29^{ab}	4.58±0.41^{ab}
Equivalent diameter (mm)	3.52±0.22^{a}	3.19±0.21^{b}	3.22±0.14^{b}	3.30±0.14^{b}	3.23±0.2^{5b}
Sphericity (%)	36.78±1.90^{a}	35.86±2.41^{ab}	33.93±1.83^{c}	34.76±1.57^{bc}	34.72±0.96^{bc}
Grain volume (m^3)	23.01±4.46^{a}	17.21±3.49^{b}	17.64±2.40^{b}	18.99±2.49^{b}	17.88±4.31^{b}
Surface area (mm^2)	3.76±0.36^{b}	3.36+0.36^{b}	3.27±0.22^{b}	3.41±0.21^{b}	3.33±0.36^{b}
Aspect ratio (AR)	0.25±0.02^{a}	0.24±0.02^{ab}	0.21±0.02^{c}	0.22±0.02^{bc}	0.22±0.02^{bc}
1000P (g)	27.04±1.11^{a}	22.99±1.28^{c}	24.46±1.14^{c}	27.24±1.22^{a}	24.24±1.44^{b}
Bulk density (g/cm^3)	63.5±0.79^{a}	62.41±3.28^{a}	61.96±1.60^{a}	62.67±1.13^{a}	63.75±2.45^{a}

Mean values within the same row with the same superscript are not significantly different ($p \geq 0.05$).

This report corroborated Mir *et al.* (2013) findings. Al-Mahasneh and Rababah (2007) reported that paddy grains with low sphericity were suggested to slide rather than roll on the surface, which is a property that is quite important in the design of grain hoppers. The mean grain volume values for the paddy were 23.01 m^3, 17.21 m^3, 18.99 m^3, 17.64 m^3 and 17.88 m^3 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. No significant difference $p \geq 0.05$ was observed in the surface area among the varieties. It is paramount during modelling of cooling, aeration, grain drying and heating to have knowledge of grain surface area (Al-Mahasneh and Rababah, 2007).

The paddy grains surface area and volume values were almost similar to Sorkheh and Sazandegi rice varieties as reported by Varnamkhasti *et al.* (2008). Mir *et al.* (2013) also reported the use of surface to volume ratio to study the impact of surface area on drying rates of particulate materials. Moreso, the ratio of surface area to volume affects drying time and energy requirements. Aspect ratio relates the paddy width to length. Aspect ratio is needed to classify paddy and examine the extent of off-size in grading the market value and shows whether the paddy will roll or slide on flat surfaces (Varnamkhasti *et al*., 2008). Al-Mahasneh and Rababah (2007) reported that paddy having a larger aspect ratio means that the grains will rather slide than roll. NERICA 8 (0.25) had the highest aspect ratio while the least was found in FARO 61 (0.21).

The aspect ratio of paddy in FARO 52, FARO 61 and NERICA 8 were significantly different ($p \leq 0.05$) while FARO 60 and FARO 44 were not significantly different. Varnamkhasti *et al*. (2008) reported that mean aspect ratios could range from 0.21 to 0.28. Thousand paddy weights varied from 22.99 to 27.24 g among varieties and were significantly different ($p \leq 0.05$). The highest thousand paddy weight was found in FARO 60 while the least was in FARO 52. A thousand paddy weight values between 20 and 30 g are considered good paddies while those less than 20 g could signify presence of the immature, damaged, and unfilled grains. The bulk density of the paddy shows no significant difference among the varieties. Among the five varieties studied, FARO 44 had the highest bulk density and FARO 61 had the lowest. Bulk density values are useful in the design of silos and storage bins. Since bulk density of FARO 61 is the lowest when compared with FARO 44, FARO 52, FAR0 60 and NERICA 8. Based on the result, a large silo will be required for FARO 61 when compared with other four varieties.

4.2 Quality Attributes of White Rice

Table 4.2 showed the quality attributes of white rice. The longest milled rice length was recorded in NERICA 8 (6.48 mm) and the least in FARO 52 (6.10 mm). No significant difference ($p \geq 0.05$) was observed in the milled rice length (size) of FARO 44 and FARO 60. Milled rice length to width ratio (shape) ranged from 3.09 mm in FARO 44 to 3.50 mm in FARO 61. The milled rice varieties falls under medium milled rice in length (size) and slender milled rice in length to width ratio (shape) based on IRRI classification. The physical appearance of milled rice is an important quality criteria for consumers and preference for grain size and shape vary from one group of consumers to another and from one country to another (Cruz and Khush, 2002).

The milling recovery of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 66.68%, 65.32%, 67.39%, 68.28%, and 68.40%, respectively. There was significant difference ($p \leq 0.05$) in the milling recovery of the NERICA 8, FARO 61, FARO 52 and FARO 44, respectively. However, there was no significant difference in the milling recovery of FARO 44 and FARO 60. The difference in the milling recovery may be related to the different behaviour of rice varieties during separation of husk and bran from paddy due to paddy shape, porosity of starch granules and presence of chalkiness. FARO 44 had the highest milling recovery (68.40%) while FARO 52 had the lowest (65.32%). Broken milled rice ranges from 18.82 to 41.88% and head milled rice ranges from 12.76 to 48.08%. The significant difference in the obtained broken and head milled rice of the varieties can be ascribed to their physical, mechanical and morphological properties. According to Wiset *et al.* (2001), rice variety with higher size is more susceptible to cracking and breakage during milling. Therefore these non-parboiled rice varieties could be regarded to as low quality as shown in Table 4.2. The chalkiness levels of the milled rice were high, ranging from 65.23 to 83%.

Table 4.2. Quality attributes of white rice

Quality attributes	NERICA 8	FARO 52	FARO 61	FARO 60	FARO 44
Milled length (mm)	6.31 ± 0.41^{ab}	6.10 ± 0.34^{b}	6.48 ± 0.29^{a}	6.40 ± 0.42^{ab}	6.14 ± 0.36^{ab}
Milled length to width ratio	3.28 ± 0.28^{ab}	3.35 ± 0.23^{ab}	3.50 ± 0.25^{a}	3.33 ± 0.278^{ab}	3.09 ± 0.34^{b}
Cooking time (min)	12.20 ± 1.75^{d}	18.4 ± 0.52^{b}	15.7 ± 0.48^{d}	17.30 ± 0.48^{c}	21.50 ± 1.58^{a}
Broken milled rice (%)	29.84 ± 0.54^{c}	41.12 ± 0.28^{b}	41.88 ± 0.32^{a}	18.82 ± 0.21^{d}	41.20 ± 0.65^{b}
Head milled rice (%)	36.84 ± 0.71^{c}	24.20 ± 0.34^{e}	12.76 ± 0.09^{d}	48.08 ± 0.50^{a}	46.80 ± 0.64^{b}
Milling recovery (%)	66.68 ± 0.43^{c}	65.32 ± 0.21^{d}	67.39 ± 0.21^{b}	68.28 ± 0.12^{a}	68.40 ± 0.65^{a}
Chalkiness (%)	73.11 ± 0.90^{c}	79.56 ± 1.21^{b}	83.00 ± 1.02^{a}	65.23 ± 1.20^{d}	80.34 ± 1.65^{b}
L*	16.40 ± 1.23^{c}	20.14 ± 1.78^{b}	15.99 ± 1.47^{c}	17.08 ± 1.59^{c}	22.37 ± 2.14^{a}
a*	2.54 ± 0.42^{a}	1.71 ± 0.39^{b}	0.47 ± 0.45^{c}	2.44 ± 0.422^{a}	1.33 ± 0.54^{b}
b*	23.52 ± 0.71^{a}	19.96 ± 1.42^{c}	23.52 ± 0.71^{a}	18.15 ± 0.65^{d}	22.31 ± 1.31^{b}
Water uptake ratio	2.80 ± 0.18^{d}	3.38 ± 0.16^{c}	3.87 ± 0.02^{a}	3.56 ± 0.11^{b}	2.68 ± 0.28^{d}

Mean values within the same row with the same superscript are not significantly different ($p\geq0.05$).

According to Futakuchi *et al.* (2013), chalkiness indirectly contributes to rice breakage through easy cracking, resulting into low quality and market value. This implies that there is need to subject these varieties to parboiling in order to improve their physical quality. Table 4.2 showed significant differences ($p \leq 0.05$) in the L, a* and b* of the rice varieties. The milled rice of FARO 44 (L* = 22.37) was found to be the lightest and FARO 61 (L* = 15.99) was the least, NERICA 8 (2.54) had the highest a* value while FARO 61 (0.47) had the lowest b* value. Furthermore, the b* value was found to be higher in FARO 61 and NERICA 8 (23.52) and the least was in FARO 60 (18.15).

The difference in the colour of the white rice may be due to the difference in the genetic makeup and coloured pigments (Kaur *et al*., 2013). The cooking properties of the white rice are important as rice is consumed almost immediately after cooking. Cooking time and water uptake ratio is an important cooking quality indicator of rice. The cooking time correlates with fuel consumption. The cooking times of the white rice of the different varieties were significantly different ($p \leq 0.05$). The cooking time ranged from 12.20 min to 21.5 min with FARO 44 having the longest cooking time while NERICA 8 had the shortest cooking time. The difference in the cooking time of the rice varieties could be ascribed to the variation in their gelatinization temperature since gelatinization temperature have direct influence on the cooking time of white rice. Higher gelatinization temperature value has been asserted to the longer time it takes to cook rice. The values of water uptake ratio reported by Frei *et al.* (2003) were similar to the values obtained for the water uptake ratio of the white rice of the varieties. However, the highest water uptake ratio (3.87) was obtained in FARO 61. The highest water uptake ratio obtained in FARO 61 might be due to the amylose content. High amylose content in rice might be correlated to ability to absorb more water upon cooking (Frei and Becker 2003).

4.3 Energy Consumption in White Rice Processing

The average energy consumption at each unit operation in processing the rice varieties into white rice is depicted in Figure 4.1. The total energy consumption for the varieties ranges from 2.31 to 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 was similar to the findings of Goyal *et al.* (2014) that the major portion of the total energy consumed in milling of paddy into white rice is due to the polishing. The average energy consumption in dehusking operation (1.040 ± 0.015 MJ) was next to polishing before cleaning operation (0.048 ± 0.019 MJ). 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 of the varieties. According to Wang (2008), processing duration at each unit operation has a lot of impact on energy consumption. Roy *et al.* (2003) and Goyal *et al*. (2014) also reported that the energy consumption for milling rice depends on paddy/grain type, quantity of grains, process, quality of final product, type/capacity/age or combination of equipment used, power source, efficiency of driver and power transmission. Electrical energy took the highest energy portion with 96.42% while the human energy consumed 3.58% of the total energy (Fig 4.2). This implies that white rice production is electrical energy dependent.

4.4 Energy Consumption in Parboiled Rice Processing

The average energy consumption required in processing paddy into polished parboiled rice varied from one unit operation to another (Figure 4.3). Drying operation was observed to be the highest energy consuming operation with 24.113 ± 1.24 MJ. This maybe as a result of the time required to dry the paddy of the varieties to desired moisture content. Steaming and soaking were also observed to be high in energy consumption with 21.872 ± 0.209 MJ and 10.757 MJ respectively. Goyal *et al.* (2014) and 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. 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 (Fig. 4.2). Therefore, rice parboiling process is thermal energy dependent.

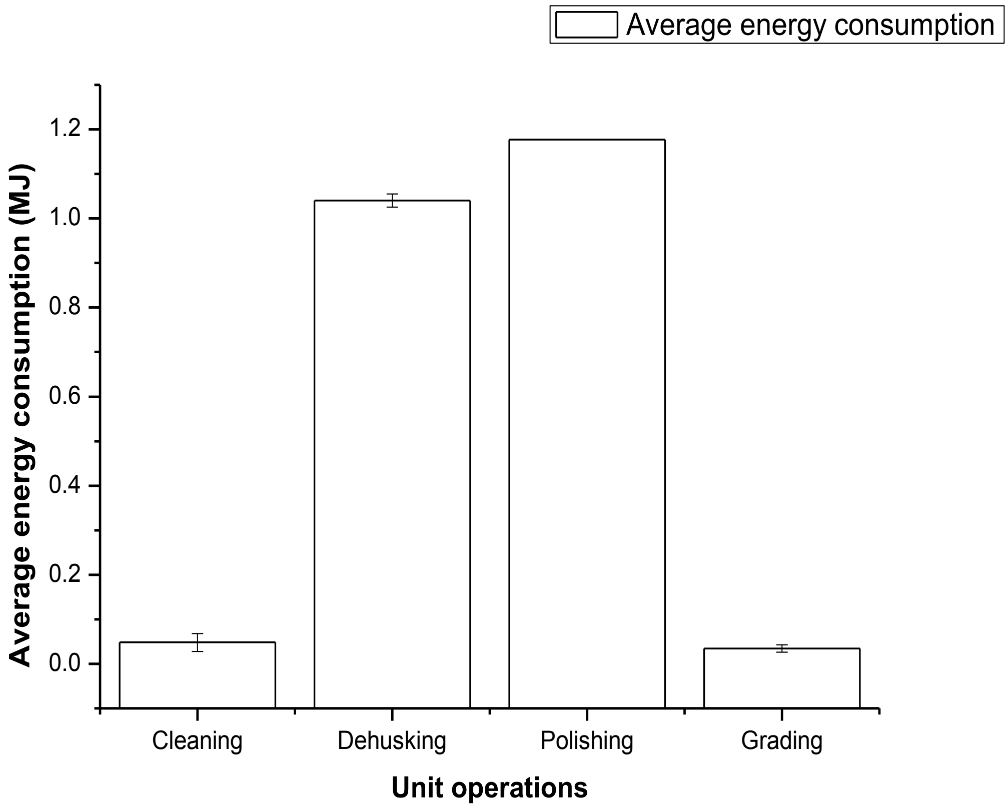


Fig. 4.1. Average energy intensity pattern in processing paddy rice into white rice

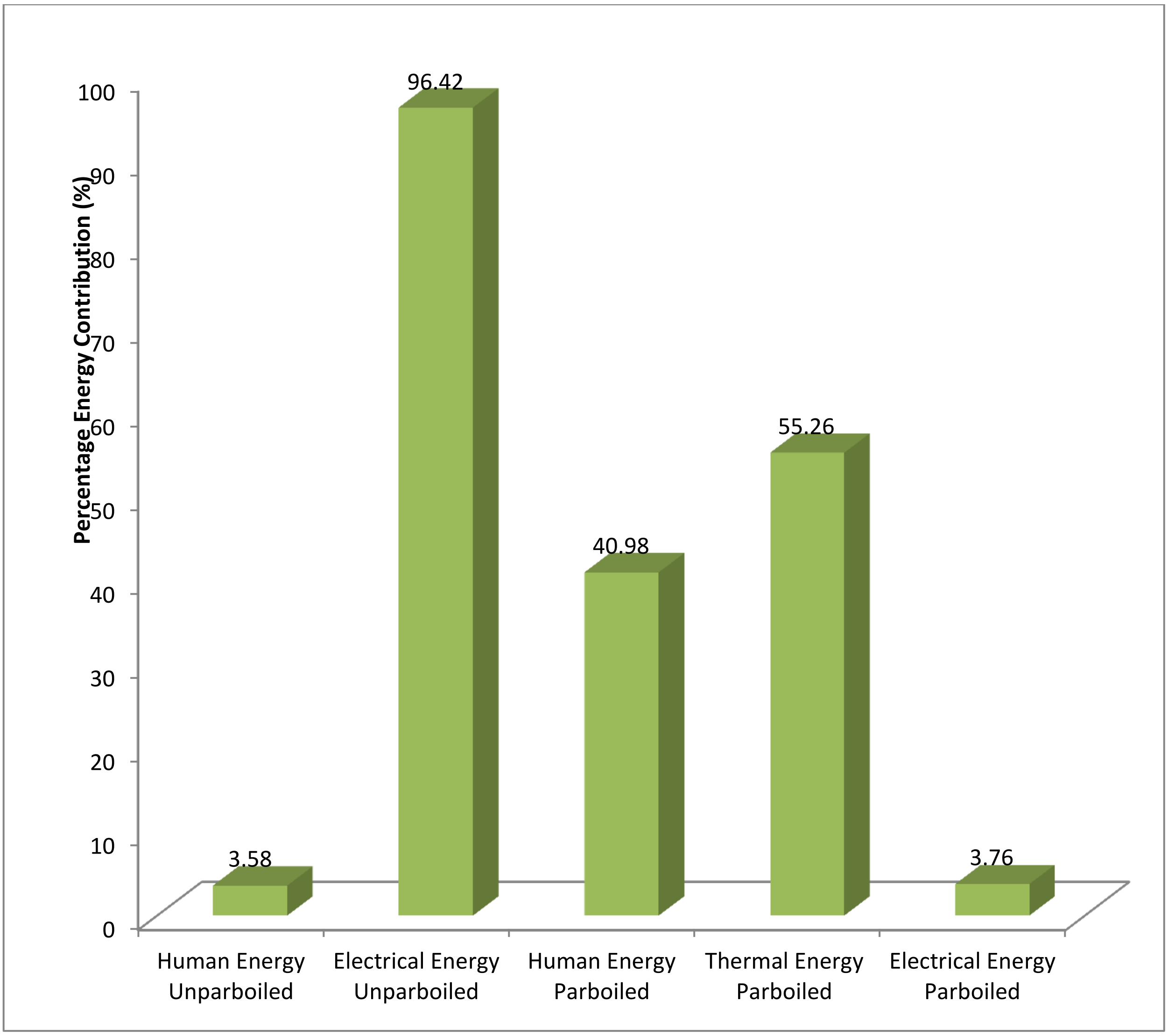


Fig. 4.2. Forms of energy used during rice processing

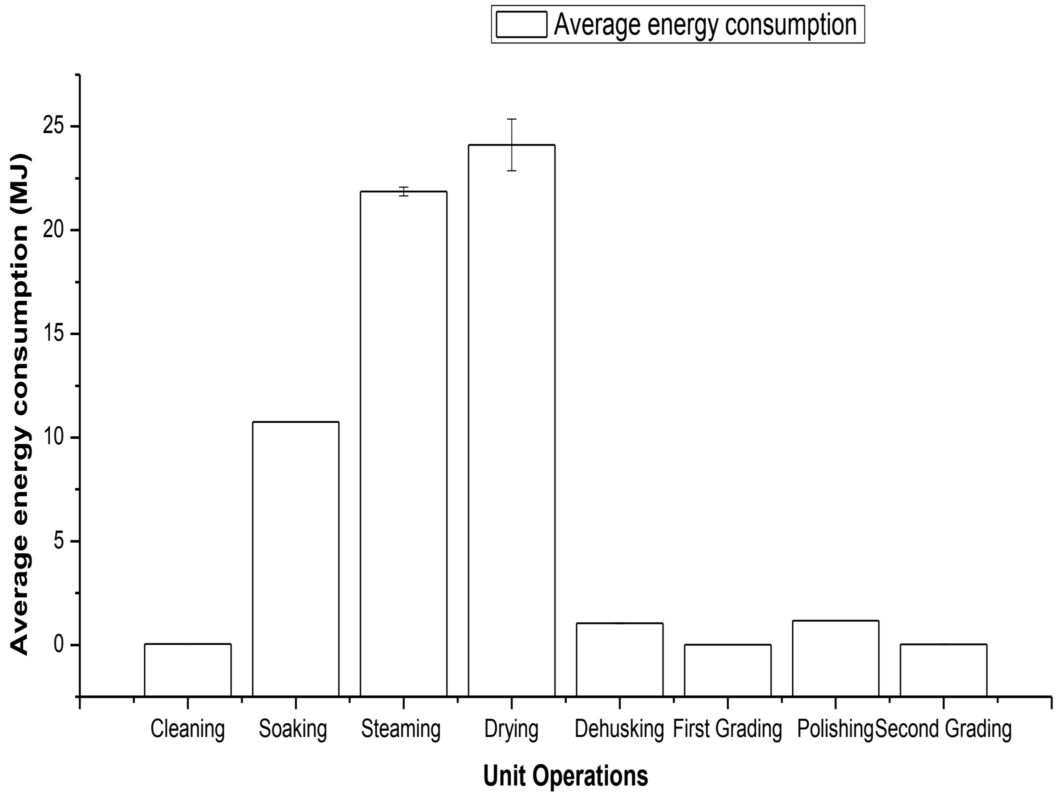


Fig. 4.3. Average energy consumption pattern in processing paddy rice into polished parboiled rice

4.5 Taguchi Modelling of Impacts of Processing Parameters on Total Energy Consumption of Rice Varieties

The impacts of different processing parameters on total energy consumption was examined in order to minimize the energy consumption during parboiling as it has been reported by Kwofie *et al.* (2016), that parboiling is an energy-intensive process and has direct implication on production cost. Table 4.3 shows the impacts of processing parameters on total energy consumption using Taguchi techniques. The lower the better signal to noise ratio (S/N) of Taguchi indicated that processing parameters 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 varieties. However, the least energy consumption differs across the varieties based on the processing parameters combinations. 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 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 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 followed a similar trend in terms of processing parameters that were observed in FARO 44, FARO 52 and FAR0 60. The total energy consumption at 75°C soaking temperature, 13 h soaking time, 20 min steaming time and 16% paddy moisture content and 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content were not significant at $p>0.05$. From the results, it can be deduced that the right combination of processing parameters has been identified as a way to conserve energy.

Table 4.3. Impacts of processing parameters on total energy consumption using Taguchi technique

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^{c}	-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

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Where, EC 8, EC 52, EC 61, EC 60 and EC 44 represent Total Energy Consumption for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

A similar finding was reported by Roy *et al.,* (2003), who stated that the energy consumption varied from process to process. According to Kwofie and Ngadi (2017), the intensity of energy consumption are influenced by the quantity of rice being processed, parboiling method used, variety of rice, state of rice (rough or dehusked) and processing parameters such as the soaking temperature and time etc. Table 4.4 shows the ranks of processing parameters on total energy consumption, which represent the S/N ratio, mean values, delta values, and ranks of each processing parameters. The ranking of processing parameters, based on the signal to noise (S/N) of total energy consumption was found to be most significant at paddy moisture content (%) and steaming time (min) ranked second. This trend was in line with Goyal *et al.* (2014) findings which stated that the drying operation was the highest consuming operation in rice parboiling. Also, Islam *et al.* (2004) and Goyal *et al.* (2014) 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 total energy consumption were expressed as equations 4.1 to 4.5.

$$TEC\ (A) = 44.52 + 0.1682S_{temp} + 0.9829S_{time} + 0.9248ST - 2.4474MC \qquad 4.1$$

$R^2 = 0.959$ $R^2_{(adj)} = 0.92$

$$TEC(B) = 45.73 + 0.1804S_{temp} + 1.0752S_{time} + 0.8371ST - 2.4261MC \qquad 4.2$$

$R^2 = 0.947$ $R^2_{(adj)} = 0.890$

$$\mathrm{T}EC(C) = 46.28 + 0.1679S_{temp} + 1.0120S_{time} + 0.8242ST - 2.5098MC \qquad 4.3$$

$R^2 = 0.966$ $R^2_{(adj)} = 0.930$

$$TEC(D) = 47.69 + 0.1699S_{temp} + 0.9175S_{time} + 0.8676ST - 2.4301MC \qquad 4.4$$

$R^2 = 0.949$ $R^2_{(adj)} = 0.890$

$$TEC(E) = 56.49 + 0.1022S_{temp} + 0.9123S_{time} + 0.7583ST - 2.4698MC \qquad 4.5$$

$R^2 = 0.945$ $R^2_{(adj)} = 0.880$

where, S_{temp}, S_{time}, ST, MC, TEC, E, B, D, C, and A represent soaking temperature, soaking time, steaming time, moisture content, energy consumption, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The generated models have R^2 ranging from 0.945 to 0.966 while R^2_{adj} ranges from 0.880 to 0.930. There R^2 and R^2_{adj} values 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.

Table 4.4. Ranks of processing parameters on total energy consumption

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) 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

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 polished parboiled rice. The generated mean square error (MSE) between the experimental 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. High and low values were obtained for R^2 and MSE values from the developed models, thus, shows that the models are fit to predict total energy consumption of the varieties during the rice processing.

4.6 Modelling the Impacts of Processing Parameters on Quality Attributes using Taguchi Technique

4.6.1 Taguchi modelling of brown rice recovery

High brown rice recovery signifies high market value for processors of brown rice. The impacts of processing parameters on brown rice recovery were shown in Table 4.5. From the results, the brown rice recovery varied among varieties. The highest brown rice recovery ranged from 78.55% to 82.40% across the varieties. The variation in the brown rice recovery can be traced to the intrinsic behaviour of each variety under different processing parameters. According to Rebeira *et al.* (2014), diversity of grain quality characteristic has influence on brown rice recovery and the recovery could range from 77-80% among different varieties. The higher the signal to noise ratio (S/N) the better was considered to optimize the processing parameters that had the highest brown rice recovery. Chandrasekar *et al.* (2015) also used a similar approach for optimization in their work. FARO 44 had 79.41% brown rice recovery at 65 °C soaking temperature -16h soaking time - 30min steaming time - 16% moisture content at 38 S/N.

For FARO 52, the highest signal to noise ratio was observed at 37.97 with 79.18% brown rice recovery at 70 °C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content while FARO 60 had 78.55% highest brown rice recovery with no significant difference ($p \geq 0.05$) in the brown rice recovery at processing conditions of 65 °C soaking temperature, soaking time 10 h, 20 min steaming time and 12% paddy moisture content; 75 °C soaking temperature,

Table 4.5. Impacts of processing parameters on brown rice recovery using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (Min)	Paddy Moisture Content (%)	BRR 44 %	S/N	BRR 52 %	S/N	BRR 60 %	S/N	BRR 61 %	S/N	BRR 8 %	S/N
65.00	10.00	20.00	12.00	78.11^{dc}	37.85	77.31^{f}	37.77	78.55^{a}	37.90	77.87^{b}	37.83	79.56^{f}	38.01
65.00	13.00	25.00	14.00	77.90^{fe}	37.83	78.65^{b}	37.91	77.94^{c}	37.83	77.53^{c}	37.79	79.47^{f}	38.00
65.00	16.00	30.00	16.00	79.41^{a}	38.00	78.28^{de}	37.87	78.24^{b}	37.87	78.51^{a}	37.90	80.17^{de}	38.08
70.00	10.00	25.00	16.00	78.20^{bcd}	37.86	79.18^{a}	37.97	77.58^{d}	37.80	77.62^{c}	37.80	80.02^{e}	38.06
70.00	13.00	30.00	12.00	78.27^{bc}	37.87	78.23^{de}	37.87	77.70^{d}	37.81	77.91^{b}	37.83	82.40^{a}	38.32
70.00	16.00	20.00	14.00	78.39^{b}	37.89	78.14^{e}	37.86	77.78^{cd}	37.82	77.03^{d}	37.73	80.24^{cd}	38.09
75.00	10.00	30.00	14.00	77.81^{f}	37.82	78.65^{b}	37.91	77.28^{e}	37.76	78.64^{a}	37.91	80.06^{de}	38.07
75.00	13.00	20.00	16.00	78.33^{f}	37.88	78.49^{bc}	37.90	78.46^{a}	37.89	77.93^{b}	37.83	80.42^{c}	38.11
75.00	16.00	25.00	12.00	78.05^{ed}	37.85	78.42^{cd}	37.89	78.54^{a}	37.90	78.05^{b}	37.85	81.19^{b}	38.19

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Where, BRR means brown rice recovery for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

13 h soaking time, 20 min steaming time and 16% paddy moisture content and 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content respectively. FARO 61 had 78.64% highest brown rice recovery with S/N (37.91). However, the brown rice recovery at 75 °C soaking temperature, 10 h soaking time, 30 min steaming time and 14% paddy moisture content and 65 °C soaking temperature, 16 h soaking time, 30 min steaming time, 16% paddy moisture content, showed there was no significant difference at ($p \geq 0.05$). The highest brown rice recovery was 82.40% at S/N (38.32) for NERICA 8, at 70°C soaking temperature, 13 h soaking time, 30 min steaming time and 12% moisture content as shown in Table 4.5. The differences in the values of the brown recovery are similar to what was reported by Singh *et al*. (2012) and Mir *et al.* (2013).

The ranks of processing parameters impacts on brown rice recovery were presented in Table 4.6. It was observed that in FARO 44 and FARO 60, paddy moisture content had the most significant influence on the brown rice recovery. At high moisture content, husk has the tendency to be easily removed thus paving way for high brown rice recovery. While in FARO 52 and FARO 61, steaming time influenced brown rice recovery the most. Soponronnarit *et al.* (2006) reported steaming to have increased hardness of the rice grains after parboiling, thus, leading to an increase in the brown rice recovery of FARO 52 and FARO 61. For NERICA 8, the ranks of processing parameters were soaking temperature > paddy moisture content > soaking time > steaming time. The difference in the genetic makeup of the varieties might be the reasons for the observed dynamic behaviour in them. The generated predictive Taguchi models for brown rice recovery were expressed as follows in equations 4.6 to 4.10.

$$BRR\ (A) = 77.591 - 0.041S_{temp} + 0.096S_{time} + 0.022ST + 0.126MC \qquad 4.6$$

$R^2 = 0.689$ $\qquad R^2_{(adj)} = 0.379$

$$BBR\ (B) = 72.186 + 0.0439S_{temp} - 0.017S_{time} + 0.040ST + 0.166MC \qquad 4.7$$

$R^2 = 0.596$ $\qquad R^2_{(adj)} = 0.192$

$$BBR\ (C) = 80.130 - 0.015S_{temp} + 0.064S_{time} - 0.0526ST + 0.042M \qquad 4.8$$

$R^2 = 0.416$ $\qquad R^2_{(adj)} = 0.000$

Table 4.6. Ranks of processing parameters on brown rice recovery using Taguchi technique

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	37.89	37.85	37.87	37.86
2	37.87	37.86	37.85	37.85
3	37.85	37.91	37.9	37.91
Delta	0.05	0.06	0.05	0.07
Rank	4	2	3	1
FARO 52				
1	37.85	37.88	37.84	37.84
2	37.9	37.89	37.93	37.9
3	37.9	37.87	37.88	37.91
Delta	0.05	0.02	0.09	0.07
Rank	3	4	1	2
FARO 60				
1	37.87	37.82	37.87	37.87
2	37.81	37.85	37.84	37.8
3	37.85	37.86	37.81	37.85
Delta	0.06	0.04	0.06	0.07
Rank	2	4	3	1
FARO 61				
1	37.84	37.85	37.8	37.84
2	37.79	37.82	37.81	37.81
3	37.87	37.83	37.88	37.84
Delta	0.08	0.03	0.08	0.03
Rank	2	4	1	3
NERICA 8				
1	38.03	38.05	38.07	38.17
2	38.16	38.14	38.09	38.05
3	38.12	38.12	38.16	38.08
Delta	0.12	0.09	0.09	0.12
Rank	1	3	4	2

$$BBR\ (D) = 74.488 + 0.024S_{temp} - 0.029S_{time} + 0.075ST + 0.019MC \qquad 4.9$$

$R^2 = 0.506$ $\qquad$ $R^2_{(adj)} = 0.111$

$$BRR(E) = 74.185 + 0.082S_{temp} + 0.109S_{time} + 0.0804ST - 0.211MC \qquad 4.10$$

$R^2 = 0.567$ $\qquad$ $R^2_{(adj)} = 0.134$

where, S_{temp}, S_{time}, ST, MC, BBR, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, paddy moisture content, brown rice recovery, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44. The models have R^2 that ranges from 0.416 to 0.689 while R^2_{adj} was from 0.000 to 0.379. The R^2 for brown rice recovery were 0.567, 0.596, 0.416, 0.506 and 0.689 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The mean square error (MSE) for brown rice recovery obtained between the experimental and predicted values were 0.313, 0.111, 4.294, 0.106 and 0.091for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The obtained R^2 values were less than the recommended R^2 (≥ 0.75) by Koocheki *et al.* (2009) and Chauhan and Gupta (2004) in order to have fitted model. Therefore, the generated models for brown rice recovery were not fit to predict brown rice recovery of the varieties using Taguchi technique.

4.6.2 Taguchi modelling of head brown rice

Head brown rice is one of the quality indices of brown rice processors because it is part of the indices consumers of brown rice use for acceptability. Also, high head brown rice yield translate to economic value for rice processors, most especially those that specialized in producing brown rice. Table 4.7 depicts the impacts of processing parameters on head brown rice. The highest head brown rice ranges from 72.88% to 81.94%. The variation in the yield of the head brown rice can be traced to the difference in the compact arrangement of starch granule after parboiling.

The ability of the varieties to resist dehusking pressure is another factor that might cause variation in their yield. According to Islam *et al.* (2004), during parboiling, starch gelatinized partly or completely depending on the processing conditions. Rice varieties that undergo complete starch gelatinization are expected to have high head brown rice. Based on the larger the head brown rice, the better the signal to noise ratio (S/N) of Taguchi techniques, NERICA 8 had 81.94% of head brown rice at 70°C soaking temperature, 13 h soaking time, 30 min steaming time and 12% paddy moisture content.

Table 4.7. Impacts of processing parameters on the head brown rice using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	HBR 44 %	S/N	HBR 52 %	S/N	HBR 60 %	S/N	HBR 61 %	S/N	HBR 8 %	S/N
65.00	10.00	20.00	12.00	77.55[b]	37.79	76.44[e]	37.67	78.08[a]	37.85	76.24[bc]	37.64	77.14[f]	37.75
65.00	13.00	25.00	14.00	77.43[b]	37.78	78.14[ab]	37.86	77.51[ab]	37.79	76.20[bc]	37.64	78.81[de]	37.93
65.00	16.00	30.00	16.00	79.02[a]	37.95	76.86[cde]	37.71	77.79[a]	37.82	77.74[a]	37.81	79.98[bc]	38.06
70.00	10.00	25.00	16.00	77.78[b]	37.82	78.74[a]	37.92	77.51[ab]	37.79	74.55[d]	37.45	79.57[cd]	38.01
70.00	13.00	30.00	12.00	78.16[ab]	37.86	77.39[cde]	37.77	77.54[ab]	37.79	75.85[c]	37.60	81.94[a]	38.27
70.00	16.00	20.00	14.00	78.16[ab]	37.86	77.61[bcd]	37.80	72.88[c]	37.25	75.81[c]	37.59	79.41[cd]	38.00
75.00	10.00	30.00	14.00	77.13[b]	37.74	78.47[ab]	37.89	76.70[b]	37.70	77.24[a]	37.76	79.41[cd]	38.00
75.00	13.00	20.00	16.00	78.00[b]	37.84	78.39[abc]	37.88	78.01[a]	37.84	77.08[ab]	37.74	78.18[e]	37.86
75.00	16.00	25.00	12.00	77.41[b]	37.78	78.05[abc]	37.85	78.22[a]	37.87	77.51[a]	37.79	80.63[b]	38.13

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Where, HBR means head brown rice for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

For FARO 60, the highest S/N ratio (37.87) was observed at 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content, with 78.22% head brown rice. FARO 61 had 77.74% highest head brown rice with no significant difference ($p>0.05$) in the head brown rice at processing conditions of 65°C soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content, 75°C soaking temperature, 10 h soaking time, steaming time 30 min and 14% paddy moisture content and 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content respectively. Highest head brown rice for NERICA 8 was 81.94% with S/N (38.27). The differences in the values of the head brown rice yield were similar to the findings of Ayamdoo *et al.* (2013).

The ranks of processing parameters on head brown rice were presented in Table 4.8. The ranking was based on their impacts on the rice varieties. Soaking temperature had the most significant influence on head brown rice of FARO 44, FARO 60 and FARO 61. A similar finding was reported by Leethanapanich *et al.* (2016). Soaking temperatures accelerate hydration rates as well as reduced chalkiness and fissures as a result of simultaneous swelling and rearrangement of starch granules. However, in FARO 52, paddy moisture content had the most significant effect while in NERICA 8, it was steaming time. According to Roy *et al.* (2003), head rice yield can also be affected by the drying condition and moisture content. The differences that were observed in the varieties in respect to the processing parameters can be related to the difference in the physical, mechanical and morphological properties of the varieties. The generated predictive Taguchi models for head brown rice were expressed in equations 4.11 to 4.15.

$$HBR\ (A) = 77.264 - 0.0486S_{temp} - 0.11802S_{time} + 0.019ST + 0.139MC \qquad 4.11$$

$R^2 = 0.640$ $\qquad$ $R^2_{(adj)} = 0.281$

$$HBR\ (B) = 67.834 + 0.116S_{temp} - 0.062S_{time} + 0.009ST + 0.175MC \qquad 4.12$$

$R^2 = 0.619$ $\qquad$ $R^2_{(adj)} = 0.238$

$$HBR\ (C) = 78.69 - 0.015S_{temp} - 0.188S_{time} + 0.102ST - 0.044MC \qquad 4.13$$

$R^2 = 0.161$ $\qquad$ $R^2_{(adj)} = 0.00$

Table 4.8. Ranks of processing parameters on head brown rice yield using Taguchi technique

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	9.635	5.673	9.726	9.939
2	13.297	12.435	7.326	8.007
3	6.334	11.157	12.213	11.319
Delta	6.963	6.762	4.888	3.312
Rank	1	2	3	4
FARO 52				
1	4.518	10.768	5.452	3.934
2	7.117	7.774	10.243	13.661
3	13.167	4.462	6.535	4.226
Delta	8.649	6.306	4.791	9.727
Rank	2	3	4	1
FARO 60				
1	14.67	13.83	12.75	16.75
2	19.48	17.37	19.02	13.14
3	11.4	14.34	13.78	15.66
Delta	8.08	3.54	6.27	3.61
Rank	1	4	2	3
FARO 61				
1	-1.1429	-4.3183	-0.9289	-3.0366
2	-4.6764	-0.1657	-2.7846	-2.1085
3	1.0293	-0.306	-1.0766	0.355
Delta	5.7057	4.1526	1.8556	3.3915
Rank	1	2	4	3
NERICA 8				
1	5.3478	3.0556	-0.2744	3.0273
2	9.9531	3.4693	7.989	7.9964
3	3.02	11.796	10.6064	7.2973
Delta	6.9332	8.7403	10.8808	4.9691
Rank	3	2	1	4

$$HBR\ (D) = 69.293 + 0.055S_{temp} + 0.1669S_{time} + 0.0562ST - 0.019MC \qquad 4.14$$

$R^2 = 0.288 \qquad R^2_{(adj)} = 0.000$

$$HBR\ (E) = 68.084 + 0.076S_{temp} + 0.217S_{time} + 0.219ST - 0.165MC \qquad 4.15$$

$R^2 = 0.743 \qquad R^2_{(adj)} = 0.485$

where, S_{temp}, S_{time}, ST, MC, HBR, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, paddy moisture content, head brown rice, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44. The models have R^2 values that ranged from 0.161 to 0.743 while R^2_{adj} was from 0 to 0.485. The R^2 values for head brown rice were 0.743, 0.619, 0.288, 0.161, and 0.640 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The mean square error (MSE) for head brown rice obtained between the experimental and predicted values were 0.436, 0.202, 0.646, 2.050 and 0.682 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. Therefore, the obtained Taguchi predictive models were not fit to predict the head brown rice.

4.6.3 Taguchi modelling of milling recovery

Table 4.9 depicts the impacts of processing parameters on milling recovery. The highest milling recovery obtained for the varieties ranged from 70.87% to 73.54%. Akhter *et al.* (2015), reported similar findings that milling recovery ranged from 69.6 to 72.5%. The higher the milling recovery the better of signal to noise ratio (S/N) of Taguchi analysis, showed that FARO 44 had 73.54% highest milling recovery at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content while the least was observed in NERICA 8 (70.87%) at 70°C soaking temperature, 13 h soaking time, 30 min steaming time and 12% paddy moisture content. The highest milling recovery in FARO 52 was 71.47%, at S/N ratio (37.08) and at 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content. In FARO 60, four different processing parameters combinations were observed not to have a significant difference ($p>0.05$) in their milling recovery. However, the highest milling recovery (72.02%) and S/N ratio (37.15) was recorded at 65°C soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content. FARO 61 had 71.76% highest milling recovery at 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content.

Table 4.9. Impacts of processing parameters on the milling recovery using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	MR 44 %	S/N	MR 52 %	S/N	MR 60 %	S/N	MR 61 %	S/N	MR 8 %	S/N
65.00	10.00	20.00	12.00	72.13^{b}	37.16	69.13^{b}	36.79	71.88^{a}	37.13	68.95^{d}	36.77	65.87^{e}	36.37
65.00	13.00	25.00	14.00	70.26^{d}	36.93	58.61^{d}	35.36	71.95^{a}	37.14	70.32^{b}	36.94	65.72^{e}	36.35
65.00	16.00	30.00	16.00	70.12^{d}	36.92	66.35^{c}	36.44	72.02^{a}	37.15	66.38^{cf}	36.44	69.00^{e}	36.78
70.00	10.00	25.00	16.00	73.54^{a}	37.33	71.23^{a}	37.05	70.30^{b}	36.94	64.55^{g}	36.20	69.64^{cb}	36.86
70.00	13.00	30.00	12.00	71.63^{bc}	37.10	71.18^{a}	37.05	71.15^{ab}	37.04	66.60^{f}	36.47	70.87^{a}	37.01
70.00	16.00	20.00	14.00	71.31^{bc}	37.06	68.86^{b}	36.76	67.79^{d}	36.62	67.97^{e}	36.65	62.79^{f}	35.96
75.00	10.00	30.00	14.00	70.02^{d}	36.90	70.72^{a}	36.99	69.33^{c}	36.82	69.42^{cd}	36.83	70.14^{ab}	36.92
75.00	13.00	20.00	16.00	70.98^{cd}	37.02	70.96^{a}	37.02	71.57^{a}	37.09	70.95^{ab}	37.02	68.74^{cd}	36.74
75.00	16.00	25.00	12.00	68.79^{e}	36.75	71.47^{a}	37.08	70.50^{b}	36.96	71.76^{a}	37.12	67.85^{d}	36.63

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). MR means milling recovery for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44

There was a clear significant difference ($p \leq 0.05$) in the milling recovery of processing parameters observed in FARO 61. The highest milling recovery for NERICA 8 was 70.87% with signal to noise ratio (37.01). The difference in the milling recovery of the varieties under different processing parameters combinations can be traced to their ability to withstand the polishing pressure of the polisher machine. Belay *et al.* (2013) reported similar findings. The ranks of processing parameters on milling recovery were presented in Table 4.10. Soaking temperature had the most significant influence on milling recovery of FARO 61, FARO 60, FARO 52 and FARO 44 while for NERICA 8, steaming duration had the most significant influence. The differences in their impact level may be related to the different behaviour of rice varieties during separation of bran from the kernel, starch granules and presence of chalkiness. The generated predictive Taguchi models for milling recovery were expressed in equations 4.20 to 4.25. The models have a coefficient of determination R^2 and R^2_{adj} ranging from 0.236 to 0.746 and 0 – 0.4912. The R^2 for milling recovery for NERICA 8, FARO 61, FARO 60, FARO 52 and FARO 44 were 0.528, 0.413, 0.479, 0.236 and 0.746 respectively.

$$MR\ (A) = 81.018 - 0.090S_{temp} - 0.304S_{time} - 0.089ST - 0.174MC \qquad 4.20$$

$R^2 = 0.528$ $\quad$ $R^2_{(adj)} = 0.056$

$$MR\ (B) = 31.79 + 0.635S_{temp} - 0.245S_{time} - 0.023ST - 0.269MC \qquad 4.21$$

$R^2 = 0.479$ $\quad$ $R^2_{(adj)} = 0.000$

$$MR\ (C) = 80.49 - 0.1482S_{temp} - 0.067S_{time} + 0.042ST + 0.031MC \qquad 4.23$$

$R^2 = 0.236$ $\quad$ $R^2_{(adj)} = 0.000$

$$MR\ (D) = 62.04 + 0.216S_{temp} + 0.177S_{time} - 0.182ST - 0.453MC \qquad 4.24$$

$R^2 = 0.413$ $\quad$ $R^2_{(adj)} = 0.000$

$$MR\ (E) = 44.13 + 0.205S_{temp} - 0.334S_{time} + 0.420ST + 0.232MC \qquad 4.25$$

$R^2 = 0.746$ $\quad$ $R^2_{(adj)} = 0.491$

where, S_{temp}, S_{time}, ST, MC, MR, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, paddy moisture content, milling recovery, NERICA 8, FARO 61, FARO 60, FARO 52 and FARO 44. The obtained R^2 and R^2_{adj} showed that the models were not fit to predict the milling recovery. The R^2 and R^2_{adj} values are not close to unity. Zaibunnisa *et al.* (2009) reported that when R^2 is closer to unity, the better the empirical model fit the experimental data.

Table 4.10. Ranks of processing parameters on milling recovery

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	37	37.13	37.08	37
2	37.17	37.02	37	36.97
3	36.89	36.91	36.97	37.09
Delta	0.27	0.22	0.11	0.12
Rank	1	2	4	3
FARO 52				
1	36.2	36.95	36.86	36.97
2	36.95	36.48	36.5	36.37
3	37.03	36.76	36.82	36.84
Delta	0.83	0.47	0.36	0.6
Rank	1	3	4	2
FARO 60				
1	37.14	36.96	36.95	37.05
2	36.87	37.09	37.01	36.86
3	36.96	36.91	37	37.06
Delta	0.27	0.18	0.06	0.2
Rank	1	3	4	2
FARO 61				
1	36.72	36.6	36.81	36.79
2	36.44	36.81	36.75	36.81
3	36.99	36.74	36.58	36.55
Delta	0.55	0.21	0.23	0.25
Rank	1	4	3	2
NERICA 8				
1	36.5	36.72	36.36	36.67
2	36.61	36.7	36.61	36.41
3	36.76	36.46	36.9	36.79
Delta	0.26	0.26	0.54	0.38
Rank	3	4	1	2

The mean square error (MSE) for milling recovery obtained between the experimental and predicted values were 1.520, 7.915, 2.931, 1.375 and 0.806 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. Taguchi predictive models R^2 were not closer to unity, therefore showed a lack of fit for predicting milling recovery.

4.6.4 Taguchi modelling of head milled rice

Head milled rice is another important factor influencing rice quality. The impacts of processing parameters on the head milled rice were showed in Table 4.11. The highest head milled rice ranges between 69.21% - 71.63% in the varieties. The applied the higher the head milled rice the better signal to noise ratio (S/N) of Taguchi showed that FARO 44 had the highest head milled rice (71.63%) at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content while the least was observed in NERICA 8 (67.64%) at 65°C soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content. The highest head milled rice in FARO 52 was 70.71% at 36.99 S/N ratio and at 70°C soaking temperature, 10 h soaking time, 25 min steaming time and 16% paddy moisture content.

No significant difference ($p \geq 0.05$) was observed in the head milled rice of FARO 60 at processing conditions of 65°C soaking temperature, 10 h soaking time, 20 min steaming time and 12% paddy moisture content, 65°C soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content, 65°C soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content and 70°C soaking temperature, 13 h soaking time, 30 min steaming time and 12% paddy moisture content. However, highest S/N ratio was observed at 65°C soaking temperature, 10 h soaking time, 20 min steaming time and 12% paddy moisture content with 71.25% head milled rice.

FARO 61 had 69.26% highest head milled rice at 36.81 S/N ratio and at processing parameters of 75°C soaking temperature, 16 h soaking time, 25min steaming time and 12% paddy moisture content. Danbaba *et al.* (2014) reported that during the parboiling process, the internal fissure were healed, resulting in higher head rice yield. Also, fissures and chalkiness have a negative impact on head milled rice (Buggenhout *et al.*, 2013). The ranking of processing conditions on head milled rice is presented in Table 4.12. Soaking temperature influenced FARO 61, FARO 60, FARO 52 and FARO 44 the most while steaming time was for NERICA 8. The generated predictive Taguchi models for head milled rice were expressed in equations 4.26 to 4.30.

Table 4.11. Impacts of processing parameters on the head milled rice

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	HMR 44 %	S/N	HMR 52 %	S/N	HMR 60 %	S/N	HMR 61 %	S/N	HMR 8 %	S/N
65.00	10.00	20.00	12.00	71.05^{ab}	37.03	68.02^{b}	36.65	71.25^{a}	37.06	67.79^{b}	36.62	59.81^{e}	35.53
65.00	13.00	25.00	14.00	69.59^{cd}	36.85	56.31^{d}	35.01	70.97^{a}	37.02	68.61^{ab}	36.73	64.25^{c}	36.16
65.00	16.00	30.00	16.00	69.69^{cd}	36.86	65.92^{c}	36.38	71.04^{a}	37.03	63.79^{f}	36.10	67.64^{b}	36.60
70.00	10.00	25.00	16.00	71.63^{a}	37.10	70.71^{a}	36.99	70.04^{bc}	36.91	61.02^{e}	35.71	67.47^{b}	36.58
70.00	13.00	30.00	12.00	71.04^{ab}	37.03	70.38^{a}	36.95	70.42^{a}	36.95	64.80^{d}	36.23	64.56^{c}	36.20
70.00	16.00	20.00	14.00	70.75^{ab}	36.99	68.18^{b}	36.67	66.93^{e}	36.51	64.48^{de}	36.19	60.80^{d}	35.68
75.00	10.00	30.00	14.00	69.31^{d}	36.82	70.22^{a}	36.93	68.43^{d}	36.71	66.50^{c}	36.46	68.61^{a}	36.73
75.00	13.00	20.00	16.00	70.50^{bc}	36.96	70.56^{a}	36.97	68.65^{d}	36.73	69.21^{a}	36.80	54.62^{f}	34.75
75.00	16.00	25.00	12.00	67.96^{e}	36.64	69.79^{a}	36.88	69.79^{c}	36.88	69.26^{a}	36.81	67.01^{b}	36.52

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Where, HMR means head milled rice for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

Table 4.12. Ranks of processing parameters on head milled rice

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	36.92	36.98	37	36.9
2	37.04	36.95	36.87	36.89
3	36.81	36.83	36.9	36.98
Delta	0.23	0.15	0.13	0.09
Rank	1	2	3	4
FARO 52				
1	36.02	36.86	36.77	36.83
2	36.87	36.31	36.29	36.2
3	36.93	36.64	36.75	36.78
Delta	0.91	0.55	0.47	0.62
Rank	1	3	4	2
FARO 60				
1	37.04	36.89	36.77	36.96
2	36.79	36.9	36.93	36.75
3	36.77	36.81	36.9	36.89
Delta	0.26	0.1	0.17	0.21
Rank	1	4	3	2
FARO 61				
1	36.48	36.26	36.54	36.56
2	36.04	36.59	36.42	36.46
3	36.69	36.36	36.26	36.2
Delta	0.65	0.32	0.28	0.35
Rank	1	3	4	2
NERICA 8				
1	36.1	36.28	35.32	36.09
2	36.15	35.7	36.42	36.19
3	36	36.27	36.51	35.98
Delta	0.15	0.58	1.19	0.21
Rank	4	2	1	3

The models have R^2 that ranged from 0.336 to 0.641. The R^2 for head milled rice for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.641, 0.436, 0.336, 0.565 and 0.448, respectively. According to Montgomery (2013), R^2 should be between 0.7 and 1 in order to have a good model. The mean square error (MSE) for head milled rice obtained between the experimental and predicted values were 0.436, 0.202, 0.646, 2.050 and 0.682 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. Based on the R^2, the models cannot be fit to predict the head milled rice. This could be as a result of a high non-linear relationship that exists between the head milled rice and the processing parameters.

$$HMR\ (A) = 78.573 - 0.086S_{temp} - 0.199S_{time} - 0.075ST + 0.147MC \qquad 4.26$$

$R^2 = 0.448$ $\quad$ $R^2_{(adj)} = 0.000$

$$\mathrm{H}MR\ (B) = 25.38 + 0.677S_{temp} - 0.281S_{time} - 0.008ST - 0.083MC \qquad 4.27$$

$R^2 = 0.436$ $\quad$ $R^2_{(adj)} = 0.000$

$$\mathrm{H}MR\ (C) = 85.505 - 0.2130S_{temp} - 0.1091S_{time} + 0.1021ST - 0.143MC \qquad 4.28$$

$R^2 = 0.565$ $\quad$ $R^2_{(adj)} = 0.129$

$$HMR\ (D) = 67.88 + 0.159S_{temp} + 0.124S_{time} - 0.213ST - 0.653MC \qquad 4.29$$

$R^2 = 0.336$ $\quad$ $R^2_{(adj)} = 0.000$

$$HMR\ (E) = 48.18 - 0.0495S_{temp} - 0.024S_{time} + 0.853ST - 0.138MC \qquad 4.30$$

$R^2 = 0.641$ $\quad$ $R^2_{(adj)} = 0.281$

where, S_{temp}, S_{time}, ST, MC, HMR, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, paddy moisture content, head milled rice, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44.

4.6.5 Taguchi modelling of chalkiness

Among the quality indices that signify a loss in rice processing is chalkiness. High level of chalkiness downgrades the physical appearance, lower milling recovery and is a determinant of market competitive price of any rice sample (Gayin *et al.*, 2009; Fofana *et al.*, 2011). The impacts of processing parameters on the chalkiness were shown in Table 4.13. The chalkiness observed ranges between 0.16% - 14.17% across the rice varieties. The lower the chalkiness the better the signal to noise ratio (S/N) of Taguchi indicated that NERICA 8 had the highest chalkiness 14.17% at 70°C soaking temperature, 13 h soaking time, 30 min steaming time and 12% paddy moisture content .

Table 4.13. Impacts of processing parameters on chalkiness using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	WB 44 %	S/N	WB 52 %	S/N	WB 60 %	S/N	WB 61 %	S/N	WB 8 %	S/N
65.00	10.00	20.00	12.00	2.15^{a}	-6.66	0.56^{de}	5.10	0.40^{b}	8.02	1.94^{g}	-27.66	10.68^{b}	-20.57
65.00	13.00	25.00	14.00	1.33^{b}	-2.49	3.94^{a}	-11.91	0.39^{b}	8.20	2.43^{f}	-27.77	2.47^{e}	-7.84
65.00	16.00	30.00	16.00	0.85^{cd}	1.43	0.62^{cde}	4.21	0.68^{a}	3.37	4.07^{d}	-27.61	1.75^{g}	-4.86
70.00	10.00	25.00	16.00	1.99^{a}	-5.97	0.97^{b}	0.30	0.38^{bc}	8.46	5.98^{a}	-27.81	3.44^{d}	-10.74
70.00	13.00	30.00	12.00	0.70^{d}	3.06	0.76^{c}	2.36	0.32^{bc}	9.80	3.61^{e}	-27.81	14.17^{a}	-23.03
70.00	16.00	20.00	14.00	0.68^{d}	3.38	0.98^{b}	0.16	0.16^{d}	16.10	5.41^{b}	-27.36	3.60^{d}	-11.13
75.00	10.00	30.00	14.00	0.90^{cd}	0.93	0.72^{cd}	2.85	0.23^{cd}	12.62	4.78^{c}	-28.16	2.10^{f}	-6.44
75.00	13.00	20.00	16.00	0.74^{cd}	2.59	0.51^{e}	5.90	0.60^{a}	4.45	1.93^{g}	-26.59	9.84^{cd}	-19.86
75.00	16.00	25.00	12.00	0.99^{c}	0.11	1.12^{b}	-0.95	0.40^{b}	8.00	4.22^{d}	-27.77	1.12^{h}	-1.01

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Where, WB means chalkiness for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

The least was observed in FARO 60 (0.16%) at 70°C soaking temperature, 16 h soaking time, 20 min steaming time and 14% paddy moisture content. For FARO 44, the lowest chalkiness (0.68%) was observed at 70°C soaking temperature, 16 h soaking time, 30 min steaming time and 12% paddy moisture content. The least chalkiness in FARO 52 was 0.51% at S/N ratio of 5.90 and at 75°C soaking temperature, 13 h soaking time, 20 min steaming time and 16% paddy moisture content. Lowest chalkiness recorded in NERICA 8 was 1.12% at 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% moisture content. Chalkiness partially or totally disappeared upon parboiling and cooking, and as a result may have no direct effect on cooking and eating qualities. The ranks of processing parameters on chalkiness were presented in Table 4.14. The ranking was based on their effect on the rice varieties. For FARO 44, soaking time was the highest in ranking, steaming time was for FARO 52, paddy moisture content in FARO 60, soaking temperature in FARO 61 while soaking time influenced NERICA 8 the most.

Buggenhout *et al.* (2013) reported that different soaking and steaming conditions have different degrees of starch gelatinization and levels on chalkiness. Starch needs to be completely gelatinized to ensure absence of chalkiness and minimal fissured grain levels in the parboiled end product and a consequence is a decreased milling breakage. The generated predictive Taguchi models for chalkiness were expressed in equations 4.36 to 4.40. The R^2 for chalkiness for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.233, 0.145, 0.213, 0.317 and 0.705 while for R^2_{adj} were 0.000, 0.000, 0.00, 0.000 and 0.410, respectively. The mean square error (MSE) for chalkiness obtained between the experimental and predicted values were 0.082, 0.878, 0.016, 1.524 and 15.576 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 respectively. The R^2 values were not fit to predict the chalkiness. This could be due to a non-linear relationship that exists between the chalkiness and the processing parameters, thus resulting in very low R^2 and R^2_{adj}.

$$WB\ (A) = 8.199 - 0.057S_{temp} - 0.140S_{time} - 0.0375ST - 0.022MC \qquad 4.36$$

$R^2 = 0.705$ $\quad$ $R^2_{(adj)} = 0.410$

$$WB\ (B) = 7.613 - 0.0924S_{temp} + 0.026S_{time} + 0.002ST - 0.029MC \qquad 4.37$$

$R^2 = 0.145$ $\quad$ $R^2_{(adj)} = 0.000$

Table 4.14. Ranks of processing parameters on chalkiness

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	-2.5729	-3.8998	-0.2305	-1.1642
2	0.1548	1.0515	-2.7832	0.6066
3	1.212	1.6422	1.8077	-0.6485
Delta	3.7849	5.542	4.5909	1.7707
Rank	3	1	2	4
FARO 52				
1	-0.8704	2.7472	3.7197	2.1655
2	0.9377	-1.2187	-4.1906	-2.9668
3	2.5997	1.1385	3.1378	3.4682
Delta	3.4701	3.9659	7.9103	6.435
Rank	4	3	1	2
FARO 60				
1	6.529	9.703	9.522	8.606
2	11.452	7.481	8.221	12.306
3	8.357	9.154	8.595	5.426
Delta	4.924	2.222	1.3	6.879
Rank	2	3	4	1
FARO 61				
1	-8.548	-11.623	-8.71	-9.799
2	-13.779	-8.189	-11.916	-11.987
3	-10.605	-13.12	-12.306	-11.146
Delta	5.232	4.931	3.596	2.188
Rank	1	2	3	4
NERICA 8				
1	-11.089	-12.584	-17.187	-14.87
2	-14.966	-16.91	-6.529	-8.469
3	-9.103	-5.665	-11.442	-11.819
Delta	5.864	11.245	10.658	6.401
Rank	4	1	2	3

$$WB\ (C) = 0.083 - 0.008S_{temp} + 0.013S_{time} + 0.003T - 0.0447MC \qquad 4.38$$

$R^2 = 0.317$ $\quad$ $R^2_{(adj)} = 0.000$

$$WB\ (D) = -7.96 + 0.0833S_{temp} + 0.0556S_{time} + 0.106ST + 0.185MC \qquad 4.39$$

$R^2 = 0.213$ $\quad$ $R^2_{(adj)} = 0.000$

$$WB\ (E) = 34.63 - 0.0611S_{temp} - 0.5412S_{time} - 0.203ST - 0.912MC \qquad 4.40$$

$R^2 = 0.233$ $\quad$ $R^2_{(adj)} = 0.000$

where, S_{temp}, $S_{time,}$ ST, MC, HMR, E, D, C, B, and A represent; soaking temperature, soaking time, steaming time, paddy moisture content, chalkiness, NERICA 8, FARO 61, FARO 60, FARO 52 and FARO 44.

4.6.6 Taguchi modelling of lightness

Lightness is another important quality indicator that determines consumers' acceptability. Production of lighter polished parboiled rice is the universal goal of a rice processor (Islam *et al.*, 2004). Table 4.15 shows the impacts of processing parameters on lightness values. From the results, the lightness of the rice varieties after polishing based on the higher the lightness values the better the signal to noise ratio (S/N) of Taguchi varies from 31.94 – 35.82. Highest lightness value (32.62) was recorded for FARO 44 at 75°C soaking temperature -10 h soaking time - 30 min steaming time - 14% paddy moisture content.

For FARO 52 and 60, the maximum lightness value was 32.64 at 75°C soaking temperature -10 h soaking time - 30 min steaming time -14% paddy moisture content. There was no significant different (p≥0.05) in the lightness value of FARO 61 at 65°C soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content; soaking temperature at 65°C, 13 h soaking time, 30 min steaming time and 16% paddy moisture content and 75°C soaking temperature, 13 h soaking time, 20 min steaming time and 16% paddy moisture content respectively. Although the maximum lightness value in FARO 61 was 31.94 at 65°C soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content. NERICA 8 shows the highest lightness value (35.82) at 70°C soaking temperature, 13 h soaking time, 30 min steaming time and 12% paddy moisture content and 75°C soaking temperature, 16 h soaking time, 25 min steaming time and 12% paddy moisture content, with no significant difference (p≥0.05) in the lightness value. From Table 4.16, the ranks of processing parameters on the lightness values varied from variety to variety.

Table 4.15. Effect of processing parameters on the lightness using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	LHT 44	S/N	LHT 52	S/N	LHT 60	S/N	LHT 61	S/N	LHT 8	S/N
65.00	10.00	20.00	12.00	26.54^{e}	28.48	27.82^{d}	28.89	27.82^{c}	28.89	29.40^{bc}	36.62	22.92^{f}	27.20
65.00	13.00	25.00	14.00	25.88^{e}	28.26	31.36^{bc}	29.93	31.36^{c}	29.93	31.94^{a}	36.73	30.76^{c}	29.76
65.00	16.00	30.00	16.00	26.84^{e}	28.58	30.98^{bc}	29.82	30.98^{bc}	29.82	31.66^{a}	36.10	25.92^{e}	28.27
70.00	10.00	25.00	16.00	26.14^{e}	28.35	31.10^{bc}	29.86	31.10^{bc}	29.86	27.38^{e}	35.71	34.30^{b}	30.71
70.00	13.00	30.00	12.00	27.80^{d}	28.88	31.70^{ab}	30.02	31.70^{ab}	30.02	30.36^{b}	36.23	35.82^{a}	31.08
70.00	16.00	20.00	14.00	32.08^{ab}	30.12	30.38^{b}	29.65	30.38^{c}	29.65	28.24^{de}	36.19	29.46^{d}	29.38
75.00	10.00	30.00	14.00	32.62^{a}	30.27	32.64^{a}	30.28	32.64^{a}	30.28	29.44^{bc}	36.46	31.64^{c}	30.00
75.00	13.00	20.00	16.00	31.42^{b}	29.94	31.50^{b}	29.97	31.50^{b}	29.97	31.42^{a}	36.80	28.82^{d}	29.19
75.00	16.00	25.00	12.00	29.64^{c}	29.44	31.28^{bc}	29.91	31.28^{bc}	29.91	29.12^{cd}	36.81	35.82^{a}	31.08

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Where, LHT means Lightness for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

Table 4.16. Ranks of processing parameters on lightness

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Moisture Content (%) S/N ratio
FARO 44				
1	28.44	29.03	29.52	28.93
2	29.12	29.03	28.68	29.55
3	29.88	29.38	29.24	28.96
Delta	1.45	0.35	0.83	0.62
Rank	1	4	2	3
FARO 52				
1	29.55	29.67	29.5	29.6
2	29.84	29.97	29.9	29.95
3	30.05	29.79	30.04	29.88
Delta	0.5	0.3	0.54	0.35
Rank	2	4	1	3
FARO 60				
1	29.55	29.67	29.5	29.6
2	29.84	29.97	29.9	29.95
3	30.05	29.79	30.04	29.88
Delta	0.5	0.3	0.54	0.35
Rank	2	4	1	3
FARO 61				
1	29.82	29.16	29.44	29.43
2	29.14	29.89	29.37	29.49
3	29.54	29.44	29.68	29.57
Delta	0.68	0.73	0.31	0.14
Rank	2	1	3	4
NERICA 8				
1	28.41	29.3	28.59	29.79
2	30.39	30.01	30.52	29.72
3	30.09	29.58	29.79	29.39
Delta	1.98	0.71	1.92	0.4
Rank	1	3	2	4

In FARO 44 and NERICA 8, soaking temperature was observed to be most ranked while steaming time was for FARO 52 and 60. Soaking time influenced FARO 61 the most. According to Sareepuang *et al.* (2008), the lightness value of parboiled rice decreased while the colour value increased with increase in soaking temperature. The generated predictive Taguchi models for lightness values were expressed in equations 4.36 to 4.40. The lightness R^2 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.499, 0.803, 0.211, 0.803 and 0.646 while for R^2_{adj} were 0.000, 0.607, 0.000, 0.607 and 0.291, respectively. The mean square error (MSE) for lightness values obtained between the experimental and predicted values were 8.618, 0.309, 1.750, 0.309 and 2.302 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. From the models, FARO 52 and FARO 60 models have the tendency of predicting the lightness value while models for FARO 44, FARO 61 and NERICA 8 were not fit to predict the lightness value.

$$LHT\ (A) = -5.40 + 0.481S_{temp} + 0.181S_{time} - 0.093ST + 0.035MC \qquad 4.41$$

$R^2 = 0.646$ $\quad$ $R^2_{(adj)} = 0.291$

$$LHT\ (B) = 9.993 + 0.175S_{temp} + 0.060S_{time} + 0.187ST + 0.232MC \qquad 4.42$$

$R^2 = 0.803$ $\quad$ $R^2_{(adj)} = 0.607$

$$LHT\ (C) = 9.993 + 0.175S_{temp} + 0.060S_{time} + 0.187ST + 0.232MC \qquad 4.43$$

$R^2 = 0.803$ $\quad$ $R^2_{(adj)} = 0.607$

$$LHT\ (D) = 31.07 - 0.101S_{temp} + 0.156S_{time} + 0.080ST + 0.132MC \qquad 4.44$$

$R^2 = 0.211$ $\quad$ $R^2_{(adj)} = 0.000$

$$LHT\ (E) = -13.71 + 0.556S_{temp} + 0.130S_{time} + 0.406ST - 0.460MC \qquad 4.45$$

$R^2 = 0.499$ $\quad$ $R^2_{(adj)} = 0.000$

where, S_{temp}, S_{time}, ST, MC, LHT, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, moisture content after drying, lightness, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44.

4.6.7 Taguchi modelling of colour

Colour is an important quality attribute in the rice industry (Islam *et al.,* 2004). Consumers frequently look at a rice sample and make a judgement decision based largely on overall appearance. Discolouration is a negative effect of parboiling as discoloured parboiled rice losses market value and customer acceptability in most countries. Table 4.17 shows the impacts of processing parameters on colour value. From the results, the colour value of the rice varieties based on the lower colour values the better the signal to noise ratio (S/N) varies from 21.55 – 26.61. The colour change in rice grain is mainly caused by Millard reaction and diffusion of husk pigments in the endosperm during soaking and steaming (Leethanapanich *et al.,* 2016).

Minimum colour value (21.55) was observed in FARO 44 at 65°C soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content. For FARO 52 and 60, the minimum colour was observed at 65°C soaking temperature, 10 h soaking time, 20 min steaming time and 12% paddy moisture content with colour value of 22.38. Minimum colour value of 21.36 was observed in FARO 61 while 26.61 was observed in NERICA 8 at 75°C soaking temperature, 13 h soaking time, 20 min steaming time and 16% paddy moisture content and 70°C soaking temperature, 16 h soaking time, 20 min steaming time and 14% paddy moisture content respectively. The difference in colour value among varieties of rice cultivars could be attributed to the difference in genetic makeup and pigments. From Table 4.18, the ranks of processing parameters on colour value varied from variety to another. Paddy moisture content was ranked first for FAR0 44 while soaking time influenced FARO 52, FARO 60 and NERICA 8 the most. Steaming time was for FARO 61.

Ejebe *et al.* (2015) reported that the translucency of rice was different depending on the variety. According to Lamberts *et al.* (2006), parboiled rice turns light yellow to amber due to Millard types of enzymatic browning. The results also agreed with Parnsakhorn and Noomhorm (2008) who stated that parboiled paddy gave lower whiteness as compared to unparboiled milled rice. The generated predictive Taguchi models for colour values were expressed in equations 4.46 to 4.50. The R^2 for colour value were 0.665, 0.733, 0.733, 0.708, 0.657 while for R^2_{adj} were 0.330, 0.466, 0.416, 0.313, and 0.416 for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8 respectively.

Table 4.17. Impacts of processing parameters on the colour using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	Colour 44	S/N	Colour 52	S/N	Colour 60	S/N	Colour 61	S/N	Colour 8	S/N
65.00	10.00	20.00	12.00	23.67[d]	-27.49	22.38[d]	-27.00	22.38[d]	-27.00	24.17[bc]	-27.66	28.52[b]	-29.10
65.00	13.00	25.00	14.00	25.06[b]	-27.98	23.88[bc]	-27.56	23.88[bc]	-27.56	24.47[b]	-27.77	28.65[b]	-29.14
65.00	16.00	30.00	16.00	21.55[e]	-26.67	23.40[cd]	-27.38	23.40[cd]	-27.38	24.01[bc]	-27.61	28.19[cb]	-29.00
70.00	10.00	25.00	16.00	24.44[bcd]	-27.76	23.25[cd]	-27.33	23.25[cd]	-27.33	24.56[b]	-27.81	28.52[b]	-29.10
70.00	13.00	30.00	12.00	24.73[bc]	-27.87	24.79[b]	-27.89	24.79[b]	-27.89	24.57[b]	-27.81	27.37[cd]	-28.75
70.00	16.00	20.00	14.00	24.35[bcd]	-27.73	23.62[c]	-27.47	23.62[c]	-27.47	23.34[c]	-27.36	26.61[d]	-28.50
75.00	10.00	30.00	14.00	26.50[a]	-28.46	23.16[cd]	-27.30	23.16[bcd]	-27.30	25.57[a]	-28.16	32.03[a]	-30.11
75.00	13.00	20.00	16.00	23.74[cd]	-27.51	24.15[bc]	-27.66	24.15[bc]	-27.66	21.36[d]	-26.59	28.46[b]	-29.08
75.00	16.00	25.00	12.00	26.11[a]	-28.34	26.97[a]	-28.62	26.97[a]	-28.62	24.45[b]	-27.77	27.37[c]	-28.75

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). Colour for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

Table 4.18. Ranks of processing parameters on colour

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	-27.38	-27.9	-27.57	-27.9
2	-27.79	-27.78	-28.03	-28.06
3	-28.1	-27.58	-27.67	-27.31
Delta	0.73	0.33	0.45	0.74
Rank	2	4	3	1
FARO 52				
1	-27.31	-27.21	-27.37	-27.83
2	-27.56	-27.7	-27.84	-27.44
3	-27.86	-27.82	-27.52	-27.46
Delta	0.54	0.62	0.46	0.39
Rank	2	1	3	4
FARO 60				
1	-27.31	-27.21	-27.37	-27.83
2	-27.56	-27.7	-27.84	-27.44
3	-27.86	-27.82	-27.52	-27.46
Delta	0.54	0.62	0.46	0.39
Rank	2	1	3	4
FARO 61				
1	-27.68	-27.88	-27.21	-27.75
2	-27.66	-27.39	-27.78	-27.76
3	-27.5	-27.58	-27.86	-27.34
Delta	0.18	0.48	0.65	0.43
Rank	4	2	1	3
NERICA 8				
1	-29.08	-29.44	-28.9	-28.86
2	-28.78	-28.99	-29	-29.25
3	-29.31	-28.75	-29.29	-29.06
Delta	0.53	0.69	0.39	0.39
Rank	2	1	3	4

The MSE for colour values were 0.713, 0.354, 0.411, 0.411 and 0.630 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. Based on the R^2 and $R^2_{adj,}$ values of the models, it can be deduced that the models cannot be fit to predict the colour value effectively.

$$CV\ (A) = 16.927 + 0.202S_{temp} - 0.145S_{time} + 0.034ST - 0.399MC \qquad 4.46$$

$R^2 = 0.665$ $\quad$ $R^2_{(adj)} = 0.330$

$$CV\ (B) = 12.332 + 0.154S_{temp} + 0.289S_{time} + 0.039ST - 0.279MC \qquad 4.47$$

$R^2 = 0.733$ $\quad$ $R^2_{(adj)} = 0.466$

$$CV\ (C) = 12.332 + 0.154S_{temp} + 0.289S_{time} + 0.039ST - 0.279MC \qquad 4.48$$

$R^2 = 0.733$ $\quad$ $R^2_{(adj)} = 0.416$

$$CV\ (D) = 28.197 - 0.0421S_{temp} - 0.139S_{time} + 0.176ST + 0.271MC \qquad 4.49$$

$R^2 = 0.708$ $\quad$ $R^2_{(adj)} = 0.416$

$$CV\ (E) = 22.017 + 0.0831S_{temp} - 0.3835S_{time} + 0.1336ST + 01590MC \qquad 4.50$$

$R^2 = 0.657$ $\quad$ $R^2_{(adj)} = 0.313$

where, S_{temp}, $S_{time,}$ ST, MC, CV, E, B, D, C and A represent; soaking temperature, soaking time, steaming time, moisture content after drying, colour value, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44.

4.6.8 Taguchi modelling of cooking time

Short cooking time results into less fuel and energy consumption. Table 4.19 shows the impacts of processing parameters on cooking time. The cooking time varies from 10 min – 50.40 min (Table 4.19). In reference to the lower the cooking time the better the signal to noise ratio (S/N) of Taguchi analysis, NERICA 8 had the shortest cooking time (10 min) at 65°C soaking temperature, 10 h soaking time, 20 min steaming time, 12% paddy moisture content. It was observed that there was no significant difference (p>0.05) in the cooking time at 65°C soaking temperature, 10 h soaking time, 20 min steaming time and 12% paddy moisture content and 65°C soaking temperature, 16 h soaking time, 30 min steaming time, 16% paddy moisture content respectively. The shortest cooking time observed in FARO 61 was 20 min while that of FARO 52 was 21.40 min. In FARO 44 and FARO 60, 22.50 min and 28.68 min were recorded has the shortest cooking time.

Table 4.19. Impacts of processing parameters on the cooking time using Taguchi techniques

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	CT 44 (min)	S/N	CT 52 (min)	S/N	CT 60 (min)	S/N	CT 61 (min)	S/N	CT 8 (min)	S/N
65.00	10.00	20.00	12.00	22.50^{f}	-27.04	21.40^{f}	-26.61	28.68^{d}	-29.15	20.00^{a}	-26.02	10.00^{f}	-20.00
65.00	13.00	25.00	14.00	30.10^{e}	-29.57	24.10^{d}	-27.64	30.60^{c}	-29.71	27.35^{a}	-28.74	22.00^{d}	-26.85
65.00	16.00	30.00	16.00	36.36^{d}	-31.21	28.16^{b}	-28.99	37.38^{a}	-31.45	28.06^{a}	-28.96	10.35^{f}	-20.30
70.00	10.00	25.00	16.00	41.43^{b}	-32.35	36.20^{a}	-31.17	31.44^{c}	-29.95	26.47^{a}	-28.46	20.00^{e}	-26.02
70.00	13.00	30.00	12.00	41.58^{b}	-32.38	26.50^{b}	-28.46	30.46^{c}	-29.67	28.00^{a}	-28.94	25.00^{b}	-27.96
70.00	16.00	20.00	14.00	42.16^{b}	-32.50	27.80^{b}	-28.88	35.40^{b}	-30.98	33.39^{a}	-30.47	23.30^{c}	-27.35
75.00	10.00	30.00	14.00	40.00^{c}	-32.04	22.53^{e}	-27.06	33.35^{c}	-30.46	29.55^{a}	-29.41	28.00^{a}	-28.94
75.00	13.00	20.00	16.00	50.40^{a}	-34.05	27.32^{bc}	-28.73	35.35^{b}	-30.97	28.03^{a}	-28.95	24.00^{c}	-27.60
75.00	16.00	25.00	12.00	41.47^{b}	-32.35	24.36^{d}	-27.73	29.36^{d}	-29.36	23.15^{a}	-27.29	25.00^{b}	-27.96

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). CT means cooking time for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

Anuonye *et al.* (2016) reported that cooking time differed with variety and ranged between 17-23 min. The difference in the cooking time may be due to varietal difference and it has been reported that rice with high protein content or a high gelatinization temperature requires more water and longer cooking time to reach the same degree of doness as rice with lower values for the properties (Juliano, 1971). From Table 4.20, the ranks of processing parameters on cooking time varied. Paddy moisture content was ranked most in FARO 52, FARO 60 and FARO 61 while soaking temperature was ranked most in FARO 44 and NERICA 8.

The models have a coefficient of determination, R^2 and R^2_{adj} ranging from 0.416 to 0.848 and 0 – 0.695. The R^2 for cooking time values were 0.638, 0.416, 0.363, 0.729 and 0.848 while R^2_{adj} 0.277, 0.000, 0.000, 0.459 and 0.695 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. FARO 44 and FARO 60 models could be suitable for predicting the cooking time while FARO 52, FARO 61 and NERICA 8 model are considered not to be good for predicting the cooking time during rice processing. This may be due to the non-linear relationship that exists between the processing parameters and cooking time and also the inherent behaviour of the variety. The generated predictive Taguchi models for cooking time values were expressed in equations 4.51 to 4.55.

$$CT\ (A) = -102.09 + 1.43S_{temp} + 0.892S_{time} + 0.096ST + 1.887MC \qquad 4.51$$

$R^2 = 0.848$ $\qquad$ $R^2{}_{(adj)} = 0.695$

$$CT\ (B) = 1.85 + 0.0183S_{temp} + 0.0106S_{time} + 0.022ST + 1.618MC \qquad 4.52$$

$R^2 = 0.416$ $\qquad$ $R^2{}_{(adj)} = 0.000$

$$CT\ (C) = 3.17 + 0.0467S_{temp} + 0.4817S_{time} + 0.0507ST + 1.306MC \qquad 4.53$$

$R^2 = 0.729$ $\qquad$ $R^2{}_{(adj)} = 0.459$

$$CT\ (D) = -8.30 + 01773S_{temp} + 0.477S_{time} + 0.139ST + 0.951MC \qquad 4.54$$

$R^2 = 0.363$ $\qquad$ $R^2{}_{(adj)} = 0.000$

$$CT\ (E) = -58.92 + 1.155S_{temp} + 0.0361S_{time} + 0.207ST - 0.471MC \qquad 4.55$$

$R^2 = 0.638$ $\qquad$ $R^2{}_{(adj)} = 0.277$

where, S_{temp}, S_{time}, ST, MC, CT, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, moisture content after drying, cooking time, NERICA 8, FARO 61, FARO 60, FARO 52 and FARO 44.

Table 4.20. Ranks of processing parameters on cooking time

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	-29.28	-30.48	-31.2	-30.59
2	-32.41	-32	-31.42	-31.37
3	-32.81	-32.02	-31.88	-32.54
Delta	3.54	1.54	0.68	1.94
Rank	1	3	4	2
FARO 52				
1	-27.75	-28.28	-28.07	-27.6
2	-29.51	-28.28	-28.85	-27.86
3	-27.84	-28.54	-28.17	-29.63
Delta	1.76	0.26	0.78	2.03
Rank	2	4	3	1
FARO 60				
1	-30.11	-29.85	-30.37	-29.39
2	-30.2	-30.12	-29.67	-30.39
3	-30.26	-30.6	-30.53	-30.79
Delta	0.16	0.74	0.86	1.4
Rank	4	3	2	1
FARO 61				
1	-27.91	-27.96	-28.48	-27.42
2	-29.29	-28.88	-28.16	-29.54
3	-28.55	-28.91	-29.11	-28.79
Delta	1.38	0.95	0.94	2.12
Rank	2	3	4	1
NERICA 8				
1	-22.38	-24.99	-24.98	-25.31
2	-27.11	-27.47	-26.94	-27.71
3	-28.17	-25.2	-25.73	-24.64
Delta	5.79	2.48	1.96	3.07
Rank	1	3	4	2

The mean square error (MSE) for cooking time values obtained between the experimental and predicted values were 13.324, 9.814, 8.114, 2.233 and 8.732 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively.

4.6.9 Taguchi modelling of water uptake ratio

Table 4.21 shows the impacts of processing parameters on water uptake ratio. The water uptake ratio values observed in the rice varieties under different processing conditions were similar with no differences in their significance at $p \geq 0.05$. Table 4.22 shows that soaking time and soaking temperature had the most significant effect on the water uptake ratio. The higher the signal to noise ratio the better the signal to noise ratio (S/N) of Taguchi, showed that 65°C soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content had the highest water uptake ratio of 4.11 while the least was 3.05 which was observed at 65°C soaking temperature - 12 h soaking time - 20 min steaming time - 12% paddy moisture content. A similar trend was observed in other rice varieties. The slight difference in water uptake ratio of the varieties maybe due to the differences in the processing conditions which caused changes in their starch granules as a result of the gelatinization process and their microscopic structure. The same observation was reported by Mir *et al.* (2013) and Mir and Bosco (2013). The generated predictive Taguchi model for water uptake ratio was expressed in equations 4.56. From the analysis, a single model was developed for predicting the water uptake ratio of the rice varieties.

The model has R^2 and R^2_{adj} of 0.628 and 0.254. The model is not fit enough to predict the water uptake ratio due to R^2 value.

$$WUR = 1.639 - 0.0148S_{temp} + 0.070S_{time} + 0.0275ST + 0.0913MC \qquad 4.56$$

$R^2 = 0.627$ $\qquad$ $R^2_{(adj)} = 0.254$

where, S_{temp}, S_{time}, ST, MC, WUR, E, B, D, C, and A represent; soaking temperature, soaking time, steaming time, paddy moisture content, water uptake ratio, NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44. The mean square error (MSE) for water uptake ratio values obtained between the experimental and predicted values was 0.040 for NERICA 8, FARO 61, FARO 60, FARO 61 and FARO 44, respectively.

Table 4.21. Impacts of processing parameters on water uptake ratio using Taguchi technique

Soaking Temperature (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	WUR 44	S/N	WUR 52	S/N	WUR 60	S/N	WUR 61	S/N	WUR 8	S/N
65.00	10.00	20.00	12.00	3.05^{a}	-9.67	3.05^{a}	-9.67	3.05^{a}	-9.67	3.05^{a}	-9.67	3.05^{a}	-9.67
65.00	13.00	25.00	14.00	3.21^{a}	-10.13	3.21^{a}	-10.13	3.21^{a}	-10.13	3.21^{a}	-10.13	3.21^{a}	-10.13
65.00	16.00	30.00	16.00	4.11^{a}	-12.27	4.11^{a}	-12.27	4.11^{a}	-12.27	4.11^{a}	-12.27	4.11^{a}	-12.27
70.00	10.00	25.00	16.00	3.82^{a}	-11.63	3.82^{a}	-11.63	3.82^{a}	-11.63	3.82^{a}	-11.63	3.82^{a}	-11.63
70.00	13.00	30.00	12.00	3.48^{a}	-10.82	3.48^{a}	-10.82	3.48^{a}	-10.82	3.48^{a}	-10.82	3.48^{a}	-10.82
70.00	16.00	20.00	14.00	3.72^{a}	-11.41	3.72^{a}	-11.41	3.72^{a}	-11.41	3.72^{a}	-11.41	3.72^{a}	-11.41
75.00	10.00	30.00	14.00	3.21^{a}	-10.13	3.21^{a}	-10.13	3.21^{a}	-10.13	3.21^{a}	-10.13	3.21^{a}	-10.13
75.00	13.00	20.00	16.00	3.20^{a}	-10.10	3.20^{a}	-10.10	3.20^{a}	-10.10	3.20^{a}	-10.10	3.20^{a}	-10.10
75.00	16.00	25.00	12.00	3.51^{a}	-10.89	3.51^{a}	-10.89	3.51^{a}	-10.89	3.51^{a}	-10.89	3.51^{a}	-10.89

Mean values within the same column with the same superscript are not significantly different ($p \geq 0.05$). WUR means water uptake ratio for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8.

Table 4.22. Ranks of processing parameters on water uptake ratio

Levels	Soaking Temperature (°C) S/N ratio	Soaking Time (h) S/N ratio	Steaming Time (min) S/N ratio	Paddy Moisture Content (%) S/N ratio
FARO 44				
1	-10.69	-10.48	-10.4	-10.46
2	-11.29	-10.35	-10.88	-10.56
3	-10.38	-11.52	-11.07	-11.33
Delta	0.91	1.17	0.68	0.87
Rank	2	1	4	3
FARO 52				
1	-10.69	-10.48	-10.4	-10.46
2	-11.29	-10.35	-10.88	-10.56
3	-10.38	-11.52	-11.07	-11.33
Delta	0.91	1.17	0.68	0.87
Rank	2	1	4	3
FARO 60				
1	-10.69	-10.48	-10.4	-10.46
2	-11.29	-10.35	-10.88	-10.56
3	-10.38	-11.52	-11.07	-11.33
Delta	0.91	1.17	0.68	0.87
Rank	2	1	4	3
FARO 61				
1	-10.69	-10.48	-10.4	-10.46
2	-11.29	-10.35	-10.88	-10.56
3	-10.38	-11.52	-11.07	-11.33
Delta	0.91	1.17	0.68	0.87
Rank	2	1	4	3
NERICA 8				
1	-10.69	-10.48	-10.4	-10.46
2	-11.29	-10.35	-10.88	-10.56
3	-10.38	-11.52	-11.07	-11.33
Delta	0.91	1.17	0.68	0.87
Rank	2	1	4	3

4.7 RSM Modelling of Impacts of Processing Parameters on Total Energy Consumption

The information on the impacts of processing parameters on total energy consumption of the varieties could play a vital role in ensuring energy conservation and economic viability of rice parboiling plants. The effects of different processing conditions on total energy consumption for the varieties were significant ($p \leq 0.05$) with overlapping subsets (Table 4.23). Energy consumption varied between 46.10 MJ – 75.60 MJ in FARO 44, 47.88 MJ – 76.83 MJ in FARO 52, 45.27 MJ – 73.68 MJ in FARO 60, 47.45 MJ – 76.11 MJ in FARO 61 and 48.35 MJ – 76.90 MJ in NERICA 8. It was clear that different processing parameters combinations have a significant influence on the total energy consumption. Out of all the varieties being processed, NERICA 8 shows tendency of consuming more energy than other varieties.

This result correlates with Kwofie and Ngadi (2017) findings that stated that rice varieties could influence energy consumption. All the processing parameters have an influence on the total energy consumption. However, paddy moisture content had the most significant influence on energy consumption. As moisture content decreases, energy consumption increases (Table 4.24). Similar observation was earlier recorded while studying the impacts of processing parameters on energy consumption using Taguchi techniques. The reason could be as a result of longer drying time required to reach lower moisture content. Goyal *et al.* (2014) reported that drying operation has direct influence on energy consumption.

Increase in soaking temperature, soaking time and steaming time was observed to increase total energy consumption. Kwofie and Ngadi (2017) reported a similar observation in their review on rice parboiling system, energy supply and consumption. Also, double interaction of soaking temperature and paddy moisture content was observed to have influence on total energy consumption. Table 4.24 shows the results of second order polynomial models generated for total energy consumption of the rice varieties. Coefficients of determination (R^2) values were found to be 0.915, 0.911, 0.915, 0.913 and 0.914 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 respectively. The mean square error (MSE) for total energy consumption obtained between the experimental and predicted values were 4.370, 4.690, 4.519, 4.306, and 4.716 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively.

Table 4.23. Impacts of processing parameters on total energy consumption using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	EC44 (MJ)	EC52 (MJ)	EC60 (MJ)	EC61 (MJ)	EC8 (MJ)
65.00	10.00	20.00	12.00	54.28^{ij}	55.82^{mn}	53.45^{km}	57.23^{jl}	57.86^{ij}
75.00	10.00	20.00	12.00	57.48^{ghij}	59.02^{ijkm}	56.63^{ijk}	59.00^{hijl}	59.56^{ghij}
65.00	16.00	20.00	12.00	61.78^{cdef}	64.01^{efg}	60.88^{fgh}	63.27^{ef}	63.70^{ef}
75.00	16.00	20.00	12.00	65.58^{c}	67.25^{de}	64.67^{de}	67.25^{bc}	68.19^{cd}
65.00	10.00	30.00	12.00	65.02^{c}	65.92^{ef}	63.17^{cd}	65.57^{cd}	66.84^{de}
75.00	10.00	30.00	12.00	69.57^{b}	70.26^{cd}	66.96^{ab}	70.16^{bc}	70.98^{bc}
65.00	16.00	30.00	12.00	72.36^{ab}	74.06^{ab}	70.52^{a}	73.67^{a}	74.46^{ab}
75.00	16.00	30.00	12.00	75.60^{a}	76.83^{a}	73.68^{a}	76.11^{a}	76.90^{a}
65.00	10.00	20.00	16.00	46.10^{k}	47.88^{o}	45.27^{n}	47.45^{m}	48.35^{l}
75.00	10.00	20.00	16.00	47.77^{k}	49.23^{o}	46.70^{n}	49.13^{m}	49.92^{l}
65.00	16.00	20.00	16.00	51.78^{j}	53.59^{n}	50.91^{m}	53.31^{l}	54.11^{k}
75.00	16.00	20.00	16.00	54.49^{i}	55.30^{kmn}	53.57^{km}	55.27^{kl}	56.15^{k}
65.00	10.00	30.00	16.00	55.85^{h}	56.88^{kmn}	54.00^{jkm}	56.35^{jkl}	57.18^{ijk}
75.00	10.00	30.00	16.00	56.86^{gh}	57.50^{jkm}	54.25^{jkm}	57.42^{jk}	58.26^{ij}
65.00	16.00	30.00	16.00	59.62^{efgh}	60.94^{ghij}	57.75^{hij}	60.19^{fghij}	61.04^{fghi}
75.00	16.00	30.00	16.00	63.74^{cd}	63.46^{fgh}	61.85^{efg}	63.43^{ef}	64.23^{ef}
60.00	13.00	25.00	14.00	58.44^{fgi}	59.87^{hijk}	57.08^{hijk}	59.46^{ghij}	61.00^{fghi}
80.00	13.00	25.00	14.00	60.27^{cdefg}	61.23^{ghij}	58.88^{ghi}	61.29^{fghi}	62.88^{fgh}
70.00	7.00	25.00	14.00	51.34^{j}	53.62^{n}	50.70^{m}	53.06^{l}	53.86^{k}
70.00	19.00	25.00	14.00	61.84^{cdef}	63.01^{fgh}	60.40^{fgh}	62.89^{efg}	63.86^{ef}
70.00	13.00	15.00	14.00	46.67^{k}	49.14^{o}	46.85^{n}	48.66^{m}	49.54^{l}
70.00	13.00	35.00	14.00	62.32^{cde}	62.29^{mn}	60.52^{fgh}	62.23^{efgh}	63.06^{fg}
70.00	13.00	25.00	10.00	70.10^{b}	71.10^{bc}	69.36^{bc}	71.02^{b}	71.24^{bc}
70.00	13.00	25.00	18.00	46.12^{ik}	47.99^{o}	45.42^{n}	47.81^{m}	48.74^{l}
70.00	13.00	25.00	14.00	56.64^{ghi}	58.34^{jkm}	55.90^{ijk}	57.62^{ijk}	59.17^{hij}

EC is Total energy consumption

Table 4.24. Total energy consumption polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	266.151	202.997	215.499	279.862	251.621
m_1	-5.934*	-4.756*	-4.600*	-5.934*	-5.809*
m_2	0.009*	1.172*	-0.195*	-0.081*	0.162*
m_3	1.689*	1.995*	1.905*	1.388*	2.093*
m_4	-4.261*	-2.094*	-3.706*	-5.021*	-2.933*
m_1^2	0.045*	0.039*	0.036*	0.045*	0.044*
m_2^2	0.049	0.047	0.032	0.058	0.037
m_3^2	-0.003	-0.009	-0.007	-0.004	-0.012
m_4^2	0.206*	0.183*	0.186*	0.221*	0.154*
$m_1\,m_2$	0.014	0.004	0.021	0.010	0.015
$m_1\,m_3$	0.004	0.003	0.001	0.005	0.003
$m_1\,m_4$	-0.033	-0.048	-0.034	-0.030	-0.031
$m_2\,m_3$	-0.017	-0.016	-0.011	-0.010	-0.013
$m_2\,m_4$	-0.062	-0.094	-0.059	-0.068	-0.065
$m_3\,m_4$	-0.047	-0.049	-0.046	-0.041	-0.048
R^2	0.915	0.911	0.915	0.913	0.914
R_{adj}^2	0.900	0.895	0.900	0.897	0.899

m_1 , m_2, m_3 and m_4 are Soaking temperature, Soaking time, Steaming time and Paddy moisture content, R^2 is Coefficient of determination, $R_{adj}{}^2$ is Coefficient of determination adjusted and * significant at 5% level

The models satisfied good fitness test at $p \leq 0.05$ due to high coefficients of determination (R^2). This is an indication that the generated models can be used to explain the functional relationship between soaking temperature, soaking time, steaming time, paddy moisture content and total energy consumption. However, Taguchi techniques had higher R^2 for total energy consumption models than RSM models, thus has a higher potential of predicting total energy consumption than RSM.

4.8 Modelling the Impacts of Processing Parameters on Quality Attributes using RSM

4.8.1 RSM modelling of brown rice recovery

As shown in Table 4.25, brown rice recovery varied with processing parameters combinations. Although some processing parameters shows no significant difference at ($p \geq 0.05$).The maximum brown rice recovery for FARO 44 was 79.50% and it was achieved at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% paddy moisture content. FARO 52 observed the maximum brown rice recovery (82.40%) at 80ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content while FARO 60 recorded maximum brown rice recovery (78.33%) at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% paddy moisture content, respectively.

The maximum brown rice recovery for FARO 61 was 78.44%, this was achieved at 75ºC soaking temperature, 10 h soaking time, 20 min steaming time and 12% paddy moisture content while NERICA 8 observed the maximum brown rice recovery (82.66%) at 70ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content. These results agreed with the findings of previous research by Nasirahmadi *et al.* (2014), which observed that parboiling can increase rice recovery. ANOVA of the interaction showed the significant processing conditions on brown rice recovery at $p<0.05$ for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.26).

However, the level of significance of the processing conditions varied from one variety to another (Table 4.26). In FARO 44, soaking time, steaming time and paddy moisture content had significant influence on the brown rice recovery. The negative coefficient observed in steaming time indicates reduction in brown rice recovery when steaming time increased. If paddy is steamed for a prolonged time, it causes reduction in brown rice recovery. Degree of starch gelatinization which can be affected by excess steaming plays a vital role in breakage susceptibility of parboiled rice (Buggenhout *et al.*, 2013, 2014).

Table 4.25. Impacts of processing parameters on brown rice recovery using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	BRR44 (%)	BRR52 (%)	BRR60 (%)	BRR61(%)	BRR8(%)
65.00	10.00	20.00	12.00	77.84^{hij}	77.01^{jk}	78.31^{a}	77.36^{g}	80.23^{gh}
75.00	10.00	20.00	12.00	78.56^{ef}	75.87^{m}	78.02^{cd}	78.45^{a}	79.06^{m}
65.00	16.00	20.00	12.00	77.63^{jk}	78.84^{de}	78.30^{a}	77.86^{e}	80.20^{gh}
75.00	16.00	20.00	12.00	77.79^{ijk}	78.57^{ef}	78.33^{a}	78.16^{b}	80.58^{ef}
65.00	10.00	30.00	12.00	77.62^{jk}	77.81^{gh}	77.52^{g}	77.82^{e}	79.70^{jk}
75.00	10.00	30.00	12.00	78.42^{f}	76.57^{k}	77.59^{gf}	77.89^{de}	79.11^{lm}
65.00	16.00	30.00	12.00	77.58^{k}	78.85^{de}	77.62^{gf}	78.10^{bc}	78.65^{n}
75.00	16.00	30.00	12.00	77.62^{jk}	78.35^{ef}	77.62^{gf}	77.38^{g}	81.09^{d}
65.00	10.00	20.00	16.00	78.40^{f}	77.35^{hij}	77.59^{gf}	77.43^{g}	81.65^{b}
75.00	10.00	20.00	16.00	78.48^{ef}	79.45^{bc}	77.34^{h}	78.09^{bc}	79.32^{lm}
65.00	16.00	20.00	16.00	78.68^{cde}	77.78^{gh}	77.97^{d}	77.88^{de}	80.56^{ef}
75.00	16.00	20.00	16.00	77.86^{hij}	79.38^{bc}	77.70^{ef}	77.48^{fg}	80.70^{e}
65.00	10.00	30.00	16.00	78.90^{bc}	78.43^{ef}	77.62^{fg}	78.08^{bcd}	80.79^{e}
75.00	10.00	30.00	16.00	79.50^{a}	79.76^{b}	77.52^{g}	78.16^{b}	79.91^{ij}
65.00	16.00	30.00	16.00	79.11^{b}	77.67^{ghi}	77.97^{d}	78.41^{a}	80.04^{ih}
75.00	16.00	30.00	16.00	78.18^{g}	79.24^{cd}	77.75^{e}	76.79^{h}	81.42^{c}
60.00	13.00	25.00	14.00	77.90^{jk}	79.79^{b}	78.06^{bcd}	77.53^{fg}	80.66^{ef}
80.00	13.00	25.00	14.00	77.90^{gh}	82.40^{jk}	77.75^{ef}	77.37^{f}	80.42^{ij}
70.00	7.00	25.00	14.00	78.05^{hijk}	76.95^{fg}	77.64^{bc}	77.63^{e}	79.94^{d}
70.00	19.00	25.00	14.00	77.81^{def}	78.13^{ij}	78.12^{gf}	77.83^{bcd}	81.40^{ih}
70.00	13.00	15.00	14.00	78.61^{cde}	77.24^{hi}	77.62^{i}	78.06^{a}	79.99^{k}
70.00	13.00	35.00	14.00	78.71^{hij}	77.55^{ij}	76.74^{b}	78.40^{cde}	79.56^{m}
70.00	13.00	25.00	10.00	77.85^{cd}	77.25^{ef}	78.14^{ef}	77.91^{e}	78.99^{g}
70.00	13.00	25.00	18.00	78.84^{ih}	78.58^{ef}	77.66^{j}	77.84^{fg}	80.29^{gh}
70.00	13.00	25.00	14.00	77.88^{hij}	78.33^{ef}	75.93^{k}	77.45^{fg}	82.66^{a}

BRR means brown rice recovery, mean values in a column with same superscript are not significantly different ($p \geq 0.05$)

Table 4.26. Brown rice recovery polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	65.531	213.945	226.215	43.232	-44.673
m_1	0.365	-4.376*	-2.837*	0.632*	2.337*
m_2	0.990*	1.998*	-1.539*	1.360	-0.986*
m_3	-0.670*	0.982*	-1.012*	0.250*	0.365*
m_4	0.043*	-1.831*	-3.893*	0.076	6.594*
m_1^2	0.000	0.026*	0.020*	0.000*	-0.021*
m_2^2	0.002	-0.028*	0.056*	0.008*	-0.055*
m_3^2	0.008*	-0.011*	0.013*	0.008*	-0.029*
m_4^2	0.031*	-0.039*	0.126*	0.027*	-0.188*
$m_1\,m_2$	-0.016*	0.006	0.001	-0.018*	0.039*
$m_1\,m_3$	0.001	-0.003	0.001*	-0.010*	0.013*
$m_1\,m_4$	-0.018*	0.061*	-0.004*	-0.013*	-0.017*
$m_2\,m_3$	-0.003	-0.014*	-0.001	-0.005*	0.000*
$m_2\,m_4$	0.004	-0.086*	0.009*	-0.012*	-0.014*
$m_3\,m_4$	0.018*	-0.001	0.018*	0.007*	0.009
R^2	0.901	0.920	0.992*	0.897	0.984
R_{adj}^2	0.884	0.910	0.991	0.879	0.981

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

The negative coefficients observed in soaking temperature and paddy moisture content means increase in their conditions reduces brown rice recovery in FARO 52. Soaking temperature, soaking time, steaming time and paddy moisture content were significant and had a negative effect on brown rice recovery of FARO 60 when increased while in FARO 61, increase in soaking temperature and steaming time had a positive impact on the brown rice recovery when increased. Increase in brown rice recovery can be caused by reducing the soaking time in NERICA 8. The differences in the genetic makeup might be the reasons for their dynamic behaviour under different processing conditions. Nasirahmadi *et al.* (2014) and Leethanapanich *et al.* (2016) reported similar findings.

The generated models for predicting the brown rice recovery were presented in Table 4.26. Coefficients of determination (R^2) of the models were 0.901, 0.920, 0.992, 0.897 and 0.984 for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8 respectively (Table 4.26). Based on the obtained coefficient of determination (R^2), the generated RSM models were fit to predict brown rice recovery than Taguchi techniques. The R^2 were higher and gave assurance of little error during application of the models. Lack of fit test of the models was non-significant at $p>0.05$, thus strengthening the fitness of the model. Also, the obtained mean square error (MSE) for the models were; 0.026, 0.106, 0.015, 0.005 and 0.024 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively.

4.8.2 RSM modelling of head brown rice

The impacts of soaking temperature, soaking time, steaming time and paddy moisture content on head brown rice was depicted in Table 4.27. Some processing parameters under different combinations showed no significant difference at ($p>0.05$). The maximum head brown rice for FARO 44 was 79.26%, this was achieved at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% moisture content. FARO 52 observed the maximum head brown rice (82.19%) at 80ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% moisture content while FARO 60 recorded maximum head brown rice (77.95%) at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% moisture content respectively. The maximum head brown rice for FARO 61 was 77.61%, this was achieved at 75ºC soaking temperature, 10 h soaking time, 20 min steaming time

Table 4.27. Impacts of processing parameters on head brown rice using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	BHR44	BHR52	BHR60	BHR61	BHR8
65.00	10.00	20.00	12.00	76.92^{kj}	76.16^{h}	77.84^{bc}	75.67^{j}	77.86^{b}
75.00	10.00	20.00	12.00	78.08^{de}	75.18^{i}	77.62^{d}	76.68^{cde}	78.06^{kl}
65.00	16.00	20.00	12.00	77.24^{ih}	77.98^{de}	77.88^{ab}	76.14^{ih}	79.36^{g}
75.00	16.00	20.00	12.00	77.36^{ihg}	77.79^{de}	77.95^{a}	76.38^{efgh}	80.29^{de}
65.00	10.00	30.00	12.00	76.87^{kj}	76.86^{fg}	77.13^{j}	76.45^{defgh}	78.50^{ih}
75.00	10.00	30.00	12.00	77.94^{de}	76.05^{h}	77.15^{ij}	76.44^{defgh}	78.51^{ih}
65.00	16.00	30.00	12.00	77.26^{ih}	77.85^{de}	77.14^{j}	76.73^{cd}	78.32^{ijk}
75.00	16.00	30.00	12.00	76.91^{kj}	77.75^{de}	77.18^{hij}	76.31^{fgh}	80.77^{bcd}
65.00	10.00	20.00	16.00	77.87^{dc}	76.45^{gh}	77.11^{j}	75.88^{ij}	80.52^{cd}
75.00	10.00	20.00	16.00	78.12^{dc}	79.09^{bc}	76.87^{m}	76.49^{defg}	78.44^{hij}
65.00	16.00	20.00	16.00	78.13^{dc}	77.06^{f}	77.39^{e}	76.43^{defgh}	80.22^{def}
75.00	16.00	20.00	16.00	76.96^{kj}	78.94^{c}	77.15^{ij}	76.21^{gh}	80.03^{ef}
65.00	10.00	30.00	16.00	78.69^{b}	77.10^{f}	77.38^{e}	76.81^{bc}	80.18^{def}
75.00	10.00	30.00	16.00	79.26^{a}	79.42^{l}	77.24^{ghi}	77.21^{b}	79.31^{g}
65.00	16.00	30.00	16.00	78.66^{b}	76.46^{gh}	77.54^{d}	77.61^{a}	79.89^{f}
75.00	16.00	30.00	16.00	76.75^{k}	78.79^{c}	77.27^{fgh}	76.39^{efgh}	80.54^{bcd}
60.00	13.00	25.00	14.00	77.36^{ihg}	78.93^{c}	77.62^{d}	76.47^{defg}	79.94^{ef}
80.00	13.00	25.00	14.00	77.12^{ij}	82.19^{a}	77.35^{ef}	76.59^{cdef}	80.12^{ef}
70.00	7.00	25.00	14.00	77.83^{def}	76.24^{h}	77.27^{fgh}	75.89^{ij}	77.97^{kl}
70.00	19.00	25.00	14.00	77.37^{ihg}	77.62^{e}	77.58^{d}	76.68^{cde}	80.88^{b}
70.00	13.00	15.00	14.00	77.60^{efg}	76.03^{h}	77.04^{k}	75.59^{j}	78.12^{jkl}
70.00	13.00	35.00	14.00	78.06^{icd}	76.23^{h}	76.39^{n}	77.44^{ab}	78.76^{h}
70.00	13.00	25.00	10.00	77.53^{gh}	76.79^{gf}	77.77^{c}	75.83^{j}	78.45^{hij}
70.00	13.00	25.00	18.00	78.46^{b}	78.22^{d}	77.30^{efg}	76.44^{defgh}	80.01^{ef}
70.00	13.00	25.00	14.00	77.58^{fg}	78.07^{ed}	75.62^{o}	75.87^{ij}	81.76^{a}

The values of means in the same columns bearing the same superscript are not significantly different ($p \geq 0.05$), HBR means head brown rice and 12% moisture content while NERICA 8 observed the maximum head brown rice (81.76%) at 70ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% moisture content. The variation in the head brown rice of the varieties can be traced to the differences in their starch gelatinization rate while subjected to different processing conditions. Islam *et al.* (2004) reported similar findings. Rice varieties that undergo complete starch gelatinization are expected to withstand dehusking pressure, thus resulting into high head brown rice. ANOVA of the interaction showed the significant processing conditions on head brown rice at $p<0.05$ for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8 (Table 4.28).

In FARO 44, it was observed that increase in steaming time could result into decrease in head brown rice. Increase in soaking temperature and paddy moisture content was observed to have negative influence on head brown rice of FARO 52. Increase in soaking temperature, soaking time, steaming time and paddy moisture content was observed to lead to decrease in the head brown rice of FARO 60. While for FARO 61, increase in soaking temperature and paddy moisture content was observed to have negative impact on the head brown rice. Increase in soaking temperature, soaking time, steaming time and paddy moisture were observed to have positive influence on head brown rice. The differences in the microscopic structure of the rice varieties might be the reasons for the variation in the behaviour that exist under different processing conditions. Nasirahmadi *et al.* (2014) and Leethanapanich *et al.* (2016) reported similar findings.

The generated models for predicting the head brown rice with the derived coefficients for the varieties was presented in Table 4.28. Coefficients of determination (R^2) of the models were 0.897, 0.944, 0.994, 0.861 and 0.970 for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8 respectively. The R^2 were higher and closer to unity thus given assurance of little error during their application as a model for predicting head brown rice. The obtained R^2 were higher than that of Taguchi models. The mean square errors (MSE) for the models were; 0.035, 0.101, 0.004, 0.036 and 0.053 for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8 respectively.

4.8.3 RSM modelling of milling recovery

The impacts of processing parameters on milling recovery are depicted in Table 4.29. The maximum milling recovery for FARO 44 was 73.21% and was achieved at 70ºC soaking temperature, 13 h soaking time, 15 min steaming time and 14% moisture

Table 4.28. Head brown rice polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	12.243	196.824	215.546	89.122	-72.366
m_1	1.228	-4.090*	-2.643*	-0.537*	2.265*
m_2	2.298*	2.414*	-1.344*	0.786*	0.621*
m_3	-0.097*	1.320*	-0.922*	0.054*	1.136*
m_4	1.138*	-2.047*	-3.733*	-0.276*	7.591*
m_1^2	-0.003*	0.023*	0.019*	0.007*	-0.016*
m_2^2	0.001	-0.038*	0.051*	0.014*	-0.062*
m_3^2	0.003*	-0.022*	0.011*	0.007*	-0.032*
m_4^2	0.027*	-0.050	0.122	0.022*	-0.152*
$m_1\,m_2$	-0.026*	0.003	0.001	-0.015	0.027*
$m_1\,m_3$	-0.002*	0.001	0.001	-0.007	0.008*
$m_1\,m_4$	-0.027*	0.070*	-0.005*	-0.008*	-0.038*
$m_2\,m_3$	-0.008	-0.014*	-0.003*	-0.001	-0.008*
$m_2\,m_4$	-0.025	-0.082*	0.004*	-0.001	-0.037*
$m_3\,m_4$	0.018	-0.007	0.022*	0.012	0.001*
R^2	0.897	0.944	0.994	0.861	0.970
R^2_{adj}	0.879	0.934	0.993	0.836	0.965

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, $R_{adj}{}^2$ is Coefficient of determination adjusted and * significant at 5% level

Table 4.29. Impacts of processing parameters on milling recovery using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	MR44 (%)	MR52 (%)	MR60 (%)	MR61 (%)	MR8 (%)
65.00	10.00	20.00	12.00	71.86^{cd}	68.96^{d}	71.56^{bcd}	69.65^{cd}	63.11^{k}
75.00	10.00	20.00	12.00	72.63^{d}	67.57^{m}	71.44^{bcde}	68.91^{ef}	70.28^{b}
65.00	16.00	20.00	12.00	71.53^{efgh}	70.36^{efghi}	70.93^{ef}	70.23^{bc}	69.84^{bc}
75.00	16.00	20.00	12.00	71.79^{cdef}	65.46^{m}	72.34^{a}	67.60^{jk}	69.50^{bc}
65.00	10.00	30.00	12.00	70.35^{kj}	69.39^{hij}	69.98^{h}	71.97^{a}	65.11^{ij}
75.00	10.00	30.00	12.00	71.37^{fgh}	70.93^{def}	70.24^{gh}	70.88^{b}	69.27^{bcd}
65.00	16.00	30.00	12.00	70.06^{kl}	71.51^{bcde}	70.97^{ef}	69.45^{de}	67.39^{efg}
75.00	16.00	30.00	12.00	70.49^{kj}	70.66^{fgh}	71.59^{bc}	68.68^{fghi}	65.50^{i}
65.00	10.00	20.00	16.00	71.60^{defg}	69.28^{ij}	71.93^{ab}	69.15^{def}	56.49^{l}
75.00	10.00	20.00	16.00	71.09^{hi}	73.03^{a}	71.00^{def}	66.81^{l}	67.82^{ef}
65.00	16.00	20.00	16.00	72.16^{c}	70.02^{fghij}	71.43^{bcde}	70.67^{b}	66.63^{gh}
75.00	16.00	20.00	16.00	70.55^{j}	71.20^{bcde}	70.96^{ef}	70.21^{bc}	67.32^{efg}
65.00	10.00	30.00	16.00	70.43^{jk}	66.69^{k}	70.38^{gh}	69.78^{cd}	65.83^{hi}
75.00	10.00	30.00	16.00	70.41^{jk}	72.97^{a}	69.93^{h}	68.11^{hij}	72.00^{a}
65.00	16.00	30.00	16.00	69.87^{l}	66.46^{km}	71.69^{b}	68.04^{ij}	68.37^{de}
75.00	16.00	30.00	16.00	68.84^{m}	72.21^{ab}	71.05^{cdef}	68.17^{hij}	65.36^{i}
60.00	13.00	25.00	14.00	70.63^{j}	63.51^{n}	70.56fg	70.81^{fgh}	64.22^{j}
80.00	13.00	25.00	14.00	70.44^{kj}	71.50^{bcde}	68.46^{i}	68.73^{ef}	69.09^{cd}
70.00	7.00	25.00	14.00	71.98^{c}	69.25^{ij}	70.30^{gh}	68.92^{efg}	65.32^{i}
70.00	19.00	25.00	14.00	71.27^{gh}	69.54^{hij}	71.51^{bcde}	68.79^{efg}	66.76^{fgh}
70.00	13.00	15.00	14.00	73.21^{a}	70.53^{efghi}	71.68^{b}	69.24^{def}	65.35^{i}
70.00	13.00	35.00	14.00	69.72^{l}	70.39^{efghi}	70.20^{gh}	70.82^{b}	67.08^{fg}
70.00	13.00	25.00	10.00	70.71^{ij}	71.96^{abcd}	71.73^{b}	68.81^{efg}	67.13^{fg}
70.00	13.00	25.00	18.00	67.99^{j}	72.64^{ab}	71.76^{b}	67.34^{kl}	65.41^{i}
70.00	13.00	25.00	14.00	71.41^{fgh}	70.70^{defg}	70.93^{ef}	67.92^{jk}	66.83^{fgh}

Mean values in the same columns bearing the same superscript are not significantly different ($p \geq 0.05$), MR means Milling recovery content. FARO 52 observed the maximum milling recovery (73.03%) at 75ºC soaking temperature, 10 h soaking time, 20 min steaming time and 16% moisture content while FARO 60 recorded maximum milling recovery (72.34%) at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 12% moisture content respectively. The maximum milling recovery for FARO 61 was 71.97%, this was achieved at 65ºC soaking temperature, 10 h soaking time, 30 min steaming time and 12% moisture content while NERICA 8 observed the maximum milling recovery (72.00%) at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% moisture content.

The difference in the milling recovery of the rice varieties maybe related to the difference behaviour of the rice varieties under different processing conditions during the separation of the bran from the kernels. Nasirahmadi *et al.* (2014) reported similar findings while examining the difference in the milling recovery of Fajr and Tarom rice varieties. The ANOVA results for the quadratic models showed the significant processing conditions, their interactions and the adequacy of the model on milling recovery for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.30). In FARO 44 and FARO 52, increase in steaming time was observed to lead to reduction in milling recovery.

Steaming time and soaking time gave a negative coefficient which means decrease in milling recovery when increased the conditions were increased. Soaking temperature and steaming time was observed to have negative effect on milling recovery of FARO 61 when increased while in NERICA 8, increase in soaking temperature, soaking time and steaming time were observed to increase the milling recovery but increase in paddy moisture content tend to reduce the milling recovery.

The observed difference in the processing conditions characteristics for the five varieties reveals the importance of investigating the optimum conditions for each variety. The coefficient of determination (R^2) for milling recovery for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.928, 0.870, 0.885, 0.787 and 0.928, respectively, indicating a reasonable fit of the models to the experimental data (Table 4.30).

Table 4.30. Milling recovery polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	-20.558	30.278	16.835	204.091	-82.909
m_1	1.604	2.454*	1.961*	-3.149*	2.111*
m_2	0.787*	3.813	-1.081*	-1.527	12.255*
m_3	-0.359*	-1.063*	-0.544*	-0.315*	2.067*
m_4	5.642*	-9.516	0.143	-1.003*	-5.700*
m_1^2	-0.007*	-0.033	-0.012*	0.019*	0.002
m_2^2	0.010*	-0.039*	0.005	0.027*	-0.011
m_3^2	0.002	-0.003*	0.002*	0.022*	-0.002
m_4^2	-0.120*	0.095*	0.064*	0.013	-0.012
$m_1\,m_2$	-0.013*	-0.037*	0.009	0.009	-0.139*
$m_1\,m_3$	0.004*	0.035*	0.000*	0.007*	-0.034*
$m_1\,m_4$	-0.035*	0.141*	-0.029*	0.006	0.038*
$m_2\,m_3$	-0.009*	0.011*	0.021	-0.044*	-0.088*
$m_2\,m_4$	0.002	-0.033*	-0.007	0.091*	0.011
$m_3\,m_4$	-0.002	-0.096*	0.008	-0.046*	0.117
R^2	0.928	0.870	0.787	0.885	0.928
R_{adj}^2	0.915	0.846	0.749	0.865	0.915

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

The generated predictive RSM models for milling recovery were observed to be more accurate than Taguchi generated predictive models due to their high R^2 values. Mean square errors (MSE) for the varieties were 0.078, 0.179, 0.620, 0.127 and 0.507 respectively. The MSE were low, thus justifying the reasons why the models were good for predicting the milling recovery.

4.8.4 RSM modelling of head milled rice

High head milled rice is one of the quality attributes of grain that enhance customer acceptability of rice. Table 4.31 depicts the impacts of processing parameters on head milled rice. The maximum head milled rice among the rice varieties was observed in FARO 52 (72.62%) at 75ºC soaking temperature, 10 h soaking time, 20 min steaming time and 16% paddy moisture content. FARO 44 observed the maximum head milled rice (72.37%) at 75ºC soaking temperature, 10 h soaking time, 20 min steaming time and 12% paddy moisture content while FARO 60 recorded maximum head milled rice (71.42%) at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 12% paddy moisture content respectively. The maximum head milled rice for FARO 61 was 70.11% at 65ºC soaking temperature, 10 h soaking time, 30 min steaming time and 12% moisture content. The least head milled rice among the varieties was observed in NERICA 8 (69.38%) at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% moisture content.

High level of head milled rice observed among the varieties was as a result of stronger structure of rice starch as a result of gelatinization process. The difference in the head milled rice of the varieties maybe related to dissimilarities in their morphological, physical and their ability to resist polishing pressure. The ANOVA results for the quadratic models showed the significant processing parameters, their interactions and the adequacy of the models for head milled rice of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.32). From Table 4.32, it was observed that increase in soaking temperature, soaking time, steaming time and paddy moisture content increases the head milled rice of FARO 44. However, increase in steaming time and paddy moisture content was observed to lead to reduction in head milled rice of FARO 52. Negative coefficients observed at soaking time and steaming time in FARO 60 means increase in those conditions will reduce head milled rice.

Table 4.31. Impacts of processing parameters on head milled rice using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	HMR44 (%)	HMR52 (%)	HMR60 (%)	HMR61 (%)	HMR8 (%)
65.00	10.00	20.00	12.00	71.00^{d}	67.85^{jk}	70.89^{abcd}	68.00^{de}	58.09^{h}
75.00	10.00	20.00	12.00	72.37^{a}	67.13^{k}	70.62^{bcdefg}	63.35^{n}	66.56^{cd}
65.00	16.00	20.00	12.00	70.32^{fg}	69.43^{efghi}	70.32^{efgh}	68.67^{c}	67.52^{bc}
75.00	16.00	20.00	12.00	71.56^{bc}	64.98^{m}	71.42^{a}	64.33^{m}	66.87^{c}
65.00	10.00	30.00	12.00	69.34^{jk}	68.48^{hij}	69.36^{k}	70.11^{a}	62.54^{f}
75.00	10.00	30.00	12.00	70.44^{ef}	70.27^{def}	69.69^{ijk}	66.55^{ij}	68.92^{a}
65.00	16.00	30.00	12.00	69.03^{k}	70.56^{cde}	70.24^{fghi}	67.88^{de}	64.87^{e}
75.00	16.00	30.00	12.00	69.88^{ghi}	70.03^{def}	70.82^{bcde}	66.81^{hij}	64.47^{e}
65.00	10.00	20.00	16.00	71.22^{bcd}	68.21^{ijk}	71.09^{abc}	67.97^{de}	48.54^{i}
75.00	10.00	20.00	16.00	70.89^{de}	72.62^{a}	70.01^{hij}	64.60^{ml}	57.26^{h}
65.00	16.00	20.00	16.00	71.18^{bcd}	68.75^{hij}	70.74^{bcdefg}	67.57^{def}	65.10^{e}
75.00	16.00	20.00	16.00	70.23^{fgh}	70.58^{cde}	70.14^{ghi}	67.58^{def}	64.49^{e}
65.00	10.00	30.00	16.00	70.00^{fgh}	65.87^{ab}	69.74^{ijk}	68.18^{cd}	62.81^{f}
75.00	10.00	30.00	16.00	69.46^{ijk}	72.54^{m}	69.53^{jk}	66.66^{hij}	69.38^{a}
65.00	16.00	30.00	16.00	69.30^{k}	65.77^{abc}	70.92^{abcd}	65.05^{kl}	68.49^{ab}
75.00	16.00	30.00	16.00	68.23^{l}	71.71^{n}	70.56^{cdefg}	66.97^{ghij}	66.45^{cd}
60.00	13.00	25.00	14.00	69.79^{hij}	61.57^{cde}	69.74^{ijk}	69.38^{b}	62.48^{e}
80.00	13.00	25.00	14.00	70.06^{fgh}	70.73^{n}	67.71^{l}	65.47^{k}	67.50^{bc}
70.00	7.00	25.00	14.00	71.60^{b}	68.98^{fghi}	69.73^{ijk}	67.39^{fg}	59.75^{g}
70.00	19.00	25.00	14.00	70.82^{de}	69.22^{fghi}	70.97^{abcd}	67.13^{fghi}	66.45^{cd}
70.00	13.00	15.00	14.00	72.46^{a}	69.45^{def}	70.45^{defgh}	63.64^{h}	56.97^{h}
70.00	13.00	35.00	14.00	68.08^{l}	69.63^{efgh}	69.53^{jk}	67.28^{efgh}	65.48^{de}
70.00	13.00	25.00	10.00	70.26^{fgh}	71.33^{bcd}	71.08^{abc}	66.32^{j}	65.12^{e}
70.00	13.00	25.00	18.00	67.81^{l}	72.18^{ab}	71.18^{ab}	66.39^{j}	61.95^{f}
70.00	13.00	25.00	14.00	71.10^{cd}	70.19^{def}	69.55^{jk}	64.81^{jklm}	65.47^{de}

The values of means in the same columns bearing the same superscript are not significantly different ($p \geq 0.05$), HMR means Head milled rice

Table 4.32. Head milled rice polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	-58.474	-19.741	71.265	360.256	-122.117
m_1	2.303*	3.741*	0.980*	-6.076*	2.609*
m_2	0.294*	3.782	-1.615*	-3.790	12.583*
m_3	0.380*	-0.754*	-0.989*	-0.546*	2.421*
m_4	6.534*	-9.674*	-1.677	-6.482	-4.648*
m_1^2	-0.011*	-0.041*	-0.006*	0.028*	0.000
m_2^2	0.006	-0.032*	0.028*	0.073*	-0.053*
m_3^2	-0.007*	-0.007	0.007*	0.008*	-0.038*
m_4^2	-0.122*	0.094*	0.113*	0.108*	-0.092*
$m_1 m_2$	-0.006	-0.039*	0.008*	0.040*	-0.141*
$m_1 m_3$	-0.002	0.032*	0.003	0.020*	-0.014*
$m_1 m_4$	-0.047*	0.142*	-0.025*	0.067*	-0.007
$m_2 m_3$	-0.003	0.012	0.018*	-0.038*	-0.137*
$m_2 m_4$	-0.003	-0.038	-0.003	0.001	0.197*
$m_3 m_4$	0.000	-0.089*	0.012*	-0.049*	0.187*
R^2	0.928	0.882	0.809	0.931	0.966
R_{adj}^2	0.915	0.861	0.775	0.919	0.959

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

Soaking temperature and paddy moisture content had negative effect on head milled rice of FARO 61 when increased while in NERICA 8, increase in soaking temperature, soaking time and steaming time was observed to increase head milled rice but increase in paddy moisture content tends to reduce head milled rice NERICA 8. The difference in the optimum processing parameters of the five varieties reveals the importance of investigating the optimum head milled rice for economic viability. The coefficient of determination (R^2) of head milled rice for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.966, 0.882, 0.931, 0.809, and 0.928, respectively, indicating a reasonable fit of the models with the experimental data (Table 4.32).

4.8.5 RSM modelling of chalkiness

High level of chalkiness downgrade physical quality, reduces milling recovery and head milled rice and can determine whether a particular rice sample attracts a competitive price on the market price (Gayin *et al.* 2009 and Fofana *et al.* 2011). Table 4.33 shows the impacts of processing parameters on chalkiness. The minimum chalkiness among the rice varieties were observed in FARO 52 (0.50%) and FARO 60 (0.50%), at 70ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content. FARO 44 observed minimum chalkiness (0.70%) at 80ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content while FARO 61 recorded minimum chalkiness (1.25%) at 80ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% moisture content respectively.

The minimum chalkiness observed in NERICA 8 was 1.25% at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 12% paddy moisture content. The percentage differences in the chalkiness observed in the rice varieties could to be traced to incomplete starch gelatinization that occurred during the parboiling stage. The ANOVA results for the polynomial models showed the significant processing conditions and their interactions and also the adequacy of the models for chalkiness of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.34). From Table 4.34, it was observed that an increase in soaking temperature, soaking time decreases chalkiness in FARO 44. However, for FARO 52 and FARO 60, increase in soaking temperature and paddy moisture content decreases their chalkiness.

Table 4.33. Impacts of processing parameters on chalkiness rice using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Moisture Content (%)	WB44 (%)	WB52 (%)	WB60 (%)	WB61 (%)	WB8 (%)
65.00	10.00	20.00	12.00	13.55^{b}	1.97^{f}	1.97^{f}	2.45^{e}	14.53^{b}
75.00	10.00	20.00	12.00	3.31^{jk}	1.55^{hg}	1.55^{gh}	1.30^{h}	4.72^{hij}
65.00	16.00	20.00	12.00	3.25^{jk}	2.3^{6e}	2.36^{e}	2.48^{e}	4.97^{hij}
75.00	16.00	20.00	12.00	0.96^{n}	0.66^{jk}	0.66^{jk}	1.83^{fg}	1.53^{n}
65.00	10.00	30.00	12.00	10.81^{d}	2.36^{e}	2.36^{e}	3.67^{b}	11.97^{d}
75.00	10.00	30.00	12.00	2.17l^{m}	3.47^{b}	3.47^{b}	1.58^{g}	3.47^{kl}
65.00	16.00	30.00	12.00	5.55^{f}	3.03^{c}	3.03^{c}	4.52^{a}	7.16^{f}
75.00	16.00	30.00	12.00	2.81^{kl}	1.61^{gh}	1.61^{fgh}	2.55^{e}	3.41^{klm}
65.00	10.00	20.00	16.00	12.19^{c}	2.80^{cd}	2.80^{cd}	3.86^{b}	13.16^{c}
75.00	10.00	20.00	16.00	7.11^{e}	2.66^{de}	2.66^{de}	2.95^{c}	8.78^{e}
65.00	16.00	20.00	16.00	1.48^{mn}	3.72^{b}	3.72^{c}	2.39^{e}	2.97l^{m}
75.00	16.00	20.00	16.00	3.69^{ijk}	1.55^{hg}	1.55^{gh}	1.73^{g}	5.09^{hij}
65.00	10.00	30.00	16.00	5.36^{fg}	1.03^{ij}	1.03^{ij}	3.64^{b}	6.41^{ef}
75.00	10.00	30.00	16.00	2.75^{kl}	1.55^{hg}	1.55^{gh}	1.92^{f}	4.09^{jk}
65.00	16.00	30.00	16.00	1.19^{n}	1.86^{gf}	1.86^{fg}	2.61d^{e}	2.34^{mn}
75.00	16.00	30.00	16.00	3.61^{ijk}	0.72^{jk}	0.72^{jk}	2.02^{f}	4.41^{ijk}
60.00	13.00	25.00	14.00	7.14^{e}	1.98^{f}	1.98^{f}	2.88^{cd}	8.25^{e}
80.00	13.00	25.00	14.00	0.70^{n}	1.92^{fg}	1.92^{fg}	1.25^{h}	1.75^{n}
70.00	7.00	25.00	14.00	17.45^{a}	1.36^{hi}	1.36^{hi}	2.50^{e}	19.19^{agf}
70.00	19.00	25.00	14.00	4.89^{fg}	1.55^{gh}	1.55gh	2.63^{de}	6.31^{gf}
70.00	13.00	15.00	14.00	3.39^{jk}	1.67f^{gh}	1.67^{fgh}	2.44^{e}	4.63^{hij}
70.00	13.00	35.00	14.00	1.45^{mn}	0.73^{jk}	0.73^{jk}	3.69^{b}	2.38^{mn}
70.00	13.00	25.00	10.00	3.70^{ijk}	4.30^{a}	4.30^{a}	2.50^{e}	4.63^{hij}
70.00	13.00	25.00	18.00	4.14^{hij}	4.11^{a}	4.11^{a}	2.63^{de}	5.38^{hij}
70.00	13.00	25.00	14.00	4.50^{ghi}	0.50^{k}	0.50k	3.00^{c}	5.68^{gh}

Table 4.34. Chalkiness polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	250.819	88.635	88.635	-53.775	238.349
m_1	-2.655*	-1.710*	-1.710*	1.079*	-2.433*
m_2	-15.040*	1.383	1.383	0.266	-14.065*
m_3	0.381*	-0.085*	-0.085*	0.808*	0.710*
m_4	-5.885*	-4.839	-4.839	1.469	-6.469
m_1^2	-0.008*	0.014*	0.014*	-0.009*	-0.009*
m_2^2	0.178*	0.024*	0.024*	-0.012*	0.189*
m_3^2	-0.023*	0.006*	0.006*	0.001	-0.024*
m_4^2	-0.052*	0.225*	0.225*	-0.026*	-0.058*
$m_1 m_2$	0.109*	-0.031*	-0.031*	0.008*	0.092*
$m_1 m_3$	0.010*	0.009*	0.009	-0.008*	0.008
$m_1 m_4$	0.130*	-0.003	-0.003	0.012*	0.144*
$m_2 m_3$	0.078*	-0.002	-0.002	0.013*	0.075*
$m_2 m_4$	-0.002*	0.016*	0.016*	-0.063*	0.000
$m_3 m_4$	-0.074	-0.059*	-0.059*	-0.031*	-0.081*
R^2	0.9680	0.9503	0.9503	0.9373	0.9667
R^2_{adj}	0.9623	0.9414	0.9414	0.9261	0.9608

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

The positive coefficients observed in soaking temperature and steaming time of FARO 61 means increase in those conditions increases their chalkiness. Soaking temperature and soaking time was observed to decrease chalkiness when those conditions were increased. The obtained coefficient of determination (R^2) for predicting chalkiness observed in NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.967, 0.950, 0.937, 0.950 and 0.968, respectively, indicating the tendency of the models to predict the chalkiness with better accuracy.

4.8.6 RSM modelling of lightness

Table 4.35 shows the impacts of processing parameters on the lightness values of the rice varieties. Among the rice varieties, FARO 44 had the highest lightness value. The maximum lightness value observed in FARO 44 was 46.82 at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 12% paddy moisture content. FARO 52 observed maximum lightness value (33.33) at 75ºC soaking temperature, 10 h soaking time, 20 min steaming time and 16% paddy moisture content while FARO 61 recorded maximum lightness value (33.00) at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% paddy moisture content respectively. The maximum lightness value observed in FARO 61 was 35.50 at 70ºC soaking temperature, 13 h soaking time, 35 min steaming time and 14% paddy moisture content while in NERICA 8, it was 34.97 at 75ºC soaking temperature, 10 h soaking time, 30 min steaming time and 12% paddy moisture content .

The differences in the lightness value observed in the rice varieties could to be traced to the difference in their husk pigment and also the way the pigment migrate to the endosperm when subjected to different processing parameters. Roy *et al.* (2003) reported that the degree of parboiling affects lightness values. The ANOVA results for the quadratic models showed the significant processing parameters, their interactions and the adequacy of the models for lightness values for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.36). From Table 4.36, it was observed that increase in soaking temperature increases lightness value while increase in soaking time and paddy moisture content, decreases lightness value in FARO 44. However, for FARO 52, it was observed that negative sum of square of soaking time (X_2^2) and steaming time (X_3^2), and negative interaction of soaking time and paddy moisture content (X_2X_4) reduces its lightness value.

Table 4.35. Impacts of processing parameters on lightness using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Moisture Content (%)	LHT44	LHT52	LHT60	LHT61	LHT8
65.00	10.00	20.00	12.00	27.83^{cde}	27.77^{ab}	28.17^{abcde}	28.77^{c}	25.20^{ef}
75.00	10.00	20.00	12.00	28.20^{cde}	29.53^{ab}	24.20^{cde}	30.87^{bc}	31.57^{abcde}
65.00	16.00	20.00	12.00	26.10^{de}	30.87^{ab}	24.20^{cde}	30.13^{bc}	30.47^{abcde}
75.00	16.00	20.00	12.00	46.80^{a}	30.97^{ab}	28.40^{abcde}	39.53^{a}	29.60^{bcdef}
65.00	10.00	30.00	12.00	25.73^{de}	25.97^{b}	23.40^{abc}	31.40^{bc}	29.27^{bcdef}
75.00	10.00	30.00	12.00	27.43^{cde}	31.30^{ab}	30.00^{bcde}	30.13^{bc}	34.97^{ab}
65.00	16.00	30.00	12.00	25.40^{de}	30.33^{ab}	26.10^{bcde}	29.83^{bc}	32.43^{abc}
75.00	16.00	30.00	12.00	28.30^{cde}	29.83^{ab}	25.73^{bcde}	33.17^{bc}	35.57^{ab}
65.00	10.00	20.00	16.00	27.80^{cde}	32.93^{a}	27.27^{abcde}	31.67^{bc}	23.13^{f}
75.00	10.00	20.00	16.00	38.53^{b}	33.33^{a}	28.87^{abcd}	29.27^{c}	32.67^{abc}
65.00	16.00	20.00	16.00	23.73^{e}	30.47^{ab}	22.03^{abcd}	31.77^{bc}	25.77^{def}
75.00	16.00	20.00	16.00	28.77^{cde}	28.77^{ab}	29.33^{abcd}	32.63^{bc}	33.77^{abc}
65.00	10.00	30.00	16.00	24.53^{cde}	30.33^{ab}	26.87^{abcde}	32.53^{bc}	33.47^{abc}
75.00	10.00	30.00	16.00	30.07^{a}	29.93^{ab}	33.00^{a}	33.43^{bc}	32.03^{abcd}
65.00	16.00	30.00	16.00	26.43^{de}	29.97^{ab}	29.73^{abcd}	30.83^{bc}	25.77^{def}
75.00	16.00	30.00	16.00	43.93^{cde}	30.10^{ab}	28.07^{abcde}	33.93^{bc}	34.70^{ab}
60.00	13.00	25.00	14.00	25.67^{de}	30.53^{ab}	24.87^{bcde}	32.07^{c}	31.63^{abcde}
80.00	13.00	25.00	14.00	29.63^{cde}	32.87^{a}	27.63^{abcde}	32.30^{bc}	29.70^{cdef}
70.00	7.00	25.00	14.00	25.97^{de}	27.93^{ab}	24.27^{cde}	28.07^{c}	27.73^{a}
70.00	19.00	25.00	14.00	27.50^{cde}	32.47^{a}	30.97^{ab}	30.37^{bc}	36.97^{def}
70.00	13.00	15.00	14.00	32.47^{c}	29.97^{ab}	25.20^{bcde}	28.17^{c}	25.67^{def}
70.00	13.00	35.00	14.00	26.60^{cde}	30.33^{ab}	30.03^{abc}	35.50^{ab}	33.00^{abc}
70.00	13.00	25.00	10.00	28.43^{cde}	30.60^{ab}	26.80^{abcde}	30.67^{bc}	25.27^{ef}
70.00	13.00	25.00	18.00	29.70^{cde}	32.00^{a}	31.00^{ab}	31.60^{bc}	29.00^{bcdef}
70.00	13.00	25.00	14.00	30.63^{cd}	32.53^{a}	27.80^{abcde}	30.03^{bc}	33.00^{abc}

The values of mean in the same columns bearing the same superscript are not significantly different ($p \geq 0.05$) LHT means lightness value

Table 4.36. Lightness of polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	75.644	-187.837	-23.824	143.964	-180.212
m_1	1.086*	2.854	2.088*	-3.323*	2.372*
m_2	-4.940*	6.387	1.361*	-1.870*	2.799*
m_3	-1.833	0.691	-0.802	-0.522	3.953*
m_4	-7.114*	9.356	-4.809*	1.772	6.550
m_1^2	-0.018	-0.013	-0.018*	0.027*	-0.018
m_2^2	-0.076	-0.078*	-0.012	-0.008	-0.004
m_3^2	0.001	-0.028*	-0.004	0.023*	-0.031
m_4^2	-0.026	-0.106	0.053	0.101	-0.334*
$m_1 m_2$	0.116	-0.038	-0.004	0.072*	-0.004
$m_1 m_3$	-0.023	0.010	0.004	-0.010	-0.017
$m_1 m_4$	0.082	-0.052	0.043	-0.069	0.067
$m_2 m_3$	0.055*	0.022	0.004	-0.055*	-0.035
$m_2 m_4$	-0.161*	-0.153*	-0.057	-0.096	-0.087
$m_3 m_4$	0.176	-0.022	0.062	0.064	-0.030
R^2	0.456	0.219	0.241	0.351	0.379
R_{adj}^2	0.358	0.078	0.104	0.234	0.268

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

Positive coefficients observed in soaking temperature and soaking time of FARO 60, means increase in those conditions will increase the lightness value. Increase in soaking temperature and soaking time reduces lightness value of FARO 61 while increase in sum of square of soaking temperature, soaking temperature and soaking time interaction, and soaking time and steaming time interaction, increases its lightness value. In NERICA 8, increase in steaming time, soaking temperature and soaking time increased lightness values under those conditions. The obtained lightness values coefficient of determination (R^2) for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.379, 0.219, 0.351, 0.241 and 0.456, respectively. This indicates that the generated models were not fit to predict the lightness values (Table 4.36). This is due to low R^2 (i.e < 0.70) obtained from the models coefficient of determination.

4.8.7 RSM modelling of colour

Table 4.37 shows the impacts of processing parameters on colour values. Among the rice varieties, FARO 60 had the lowest colour value. The minimum colour value observed in FARO 44 was 20.41 at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 12% paddy moisture content. FARO 52 observed minimum colour value (21.83) at 65ºC soaking temperature, 10 h soaking time, 20 min steaming time and 16% paddy moisture content while FARO 60 recorded minimum colour value (14.12) at 80ºC soaking temperature, 13 h soaking time, 25 min steaming time and 14% paddy moisture content respectively.

The minimum colour value observed in FARO 61 was 21.38 at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 12% paddy moisture content and 75ºC soaking temperature, 16 h soaking time, 30 min steaming time and 12% paddy moisture content respectively. The minimum colour value in NERICA 8 (25.36) was observed at 70ºC soaking temperature, 13 h soaking time, 15 min steaming time and 14% paddy moisture content . The percentage differences in the colour values observed in the rice varieties could to be traced to the difference in their genetic makeup, husk pigment and also the rate at which the pigment migrate to the endosperm when subjected to different processing parameters. Lamberts *et al.* (2006) and Lamberts *et al.* (2008) reported changes in colour values after parboiling. The ANOVA results for the polynomial models showed the significant processing parameters, their interactions and the adequacy of the models for colour values of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.38).

Table 4.37. Impacts of processing parameters on colour using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	CV44	CV52	CV60	CV61	CV8
65.00	10.00	20.00	12.00	24.58^{bcde}	22.61^{ef}	20.61^{a}	24.30^{bcd}	28.31^{abcde}
75.00	10.00	20.00	12.00	24.56^{bcde}	23.70^{abcdef}	20.11^{a}	24.40^{bcd}	26.98^{de}
65.00	16.00	20.00	12.00	23.03^{defg}	22.37^{ef}	20.11^{a}	24.20^{abcd}	27.83^{bcde}
75.00	16.00	20.00	12.00	20.41^{g}	24.77^{abcde}	19.74^{a}	21.38^{e}	28.00^{bcde}
65.00	10.00	30.00	12.00	26.28^{abc}	22.71^{def}	14.53^{c}	25.58^{abc}	29.47^{abcde}
75.00	10.00	30.00	12.00	25.91^{abd}	25.21^{abcde}	20.08^{a}	26.09^{ab}	28.09^{bcde}
65.00	16.00	30.00	12.00	25.51^{abcde}	23.97^{acdef}	18.41^{ab}	24.99^{abd}	28.88^{bcde}
75.00	16.00	30.00	12.00	26.33^{abc}	26.12^{ab}	15.32^{c}	21.38^{e}	27.83^{bcde}
65.00	10.00	20.00	16.00	26.35^{abc}	21.83^{f}	19.93^{a}	23.48^{cde}	28.79^{bcde}
75.00	10.00	20.00	16.00	22.90^{efg}	23.50^{bcdef}	19.08^{ab}	24.61^{abcd}	26.89^{de}
65.00	16.00	20.00	16.00	25.77^{abcde}	23.44^{bcdef}	19.35^{a}	23.33^{cde}	28.50^{bcde}
75.00	16.00	20.00	16.00	26.81^{ab}	23.20^{cdef}	21.21^{a}	22.60^{de}	29.09^{abcde}
65.00	10.00	30.00	16.00	27.54^{a}	22.39^{ef}	14.10^{c}	24.68^{abcd}	27.05^{cde}
75.00	10.00	30.00	16.00	25.66^{abcde}	25.08^{abcdef}	16.62^{bc}	26.35^{a}	33.25^{a}
65.00	16.00	30.00	16.00	21.17^{fg}	22.99^{cdef}	20.24^{a}	23.98^{abcd}	28.50^{bcde}
75.00	16.00	30.00	16.00	20.78^{g}	24.10^{abcdef}	15.71^{c}	23.41^{cde}	29.12^{abcde}
60.00	13.00	25.00	14.00	25.09^{ade}	24.27^{abcdef}	14.28^{c}	24.67^{abcd}	28.53^{bcde}
80.00	13.00	25.00	14.00	26.34^{abc}	24.71^{abcdef}	14.12^{c}	22.43^{abcd}	28.77^{bcde}
70.00	7.00	25.00	14.00	24.98^{abcd}	26.53^{a}	20.86^{a}	24.80^{de}	29.85^{abcd}
70.00	19.00	25.00	14.00	24.23^{bcde}	25.55^{abcd}	20.07^{a}	24.16^{abcd}	27.79^{bcde}
70.00	13.00	15.00	14.00	23.56^{cdef}	24.10^{abcdef}	18.28^{ab}	24.03^{abcd}	25.36^{e}
70.00	13.00	35.00	14.00	24.48^{bcde}	25.71^{abc}	20.00^{a}	24.19^{abcd}	29.28^{abcd}
70.00	13.00	25.00	10.00	24.67^{abcd}	24.51^{abcdef}	19.37^{a}	24.27^{abcd}	31.43^{abc}
70.00	13.00	25.00	18.00	24.50^{bcde}	23.07^{cdef}	19.74^{a}	23.53^{bcde}	31.95^{ab}
70.00	13.00	25.00	14.00	24.90^{abcde}	24.18^{abcdef}	19.90^{a}	24.05^{abcd}	29.28^{abcd}

Table 4.38. Colour values polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	11.891	-37.852	-300.021	13.898	54.979
m_1	-1.279*	0.949	8.790*	0.532*	0.289*
m_2	-0.037*	0.327	1.708*	2.701*	1.604*
m_3	2.063	-0.312	-0.030	0.116	0.299*
m_4	4.887*	3.756	0.526*	-3.459	-7.547
m_1^2	0.007	-0.005	-0.056*	-0.005*	-0.010
m_2^2	-0.011	0.030*	0.018	0.013	-0.024
m_3^2	-0.010	-0.001*	-0.007	0.001*	-0.024
m_4^2	-0.025	-0.074	-0.017	-0.008	0.126*
$m_1\,m_2$	0.019	-0.011	-0.054	-0.046*	-0.005
$m_1\,m_3$	0.008	0.009	0.001	0.001	0.017
$m_1\,m_4$	-0.016	-0.018	-0.016	0.046	0.057
$m_2\,m_3$	-0.038*	-0.001	0.015	-0.015*	-0.025
$m_2\,m_4$	-0.019*	-0.022*	0.089	0.027	-0.005
$m_3\,m_4$	-0.113	-0.012	-0.004	0.004	0.009
R^2	0.4556	0.2187	0.2405	0.3508	0.379
R^2_{adj}	0.3579	0.0784	0.1042	0.2343	0.2675

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

Increase in paddy moisture content, increases colour values of FARO 44 while increase in soaking temperature and soaking time decreases colour value. Sum of square of soaking time and soaking temperature and double interaction of soaking time and paddy moisture was observed to have influence on colour value in FARO 52. Soaking temperature, soaking time, paddy moisture content and sum of square of soaking temperature had significant influence on colour value of FARO 60. However, for FARO 61, it was observed that increase in soaking temperature and soaking time increases its colour value. Positive coefficients observed at soaking temperature, soaking time, steaming time and sum of square of paddy moisture content of NERICA 8, means increase in those conditions increases its colour value. Sareepuang *et al.* (2008) reported that discolouration was mainly caused by Millard reaction. The coefficient of determination (R^2) of the colour values for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.379, 0.219, 0.351, 0.241 and 0.456, respectively, indicating the non-fitness of models to predict colour values.

4.8.8 RSM modelling of cooking time

Cooking time is one of the quality indices of rice that determines how fuel and energy will be consumed. Table 4.39 shows the impacts of processing parameters on cooking time. Among the rice varieties, NERICA 8 was observed to have the lowest cooking time. The shortest cooking time observed in FARO 44 was 18.95 min at 65ºC soaking temperature, 10 h soaking time, 30 min steaming time and 16% paddy moisture content. FARO 52 observed shortest cooking time (21.51) at 65ºC soaking temperature, 16 h soaking time, 20 min steaming time and 16% paddy moisture content while FARO 60 recorded shortest cooking time (23.30) at 70ºC soaking temperature, 13 h soaking time, 15 min steaming time and 14% paddy moisture content respectively. The shortest cooking time observed in FARO 61 was 18.18 at 70ºC soaking temperature, 13 h soaking time, 15 min steaming time and 14% paddy moisture content. The shortest cooking time occurred at 65ºC soaking temperature, 16 h soaking time, 20 min steaming time and 16% moisture content in NERICA 8. The extent of starch gelatinization could lead to differences in the cooking time of the varieties. The ANOVA results for the polynomial models showed significant processing parameters and their interactions and also the adequacy of the models for the cooking time of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.40).

Table 4.39. Impacts of processing parameters on cooking time using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	CT44 (min)	CT52 (min)	CT60 (min)	CT61 (min)	CT8 (min)
65.00	10.00	20.00	12.00	22.90^{k}	21.61^{f}	28.02^{l}	20.78^{lk}	13.78^{gf}
75.00	10.00	20.00	12.00	49.27^{bc}	28.36^{d}	36.21^{e}	29.17^{b}	23.23^{abcd}
65.00	16.00	20.00	12.00	35.58^{fg}	27.43^{d}	37.52^{de}	25.64^{gh}	25.11^{abc}
75.00	16.00	20.00	12.00	41.25^{e}	27.54^{d}	35.56^{e}	20.67^{l}	25.26^{abc}
65.00	10.00	30.00	12.00	23.82^{k}	30.34^{c}	29.24^{jkl}	27.46^{ef}	14.26^{gf}
75.00	10.00	30.00	12.00	45.46^{d}	22.43^{f}	28.27^{l}	30.88^{a}	15.63^{gf}
65.00	16.00	30.00	12.00	40.47^{e}	27.55^{d}	31.42^{ghi}	26.55^{fg}	17.33^{defg}
75.00	16.00	30.00	12.00	51.46^{a}	28.53^{d}	33.38^{f}	22.68^{ij}	25.96^{abc}
65.00	10.00	20.00	16.00	29.67^{hi}	22.33^{f}	28.58^{l}	26.55^{a}	13.78^{gf}
75.00	10.00	20.00	16.00	50.45^{ab}	28.60^{d}	32.31^{gf}	31.25^{g}	14.51^{gf}
65.00	16.00	20.00	16.00	40.51^{e}	21.51^{f}	37.49^{cde}	26.02^{h}	12.75^{g}
75.00	16.00	20.00	16.00	48.36^{b}	25.26^{e}	42.15^{a}	24.87^{g}	14.57^{gf}
65.00	10.00	30.00	16.00	18.95^{l}	32.35^{b}	28.78^{lk}	26.24^{jk}	13.25^{gf}
75.00	10.00	30.00	16.00	34.38^{g}	22.50^{f}	33.68^{f}	21.77^{jk}	29.63^{a}
65.00	16.00	30.00	16.00	36.53^{f}	28.60^{d}	37.94^{c}	28.73^{bcd}	14.07^{gf}
75.00	16.00	30.00	16.00	34.93^{fg}	25.69^{e}	30.09^{ijk}	23.34^{i}	15.28^{gf}
60.00	13.00	25.00	14.00	30.62^{h}	24.43^{e}	30.86^{ghi}	28.04^{cde}	22.26^{bcde}
80.00	13.00	25.00	14.00	51.58^{a}	27.31^{d}	35.27^{ce}	27.85^{a}	26.23^{ab}
70.00	7.00	25.00	14.00	35.36^{fg}	35.44^{a}	38.62^{bc}	30.71^{a}	13.35^{gf}
70.00	19.00	25.00	14.00	27.59^{j}	27.24^{d}	36.01^{e}	31.28^{a}	25.60^{abc}
70.00	13.00	15.00	14.00	22.32^{k}	22.33^{f}	23.30^{m}	18.18^{m}	16.70^{efg}
70.00	13.00	35.00	14.00	22.41^{k}	22.54^{f}	31.18^{ghi}	30.63^{a}	24.31^{abc}
70.00	13.00	25.00	10.00	22.32^{k}	22.21^{f}	39.72^{b}	21.74^{kj}	26.93^{ab}
70.00	13.00	25.00	18.00	22.41^{k}	22.51^{f}	30.59^{hij}	28.23^{bcde}	19.61^{cdef}
70.00	13.00	25.00	14.00	28.19^{ij}	28.21^{d}	31.89^{gh}	28.98^{bc}	25.65^{abc}

Table 4.40. Cooking time polynomial regression coefficients

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	373.568	-298.798	-39.739	-412.327	-361.086
m_1	-18.541*	4.716	0.786*	6.009	5.818*
m_2	9.198*	-3.061*	2.474*	4.953*	18.848
m_3	5.776*	8.391*	5.526	7.416*	-0.717*
m_4	18.613	10.937	-6.929	14.718*	8.202*
m_1^2	0.185*	-0.018*	0.012	-0.019*	-0.040*
m_2^2	0.247*	0.102*	0.150*	0.032	-0.243*
m_3^2	-0.002	-0.052*	-0.047*	-0.054*	-0.077*
m_4^2	-0.013	-0.333*	0.203*	-0.304*	-0.309*
$m_1 m_2$	-0.255*	0.028	-0.079*	-0.114*	-0.067
$m_1 m_3$	-0.036	-0.091*	-0.041*	-0.043*	0.039
$m_1 m_4$	-0.139	-0.017	-0.011	-0.058	0.003
$m_2 m_3$	0.114*	0.008	-0.061*	0.023	-0.052*
$m_2 m_4$	-0.004	-0.136*	0.085	0.103	-0.430*
$m_3 m_4$	-0.353*	0.047	0.031	-0.124*	0.193*
R^2	0.786	0.708	0.521	0.679	0.612
R^2_{adj}	0.747	0.655	0.435	0.621	0.543

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

Increase in soaking time and steaming time, was observed to increase cooking time while increase in soaking temperature reduces cooking time in FARO 44. However for FARO 52, it was observed that an increase in steaming time increases the cooking time while increase in soaking time decreases cooking time. It was observed that increase in soaking temperature and soaking time increases cooking time in FARO 60 while increase in soaking time, steaming time and paddy moisture content increases cooking time in FARO 61. Increase in soaking temperature and paddy moisture content increases cooking time in NERICA 8 while increase in steaming time reduces its cooking time. The obtained cooking time R^2 values for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.612, 0.708, 0.679, 0.521, and 0.786, respectively. It can be inferred from the obtained R^2 of FARO 44 and FARO 52 models that the models are fit to predict cooking time (R^2>0.70) while FARO 60, FARO 61 and NERICA 8 models were not fit to predict the cooking time (R^2<0.70).

4.8.9 RSM modelling of water uptake ratio

Table 4.41 shows the impacts of processing parameters on water uptake ratio. FARO 52 had the highest water uptake ratio. According to Manful (2010), the highest water uptake ratio gave rice with the highest degree of gelatinization. The highest water uptake ratio observed in FARO 44 was 4.10 at 65ºC soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content. FARO 52 observed highest water uptake ratio (4.95) at 65ºC soaking temperature, 16 h soaking time, 20 min steaming time and 16% paddy moisture content while FARO 60 recorded highest water uptake ratio (4.07) at 75ºC soaking temperature, 16 h soaking time, 20 min steaming time and 16%paddy moisture content respectively.

The highest water uptake ratio observed in FARO 61 was 4.01 at 70ºC soaking temperature, 19 h soaking time, 25 min steaming time and 14% paddy moisture content. The highest water uptake ratio (4.83) occurred at 65ºC soaking temperature, 16 h soaking time, 30 min steaming time and 16% paddy moisture content in NERICA 8. These results are in accordance with Fofana *et al.* (2011) findings that reported significant differences in water uptake ratio under different processing parameters.

Table 4.41. Impacts of processing parameters on water uptake ratio using RSM

Soaking Temp. (°C)	Soaking Time (h)	Steaming Time (min)	Paddy Moisture Content (%)	WUR44	WUR52	WUR60	WUR61	WUR8
65	10	20	12	2.95^{lm}	3.23^{fgh}	3.23^{b}	2.81^{l}	3.55^{cd}
75	10	20	12	3.59^{cdef}	3.24^{fgh}	3.56^{ab}	3.86^{abc}	3.40^{de}
65	16	20	12	3.32^{hij}	3.57^{cdef}	3.46^{ab}	2.92^{kl}	3.23^{ef}
75	16	20	12	3.60^{cdef}	3.79^{bc}	3.65^{ab}	3.26^{ghi}	3.24^{ef}
65	10	30	12	2.78^{m}	3.64^{bcde}	3.27^{b}	3.15^{hij}	3.21^{ef}
75	10	30	12	3.40^{efghi}	2.72^{i}	3.09^{b}	3.76^{cd}	3.78^{bc}
65	16	30	12	3.59^{cdef}	3.28^{efgh}	3.49^{ab}	3.19^{ghij}	2.92^{ghi}
75	16	30	12	3.71^{cd}	3.45^{cdefg}	3.86^{ab}	3.34^{fgh}	3.34^{de}
65	10	20	16	3.46^{efgh}	3.16^{gh}	2.21^{c}	3.16^{ghij}	3.24^{ef}
75	10	20	16	3.24^{hijk}	3.35^{defgh}	3.28^{ab}	3.81^{abc}	2.98^{fgh}
65	16	20	16	3.79^{bc}	4.95^{a}	3.80^{ab}	3.48^{ef}	4.83^{a}
75	16	20	16	3.37^{efghij}	3.68^{bcd}	4.07^{a}	3.90^{abc}	3.99^{a}
65	10	30	16	3.21^{ijk}	3.55^{cdef}	3.24^{b}	3.23^{ghij}	3.17^{efg}
75	10	30	16	3.05^{kl}	3.14^{gh}	3.34^{ab}	3.34^{fgh}	2.99^{fgh}
65	16	30	16	4.10^{a}	3.43^{cdefg}	3.63^{ab}	3.11^{ij}	4.83^{a}
75	16	30	16	3.13^{jkl}	3.31^{efgh}	3.15^{bc}	3.76^{bc}	4.80^{a}
60	13	25	14	3.2^{1ijk}	3.33^{defgh}	3.20^{b}	3.12^{ij}	2.91^{ghi}
80	13	25	14	3.55^{defg}	3.73^{bc}	3.86^{ab}	3.57^{cd}	3.33^{de}
70	7	25	14	3.94^{ab}	3.94^{b}	3.76^{ab}	3.37^{fg}	2.77^{hij}
70	19	25	14	3.34^{fghij}	3.35^{defgh}	3.45^{ab}	4.01^{a}	3.37^{de}
70	13	15	14	3.16^{ijkl}	3.17^{gh}	3.44^{ab}	3.18^{ghij}	2.59^{j}
70	13	35	14	3.58^{cdef}	3.62^{bcdef}	3.09^{b}	3.79^{abc}	2.89^{hi}
70	13	25	10	3.28^{hijk}	3.33^{defgh}	3.34^{ab}	3.04^{jk}	3.28^{e}
70	13	25	18	3.04^{kl}	3.05^{h}	3.13^{b}	3.30^{fghi}	2.67^{ij}
70	13	25	14	3.15^{jkl}	3.23^{fgh}	3.29^{ab}	3.97^{ab}	2.70^{ij}

The ANOVA results for the quadratic models showed the significant processing parameters, their interactions and the adequacy of the models for water uptake ratio of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 (Table 4.42). From Table 4.42, increase in soaking time, increases water uptake ratio in FARO 44 while increase in soaking time decreases the water uptake ratio in FARO 52. However for FARO 60, increase in soaking temperature decreases the water uptake ratio. Increased soaking time, increases the water uptake ratio in FARO 60. Increase in soaking temperature, soaking time and paddy moisture content increases water uptake ratio in FARO 61. Increase in soaking time and paddy moisture content decreases water uptake ratio in NERICA 8. The coefficient of determination (R^2) for water uptake ratio values for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 were 0.674, 0.319, 0.809, 0.292 and 0.615, respectively. It can be deduced from the R^2 that the models were not fit to predict the water uptake ratio except the model for FARO 61 that has $R^2 > 0.70$.

4.9 Total Energy Consumption Simulation Using Artificial Neural Network (ANN)

Figure 4.4 shows the optimum architecture of the developed ANN model for simulating total energy consumption of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. 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 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the total energy consumption were achieved after repeated trials of different neurons and transfer function. 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.

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 4.5 represent artificial neural network simulation performance for total energy consumption.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 4.5 (a) and (b).

Table 4.42. Water uptake ratio polynomial regression coefficients models

Coefficients	FARO44	FARO52	FARO60	FARO61	NERICA8
Constant	-12.430	10.268	2.729	-56.140	66.522
m_1	0.119	-0.342	-0.136*	1.084*	-1.075
m_2	0.092*	-0.184*	0.081*	0.263*	-1.483*
m_3	-0.026	0.197	0.437	0.557	-0.685
m_4	1.541	0.552	-0.222	1.653*	-1.313*
m_1^2	0.002*	0.003*	0.002	-0.006*	0.008*
m_2^2	0.014*	0.012*	0.008*	-0.008*	0.022*
m_3^2	0.002*	0.002	0.000*	-0.005*	0.004*
m_4^2	0.001	-0.001	-0.004*	-0.052*	0.043*
$m_1\,m_2$	-0.008*	0.000	-0.004*	-0.004*	-0.002
$m_1\,m_3$	-0.002	-0.001	-0.005*	-0.002*	0.005*
$m_1\,m_4$	-0.021*	-0.007	0.002	-0.002*	-0.014*
$m_2\,m_3$	0.005*	-0.011*	-0.006*	0.000	0.003
$m_2\,m_4$	-0.001	0.010	0.013	0.016	0.076*
$m_3\,m_4$	-0.002	-0.006	0.001	-0.009	0.006
R^2	0.615	0.319	0.292	0.809	0.674
R^2_{adj}	0.546	0.197	0.164	0.775	0.615

m_4 , m_2, m_3 and m_1 are Paddy moisture content ,Soaking temperature, Steaming time and Soaking time. R^2 is Coefficient of determination, R_{adj}^2 is Coefficient of determination adjusted and * significant at 5% level

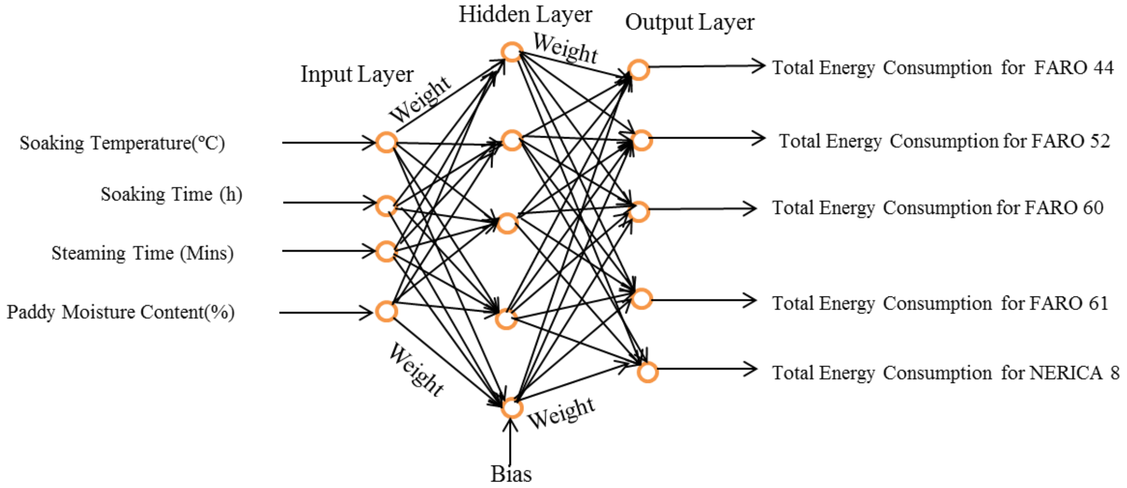


Fig. 4.4. The optimum architecture of the developed ANN model for total energy consumption

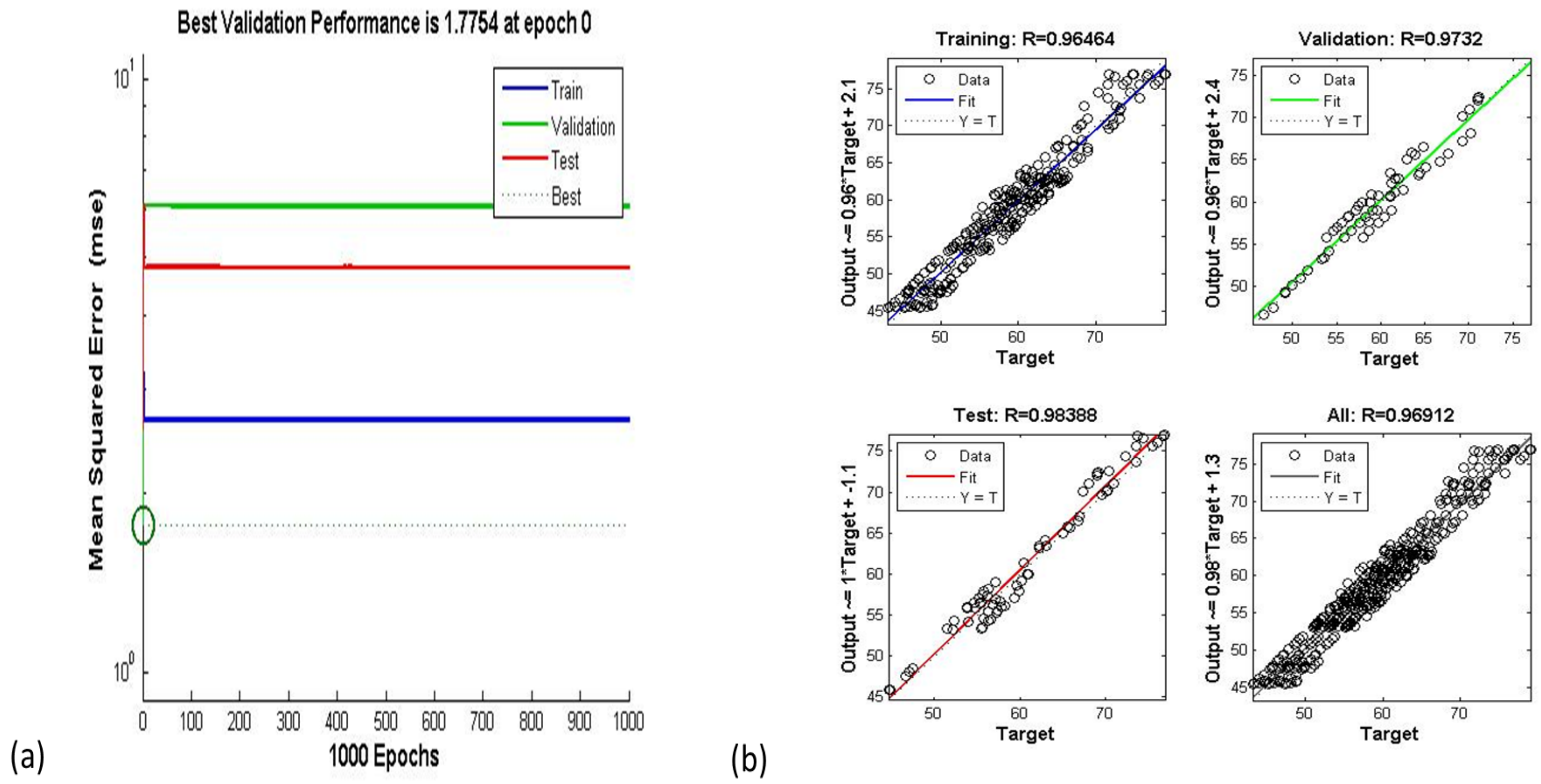


Fig. 4.5. Artificial neural network simulation performance for total energy consumption

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 (Fig. 4.5b). 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 experimental values was plotted for each variety as depicted in Fig. 4.6 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental 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 experimental 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.

4.10 Artificial Neural Network (ANN) Simulation of Quality Attributes

4.10.1 Artificial neural network simulation of brown rice recovery

Figure 4.7 shows the optimum architecture of the developed ANN model for simulating brown rice recovery of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. 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 and output layer and five outputs which are the brown rice recovery for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the brown rice recovery were achieved after repeated trials of different topology and transfer function. 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. The selection of suitable artificial neural network architecture, neurons, and transfer function is critical for successful application of ANN as a predictive model, as tangent sigmoid transfer function used influenced the ANN learning rate and its performance in predicting brown rice recovery. The optimum ANN model for brown rice recovery was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in figure 4.8a and b.

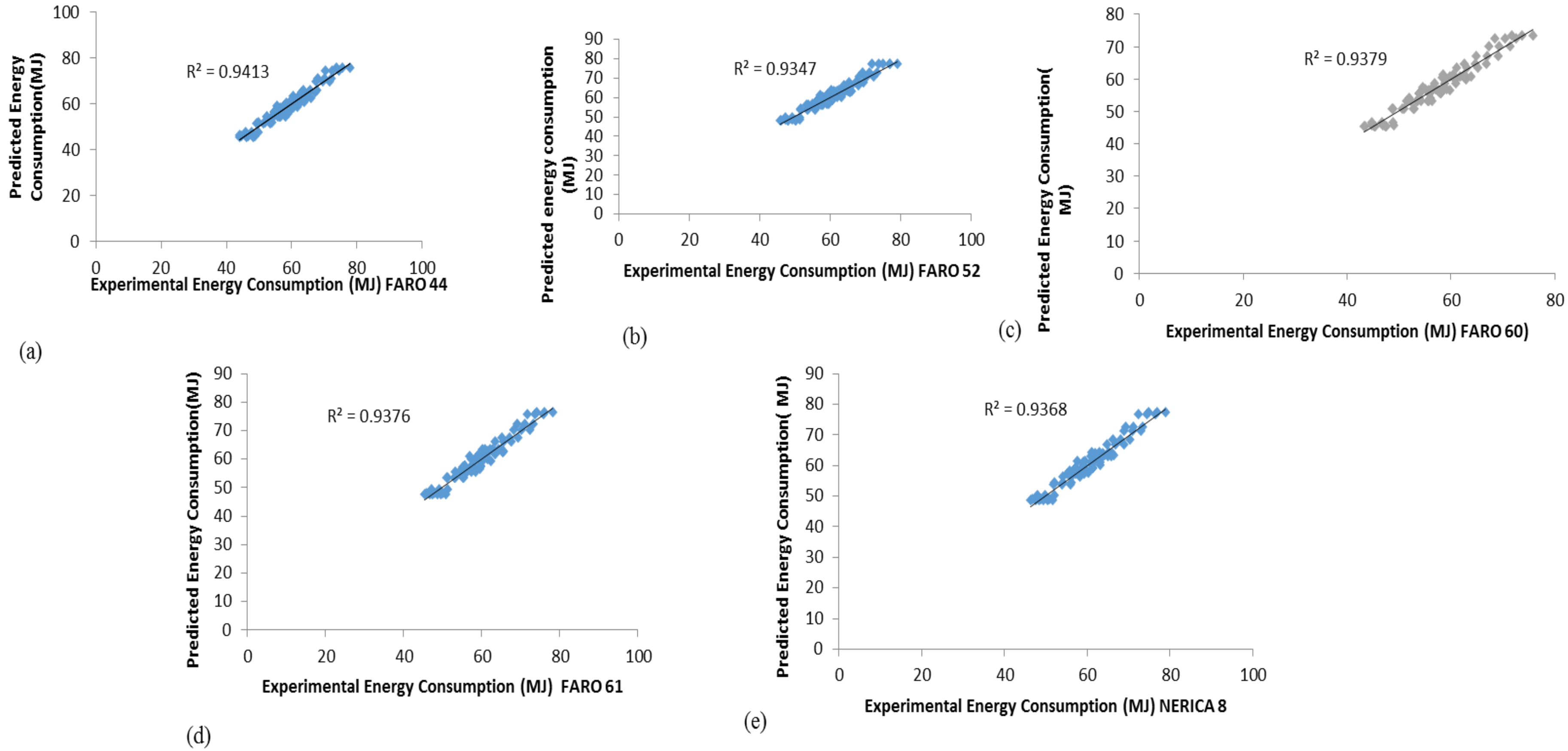


Fig. 4.6. Comparison between the experimental energy consumption values and predicted energy consumption values using ANN

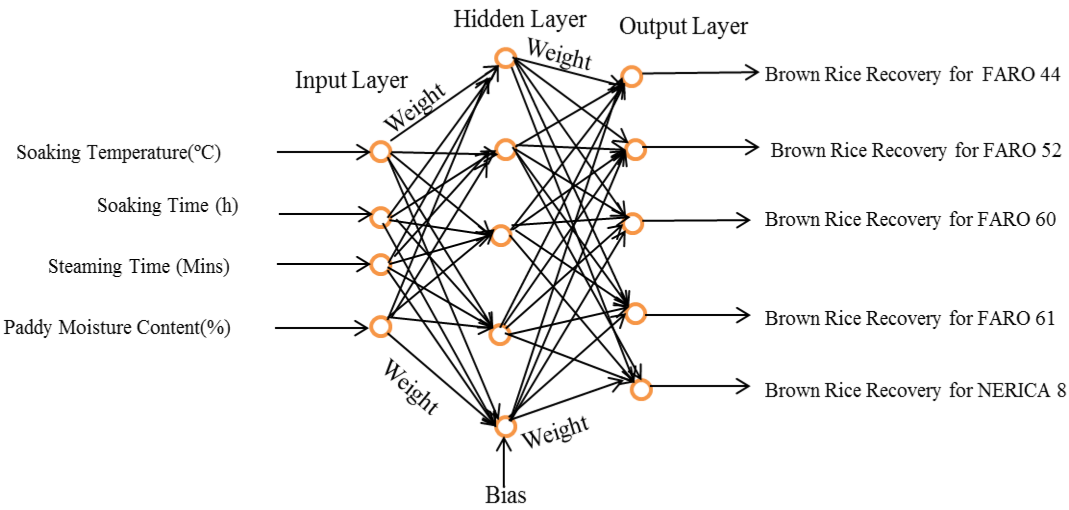


Fig. 4.7. The optimum architecture of the developed ANN model for brown rice recovery

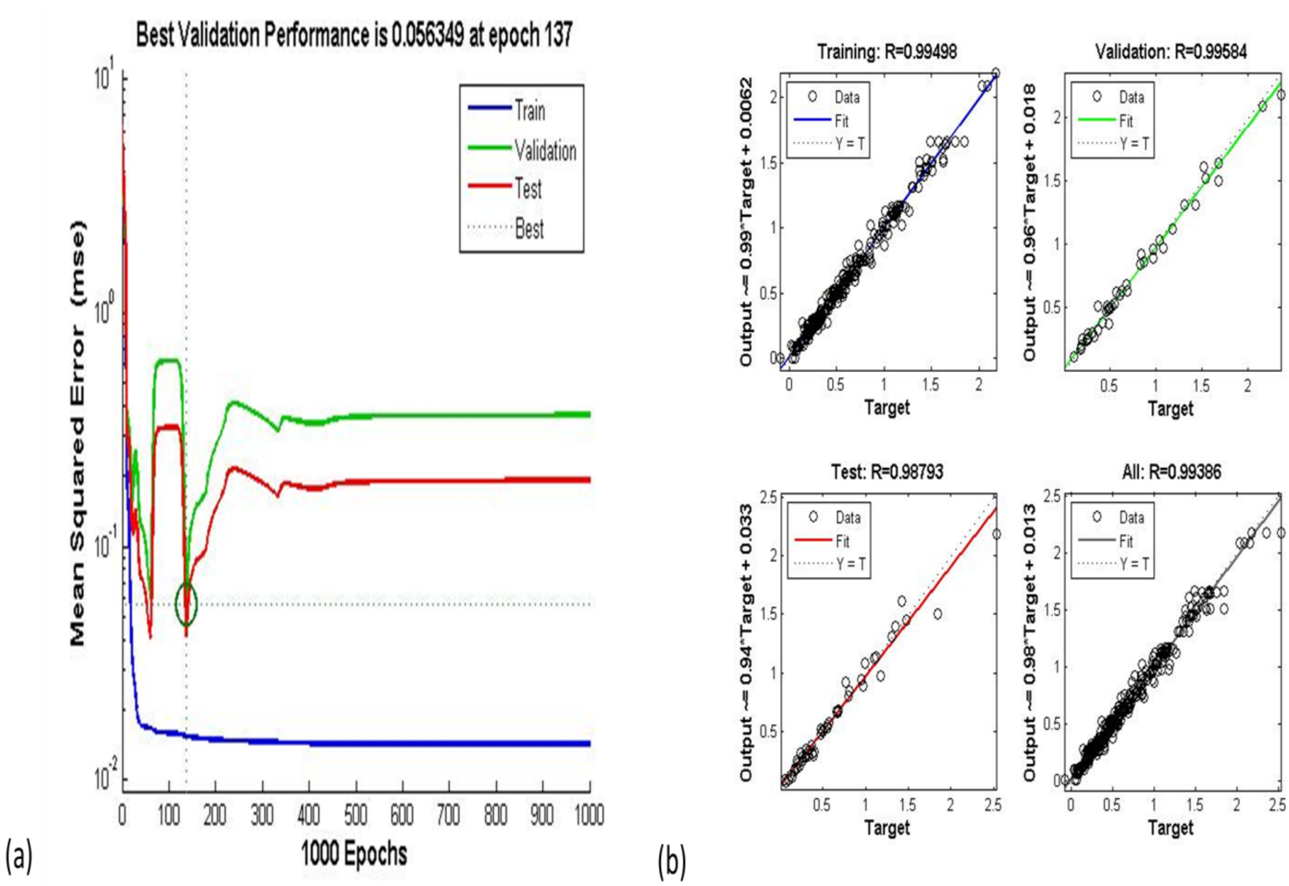


Fig. 4.8. Artificial neural network simulation performance for brown rice recovery

The Figure 4.8a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for brown rice recovery. 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 R of 0.999, 0.995, 0.987 and 0.993 for training, validation, testing and all data respectively (Fig. 4.8b). The MSE value was found to be 0.056349 at 137 epochs for the optimum architecture of the ANN model for brown rice recovery. The predictive capability of the generated ANN model for brown rice recovery was tested using unknown set of inputs data and the ANN predicted values versus experimental values (unknown inputs) were plotted for each variety as depicted in Fig. 4.9 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.979, 0.896, 0.989, 0.965 and 0.931for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively while the mean square error between the predicted values and experimental values were 0.034, 0.049, 0.017, 0.009 and 0.019 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 brown rice recovery was high.

4.10.2 Head brown rice simulation using artificial neural network

Figure 4.10 shows the optimum architecture of the developed ANN model for simulating head brown rice of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimal architecture has 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 and output layer and five outputs which are the head brown rice for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the head brown rice were achieved after repeated trials of different topology and transfer function. 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. 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.

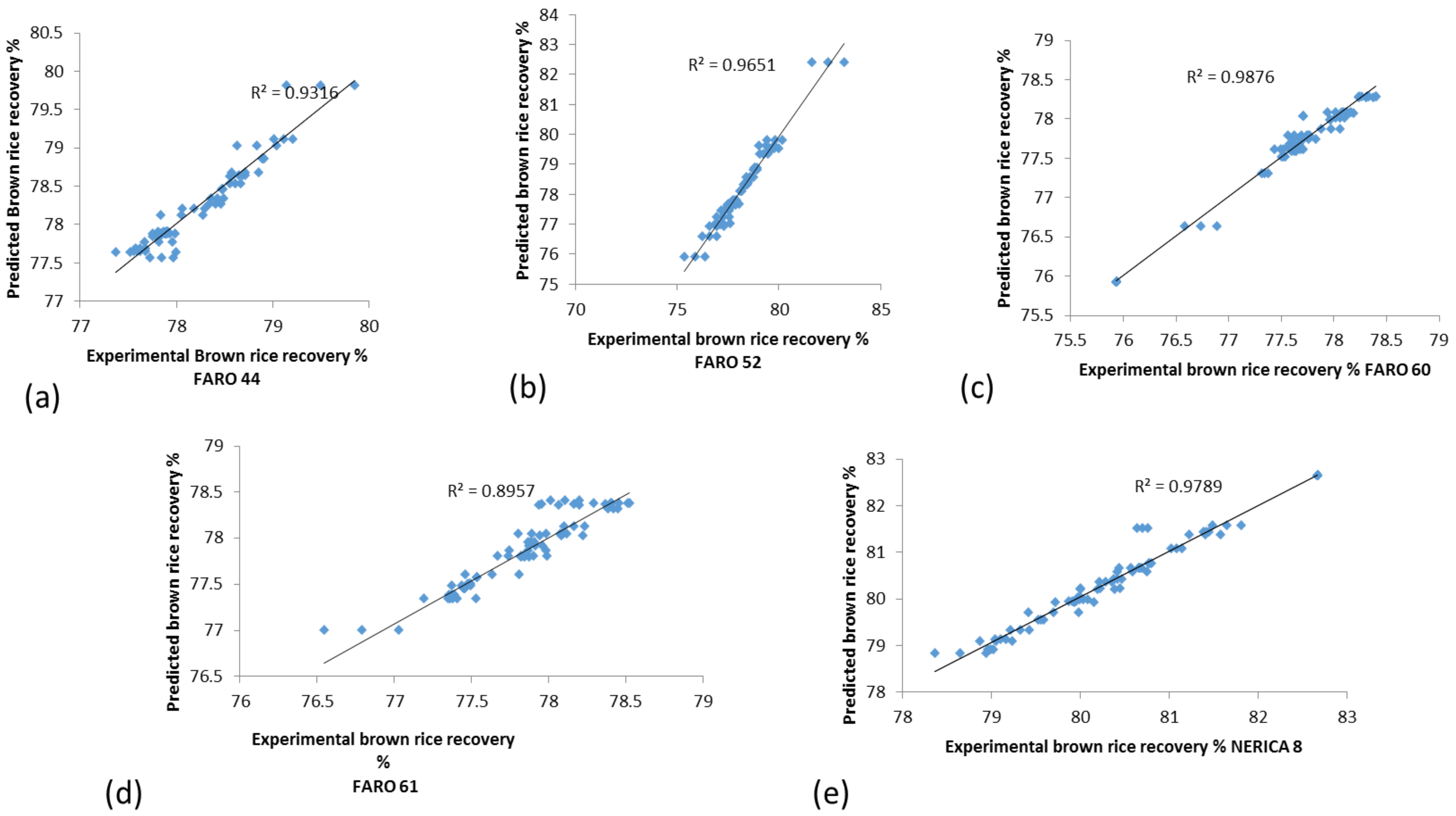


Fig. 4.9. Comparison between the experimental brown rice recovery and predicted brown rice recovery using ANN

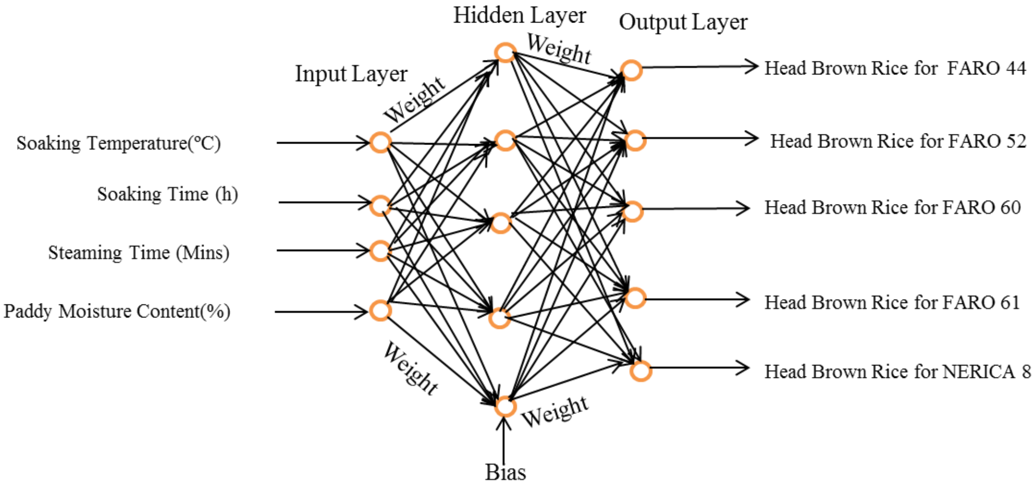


Fig. 4.10. The optimum architecture of the developed ANN model for brown rice recovery

The optimum ANN model for head brown rice was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.11a and b. The Figure 4.11a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for head brown rice. 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 R of 0.990, 0.996, 0.976 and 0.990 for training, validation, testing and all data, respectively (Fig. 4.11b). The MSE value was found to be 0.01836 at 4 epochs for the optimal architecture of the ANN model for head brown rice.

The predictive capability of the generated ANN model for head brown rice was tested using unknown set of inputs data and the ANN predicted values versus experimental values (unknown inputs) were plotted for each variety as depicted in Fig. 4.12 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.972, 0.867, 0.813, 0.954, and 0.965 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 0.051, 0.064, 0.049, 0.03, and 0.046 and 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 head brown rice was high.

4.10.3 Milling recovery simulation using artificial neural network

Figure 4.13 shows the optimum architecture of the developed ANN model for simulating milling recovery of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. 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 and output layer and five outputs which are the milling recovery NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the milling recovery were achieved after repeated trials of different topology and transfer function. 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 for milling recovery.

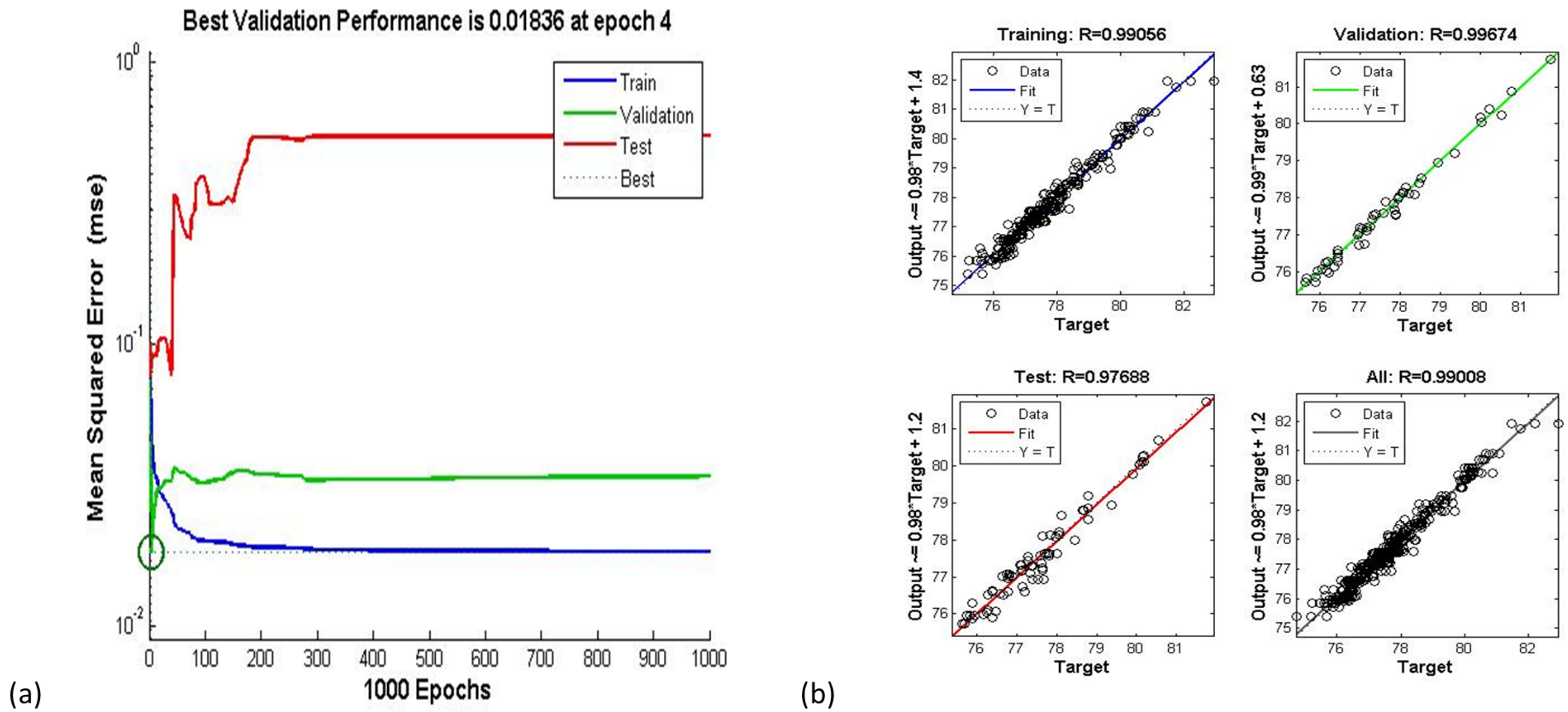


Fig. 4.11 Artificial neural network simulation performance for head brown rice

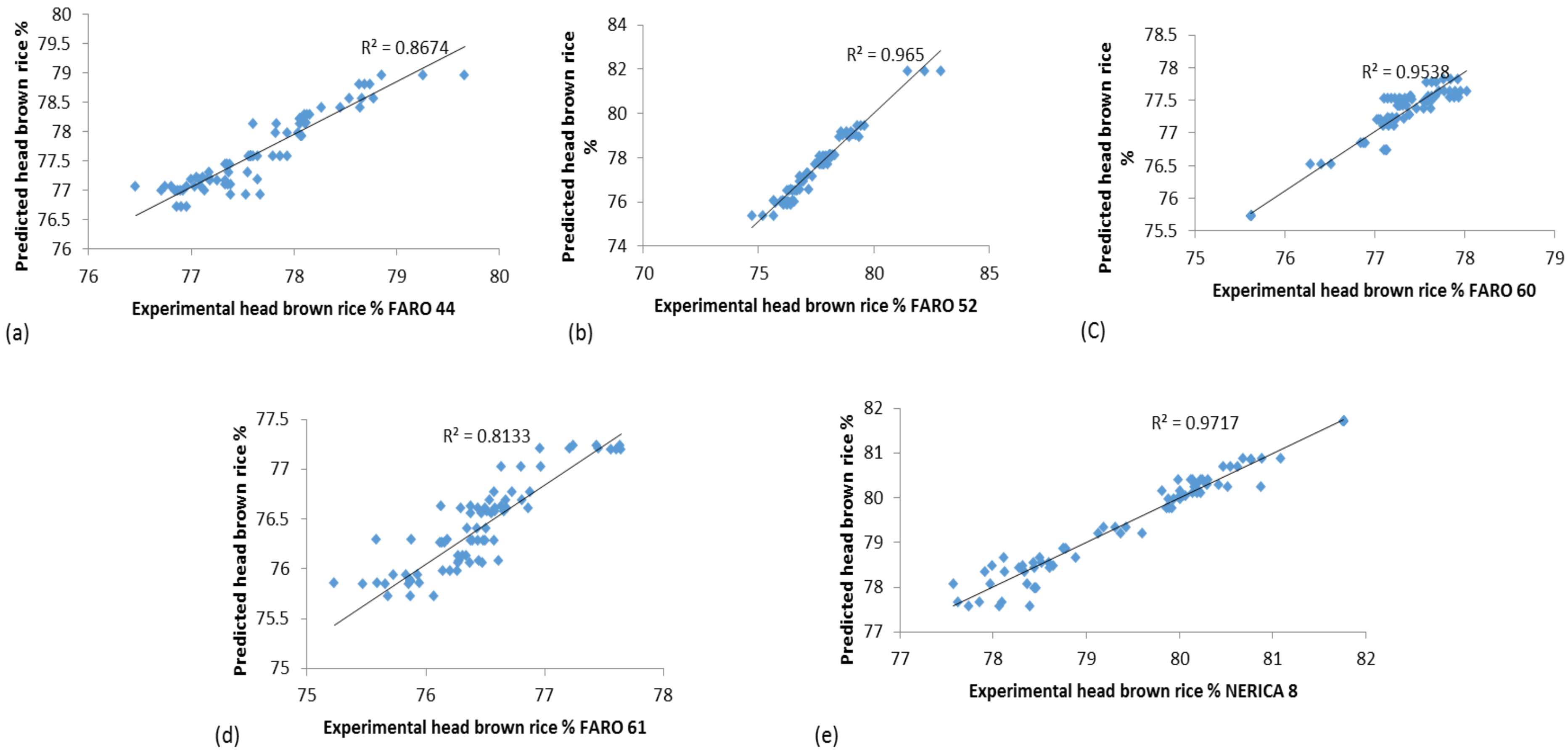


Fig. 4.12. Comparison between the experimental brown rice recovery and predicted head brown rice using ANN

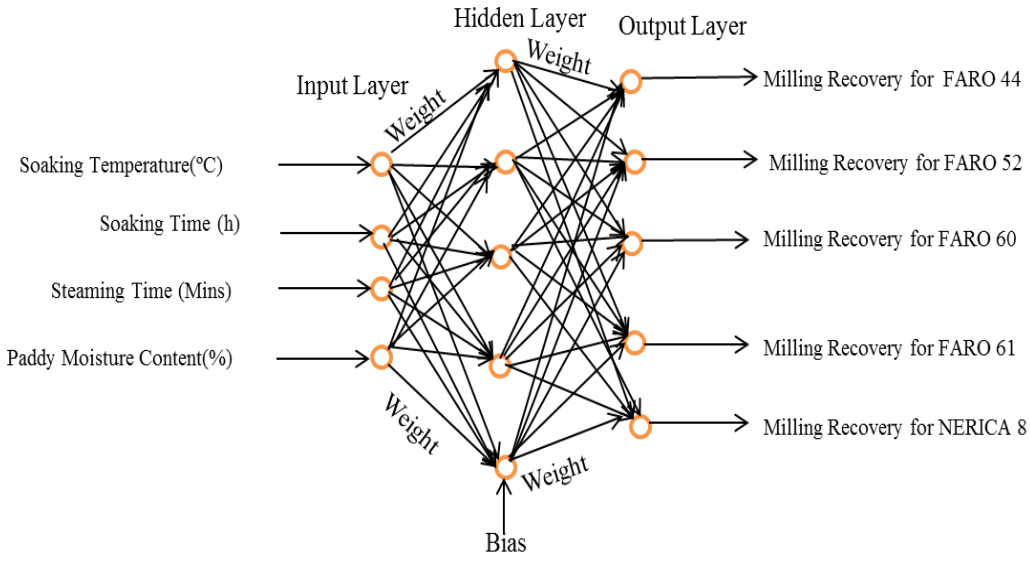
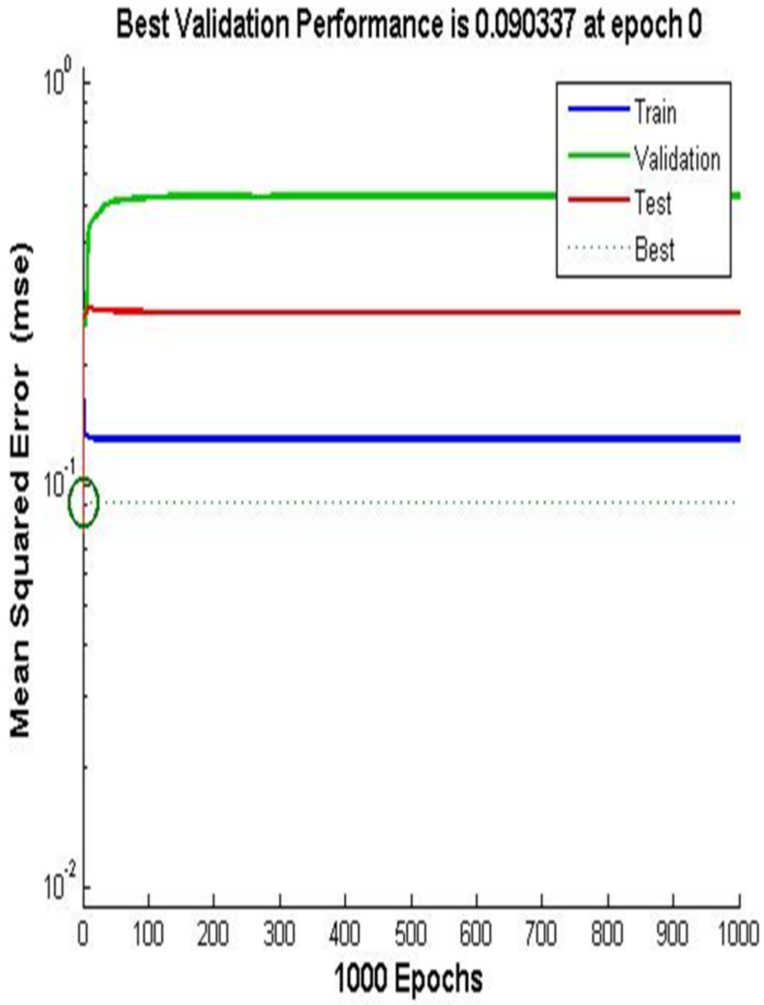


Fig. 4.13. The optimum architecture of the developed ANN model for milling recovery

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 (Yadav *et al.,* 2017). The optimum ANN model for milling recovery was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.14a and b. The Figure 4.14a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for milling recovery. The regression analysis between ANN predicted outputs and experimental data for milling recovery indicated a precise and effective prediction capability of ANN model for milling recovery with R of 0.9829, 0.9914, 0.9915 and 0.9849 for training, validation, testing and all data respectively (Fig. 4.14b). The MSE value was found to be 0.090 at 0 epochs for the optimal architecture of the ANN model for milling recovery.

The predictive capability of the generated ANN model for milling recovery was tested using unknown set of input data and the ANN predicted values versus experimental values (unknown inputs) were plotted for each variety as depicted in Fig. 4.15 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.944, 0.942, 0.954, 0.891 and 0.939 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 0.336, 0.087, 0.066, 0.280 and 0.067 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 milling recovery was high.

(a)



(b)

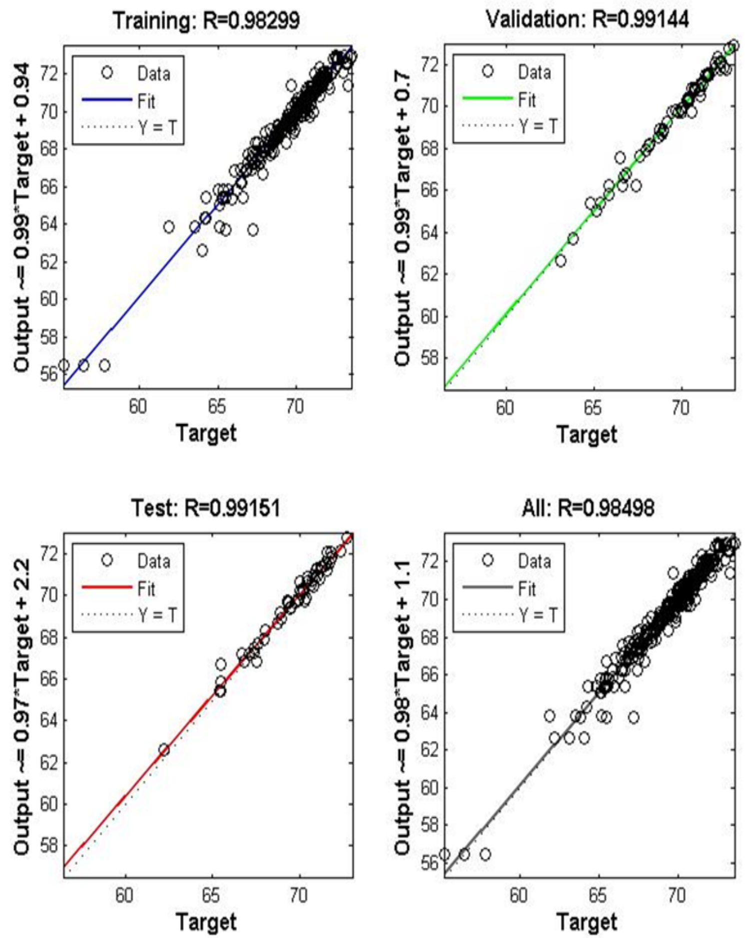


Fig. 4.14. Artificial neural network simulation performance for milling recovery

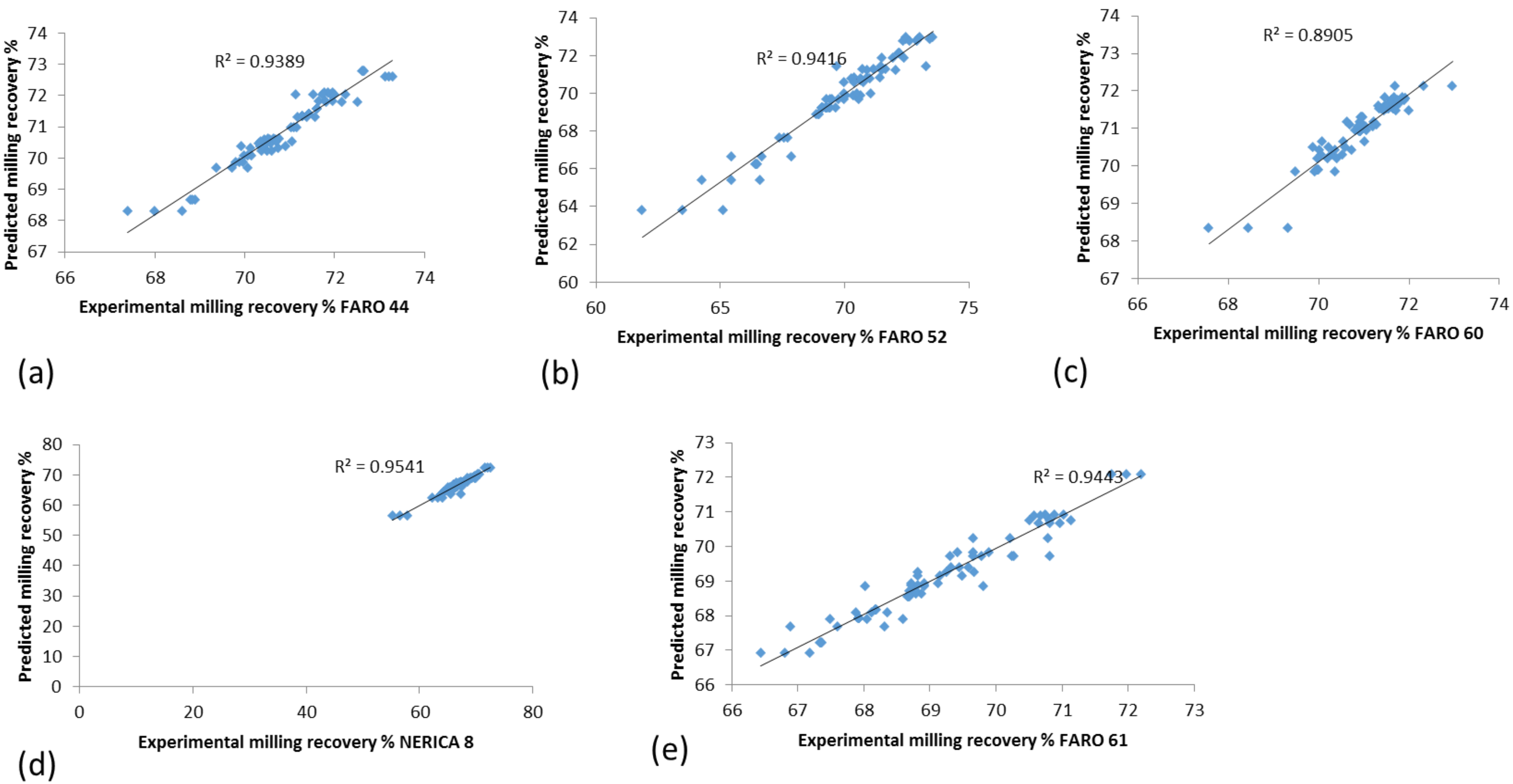


Fig. 4.15. Comparison between the experimental milling recovery values and predicted milling recovery values using ANN

4.10.4 Head milled rice simulation using artificial neural network

Figure 4.16 shows the optimum architecture of the developed ANN model for simulating head milled rice of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimum architecture had four (4) inputs (soaking temperature, soaking time, steaming time and paddy moisture content), one hidden layer with 8 neurons and tangent sigmoid function (tansig) at both hidden layer and output layer and five outputs which are the head milled rice for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the head milled rice were achieved after repeated trials of different topology and transfer function. It was observed that neural network architecture with 8 neurons at the hidden layer and one layer at the hidden layer 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.

The optimum ANN model for head milled rice was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.17a and b. The Figure 4.18a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for head milled rice. The regression analysis between ANN predicted outputs and experimental data for head milled rice indicated a precise and effective prediction capability of ANN model for head milled rice with R of 0.9108, 0.9255, 0.9472 and 0.9199 for training, validation, testing and all data respectively (Fig. 4.17b). The MSE value was found to be 3.7753 at 0 epochs for the optimal architecture of the ANN model for head milled rice. The predictive capability of the generated ANN model for head milled rice was tested using unknown set of inputs data and the ANN predicted values versus experimental values (unknown inputs) were plotted for each variety as depicted in Fig. 4.18 a, b, c, d, e.

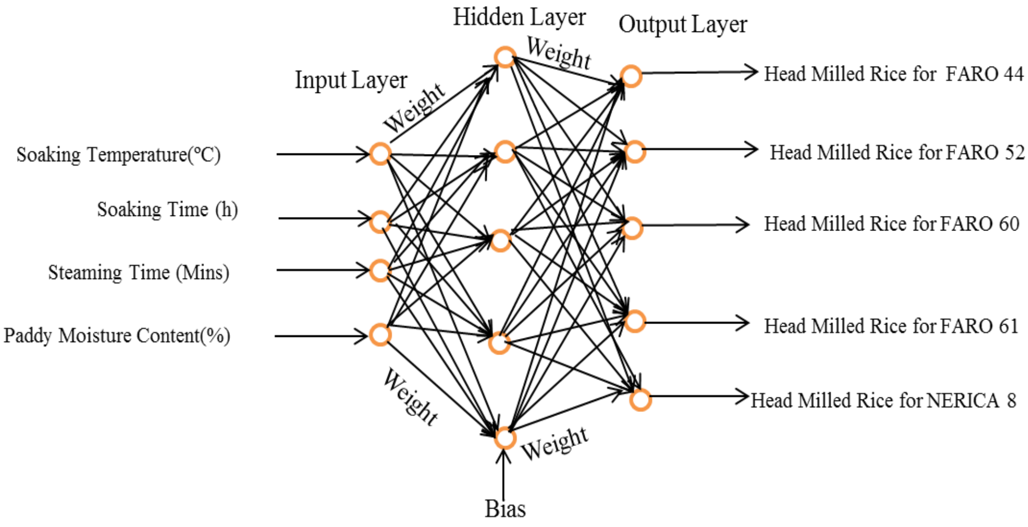


Fig. 4.16. The optimum architecture of the developed ANN model for head milled rice

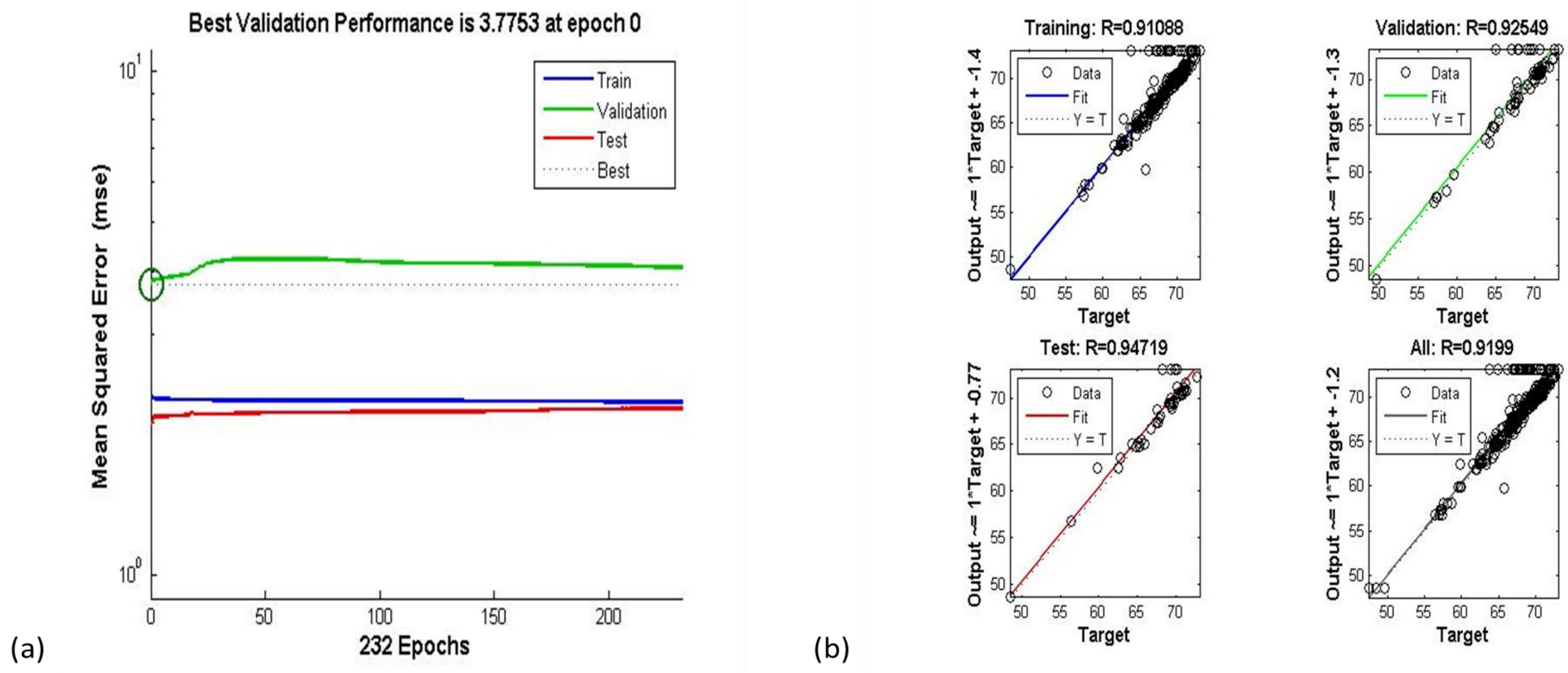


Fig. 4.17. Artificial neural network simulation performance for head milled rice

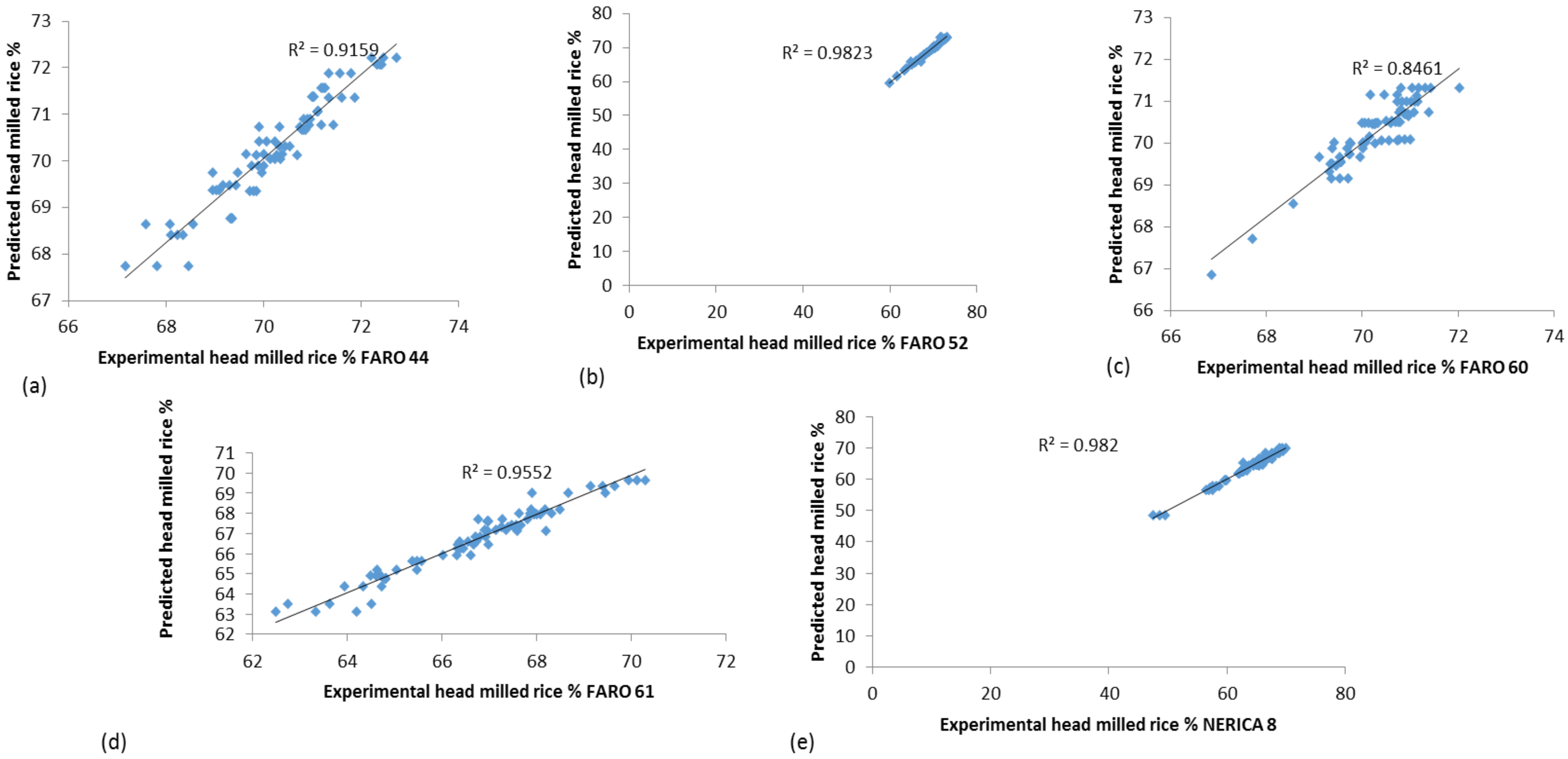


Fig. 4.18. Comparison between the experimental head milled rice and predicted head milled rice using ANN

The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.982, 0.955, 0.846, 0.982 and 0.916 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 0.327, 0.107, 0.132, 0.099 and 0.111 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 head milled rice was high.

4.10.5 Chalkiness simulation using artificial neural network

Figure 4.19 shows the optimum architecture of the developed ANN model for simulating chalkiness of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimum architecture has 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 and output layer and five outputs which are the chalkiness NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the chalkiness were achieved after repeated trials of different topology and transfer function. 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. 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 optimal ANN model for chalkiness was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.20a and b. The Figure 4.20a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for chalkiness. The regression analysis between ANN predicted outputs and experimental data for chalkiness indicated a precise and effective prediction capability of ANN model for chalkiness with R of 0.9953, 0.9817, 0.9893 and 0.9938 for training, validation, testing and all data respectively (Fig. 4.20b). The MSE value was found to be 0.14262 at 31 epochs for the optimal architecture of the ANN model for chalkiness.

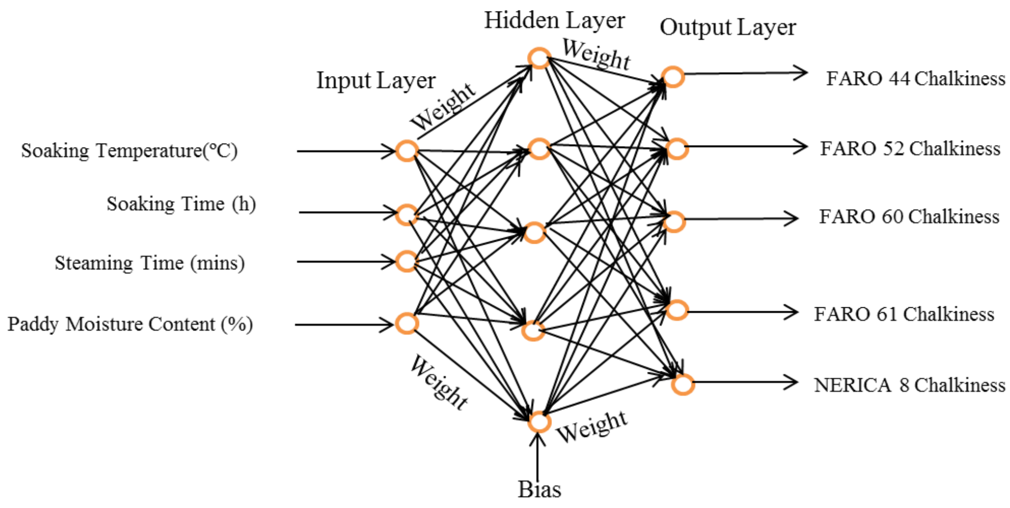


Fig. 4.19. The optimum architecture of the developed ANN model for chalkiness

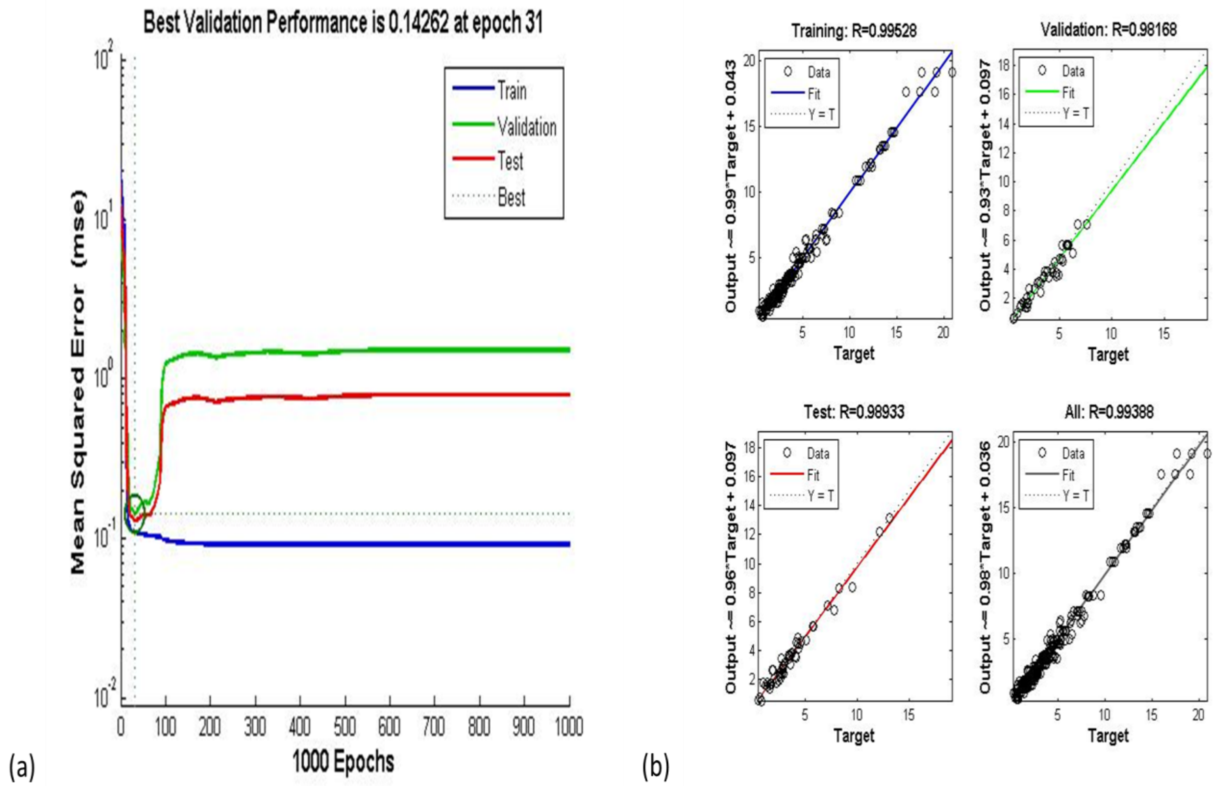


Fig. 4.20. Artificial neural network simulation performance for chalkiness

The predictive capability of the generated ANN model for chalkiness was tested using unknown set of inputs data and the ANN predicted values versus experimental values were plotted for each variety as depicted in Fig. 4.21 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.9717, 0.815, 0.976, 0.976 and 0.986 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 0.228, 0.103, 0.032, 0.032 and 0.193 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 chalkiness was high.

4.10.6 Lightness value simulation using artificial neural network

Figure 4.22 shows the optimum architecture of the developed ANN model for simulating lightness value of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimum architecture has 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 and output layer and five outputs which are the lightness for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the lightness value were achieved after repeated trials of different topology and transfer function. 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.

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 optimal ANN model for lightness value was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.23a and b. The Figure 4.23a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for lightness value. The regression analysis between ANN predicted outputs and experimental data for lightness value indicated a precise and effective prediction capability of ANN model for lightness value with R of 0.6929, 0.7405, 0.7951 and 0.7138 for training, validation, testing and all data respectively (Fig. 4.23b). The MSE value was found to be 8.7144 at 0 epochs for the optimal architecture of the ANN model for lightness value.

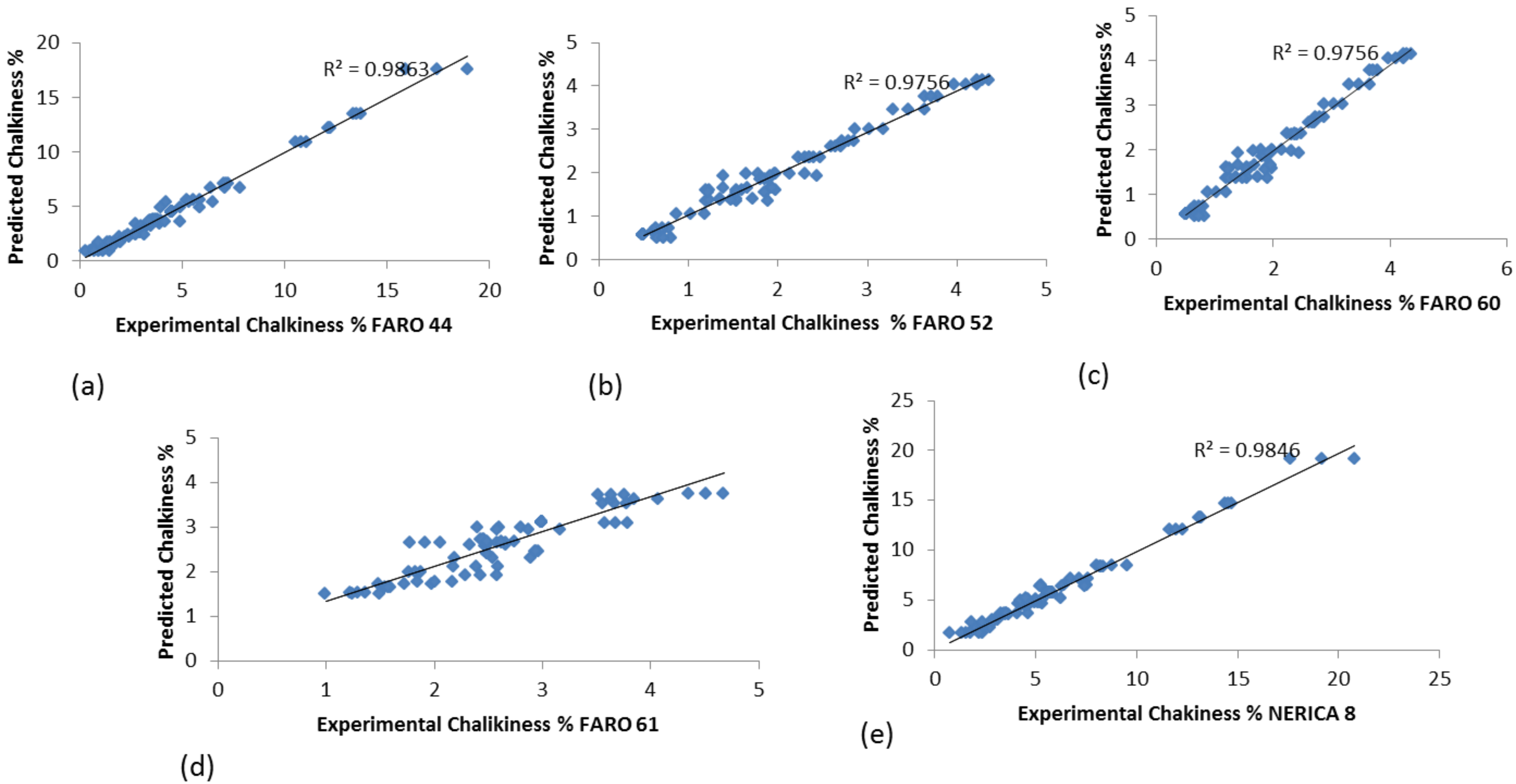


Fig. 4.21. Comparison between the experimental chalkiness and predicted chalkiness using ANN

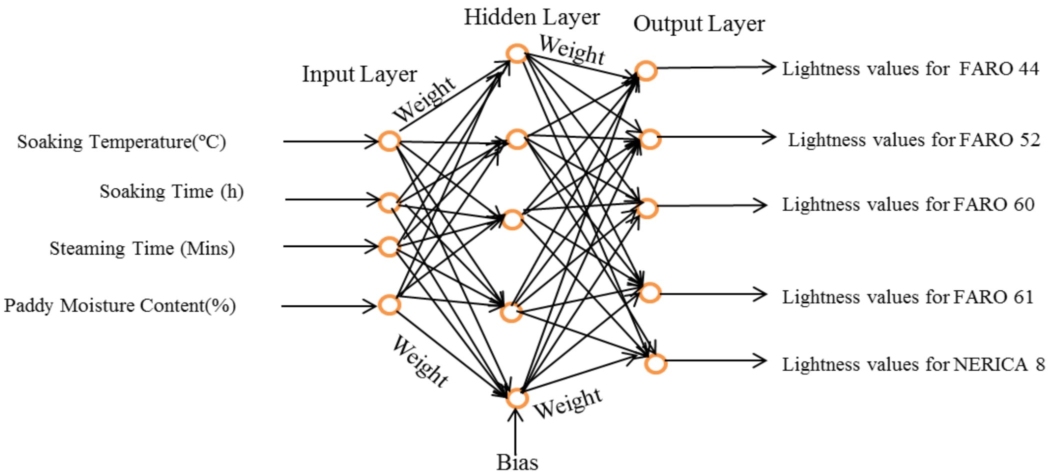


Fig. 4.22. The optimum architecture of the developed ANN model for lightness

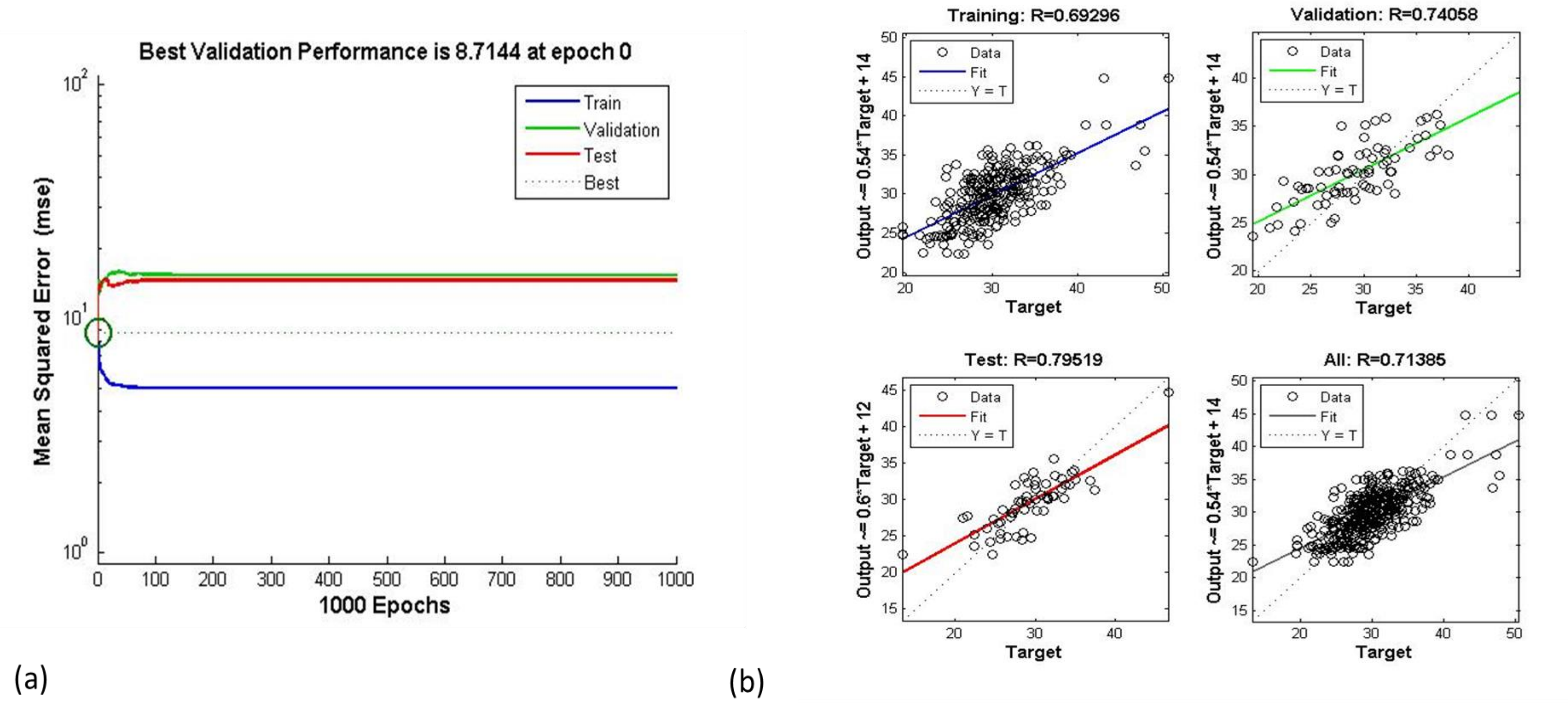


Fig. 4.23. Artificial neural network simulation performance for lightness

The predictive capability of the generated ANN model for lightness value was tested using unknown set of inputs data and the ANN predicted values versus experimental values were plotted for each variety as depicted in Fig. 4.24 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.751, 0.753, 0.766, 0.712, and 0.748 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 4.977, 2.420, 3.497, 2.595 and 7.963 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 lightness value was moderate.

4.10.7 Colour simulation using artificial neural network

Figure 4.25 shows the optimum architecture of the developed ANN model for simulating colour value of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimal architecture has 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 and output layer and five outputs which are the colour value for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the colour values were achieved after repeated trials of different topology and transfer function. 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. 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 optimal ANN model for colour value was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.26a and b. The Figure 4.26a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for colour value. The regression analysis between ANN predicted outputs and experimental data for colour value indicated a precise and effective prediction capability of ANN model for colour value with R of 0.9175, 0.8676, 0.9195 and 0.9076 for training, validation, testing and all data respectively (Fig. 4.26b). The MSE value was found to be 4.3152 at 0 epochs for the optimal architecture of the ANN model for colour value.

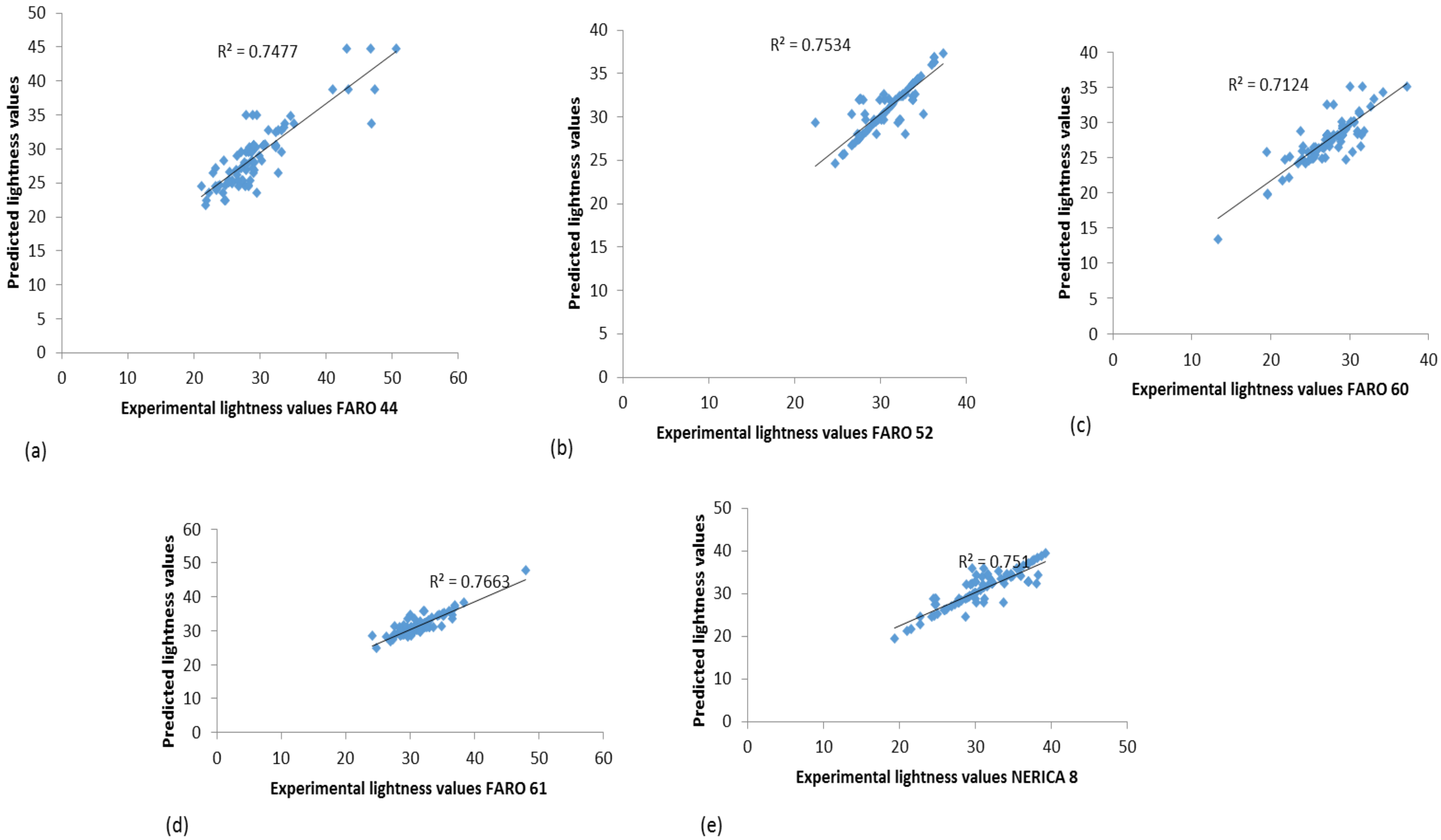


Fig. 4.24. Comparison between the experimental lightness and predicted lightness using ANN

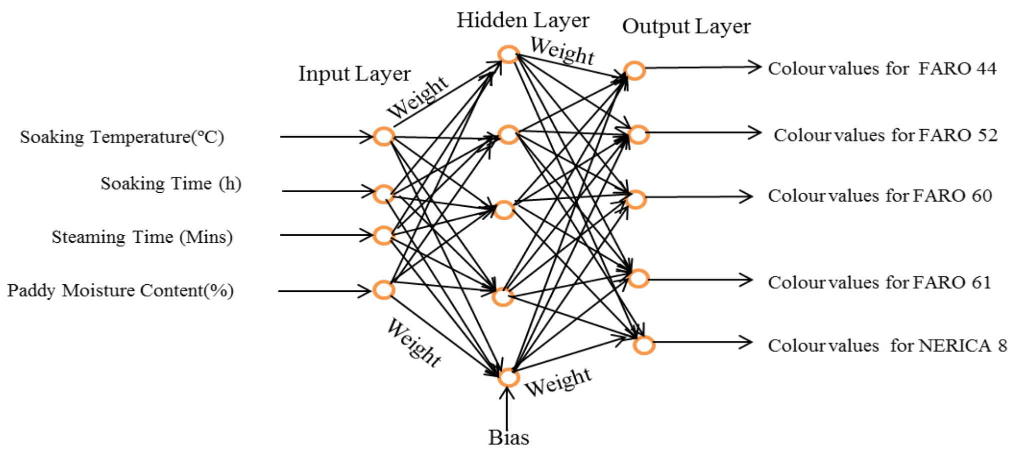
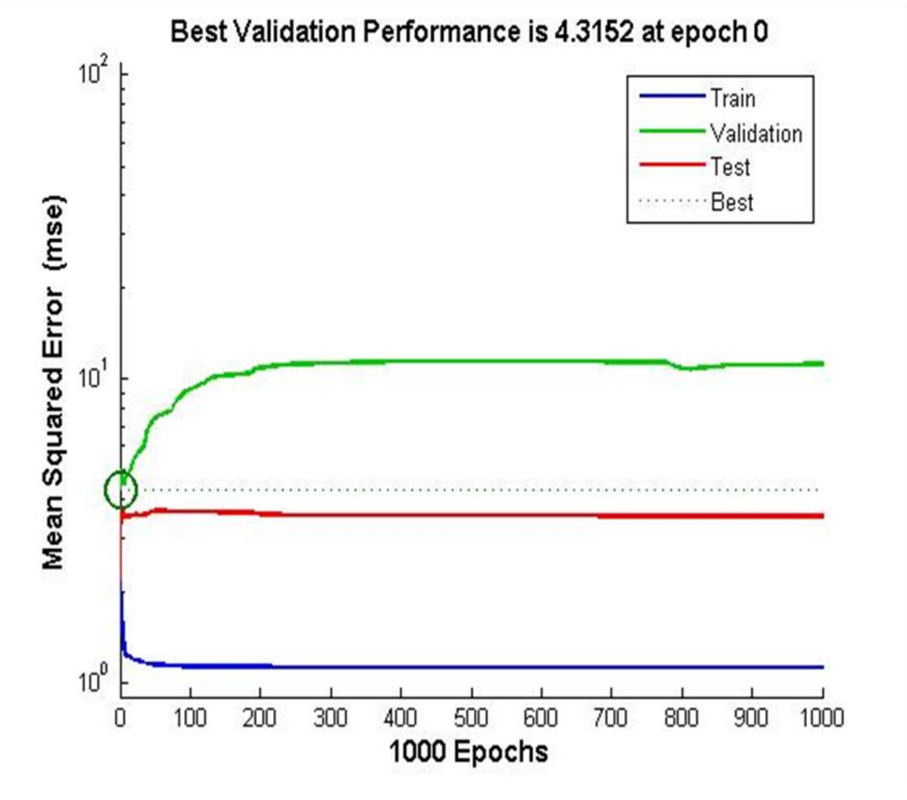


Fig. 4.25. The optimum architecture of the developed ANN model for colour



(a)

(b)

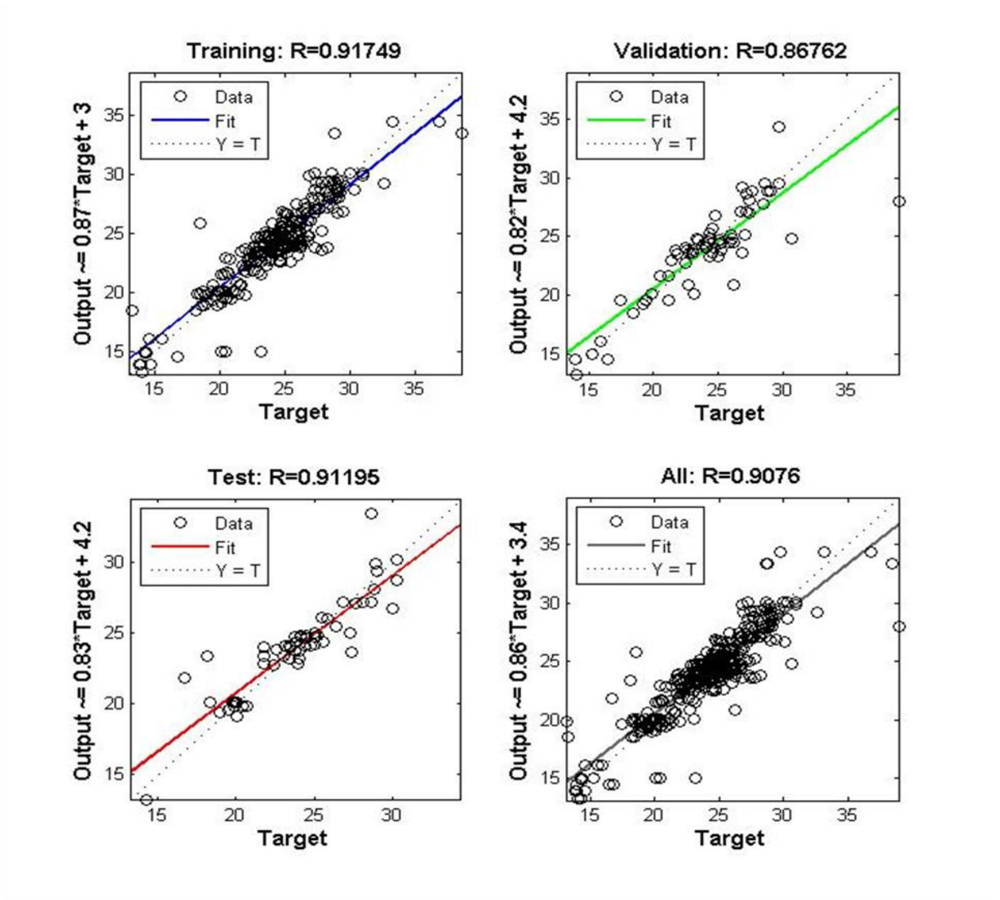


Fig. 4.26. Artificial neural network simulation performance for colour

The predictive capability of the generated ANN model for colour value was tested using unknown set of inputs data and the ANN predicted values versus experimental values were plotted for each variety as depicted in Fig. 4.27 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.795, 0.777, 0.712, 0.754, and 0.744 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 1.187, 0.550, 0.690, 1.440, and 1.039 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 colour value was moderate.

4.10.8 Cooking time simulation using artificial neural network

Figure 4.28 shows the optimum architecture of the developed ANN model for simulating cooking time of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimal 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 and output layer and five outputs which are the cooking time for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the cooking time were achieved after repeated trials of different topology and transfer function. 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. 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 optimal ANN model for cooking time was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.29a and b. The Figure 4.29a and b represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for cooking time. The regression analysis between ANN predicted outputs and experimental data for cooking time indicated a precise and effective prediction capability of ANN model for value with a correlation coefficient (R) of 0.981, 0.890, 0.908 and 0.958 for training, validation, testing and all data respectively (Fig. 4.29b). The MSE value was found to be 11.439 at 68 epochs for the optimum architecture of the ANN model for cooking time.

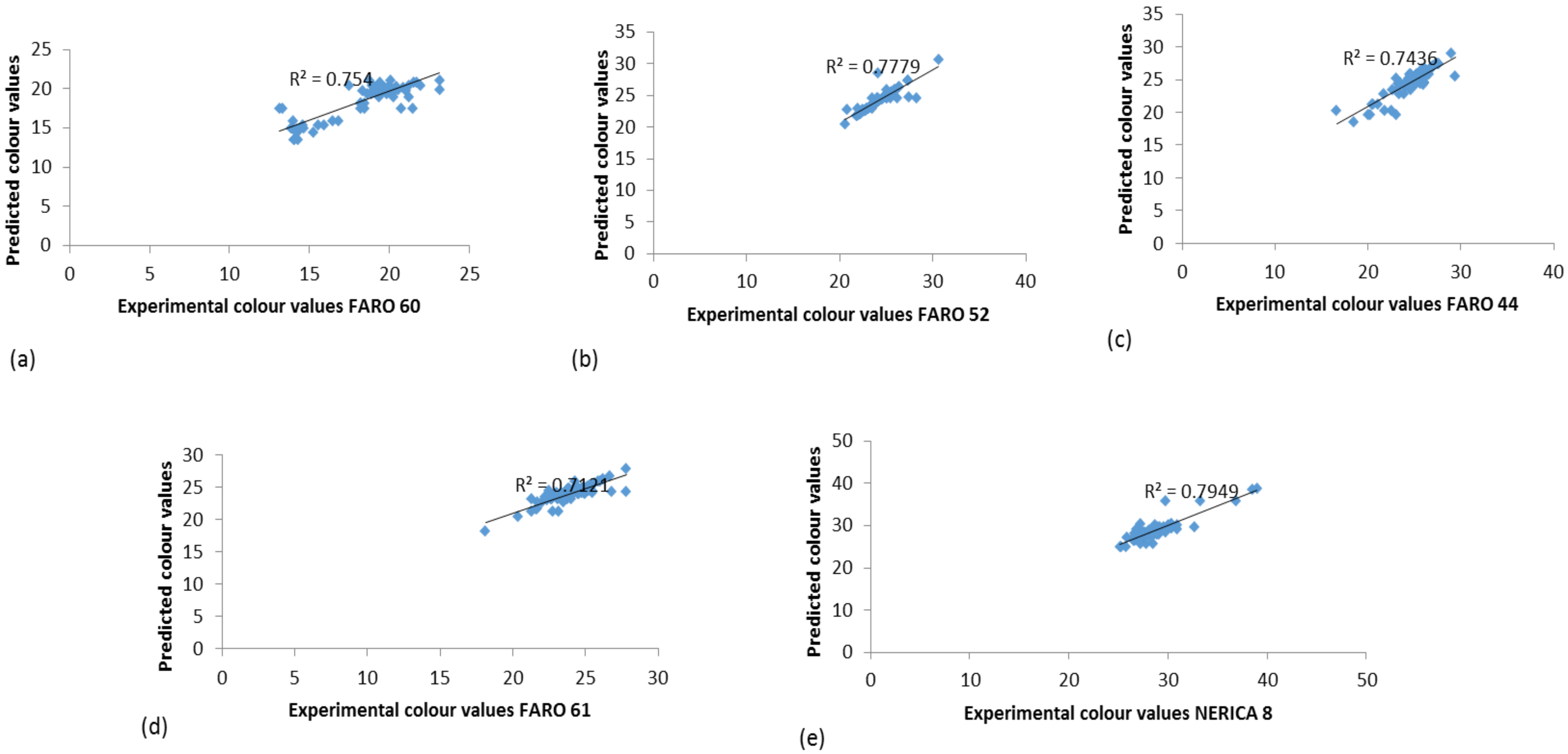


Fig. 4.27. Comparison between the experimental colour and predicted colour using ANN

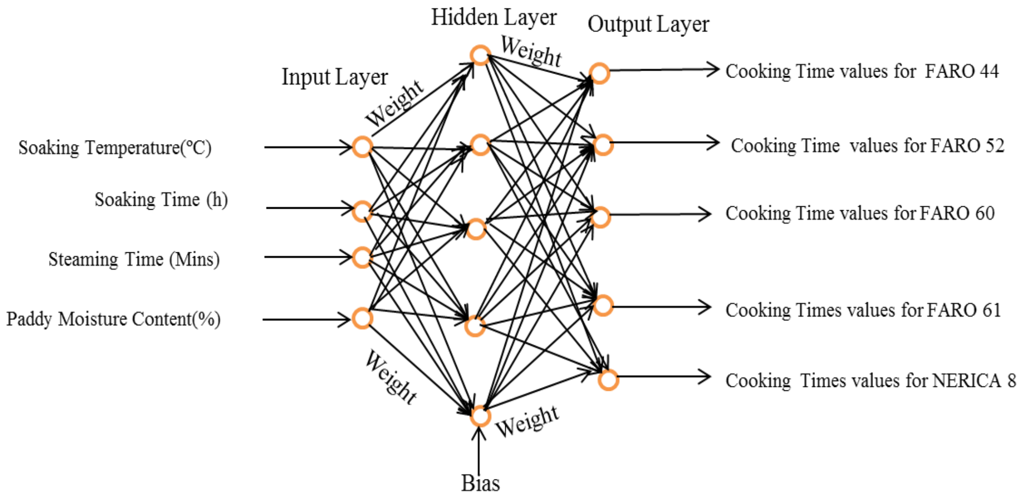


Fig. 4.28. The optimum architecture of the developed ANN model for cooking time

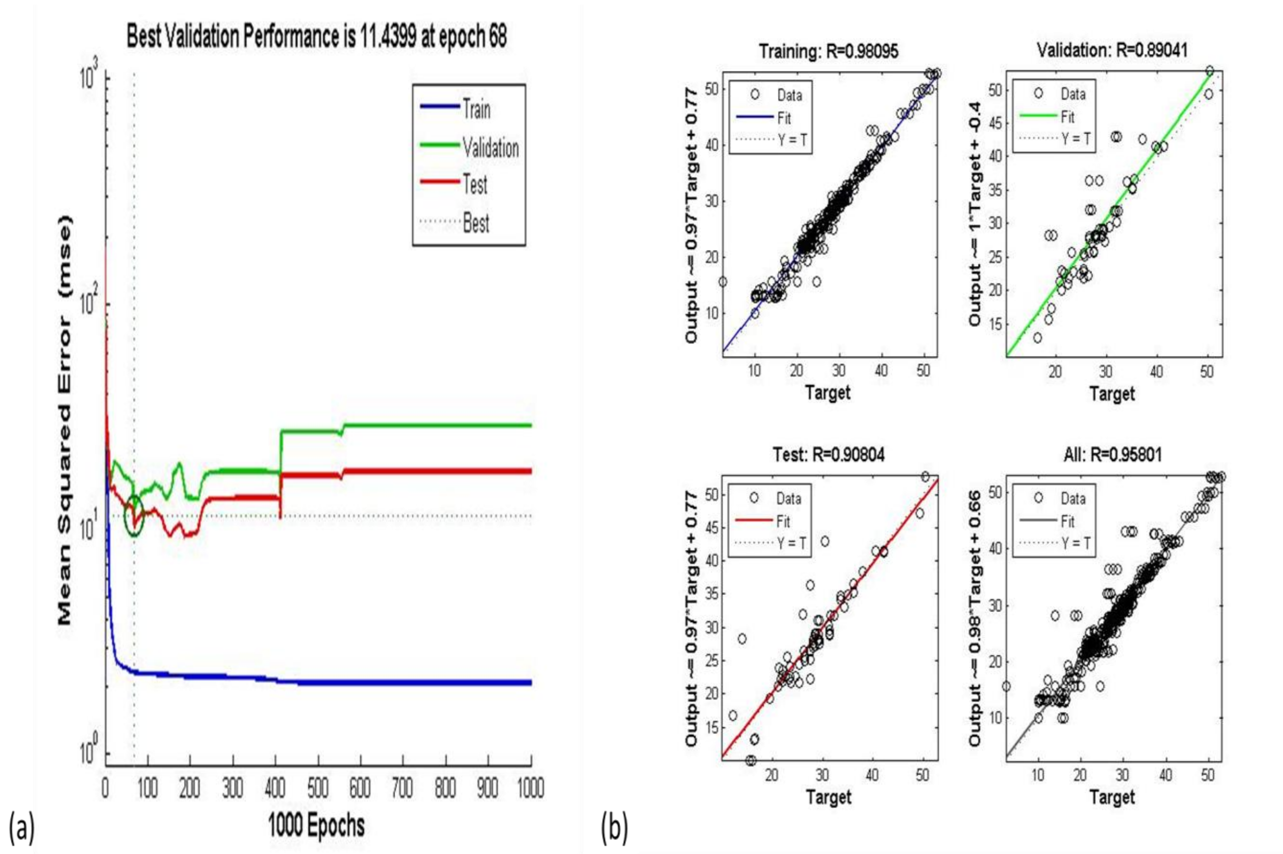


Fig. 4.29. Artificial neural network simulation performance for cooking time

The predictive capability of the generated ANN model for cooking time was tested using unknown set of inputs data and the ANN predicted values versus experimental values were plotted for each variety as depicted in Fig. 4.30 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.717, 0.737, 0.881, 0.729, and 0.989 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 10.873, 3.838, 1.601, 5.881 and 1.052 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The result showed that the predictive accuracy of the ANN model for cooking time was high.

4.10.9 Water uptake ratio simulation using artificial neural network

Figure 4.31 show the optimum architecture of the developed ANN model for simulating water uptake ratio of NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 during processing. The optimal 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 and output layer and five outputs which are the water uptake ratio for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. The optimum topology and transfer function for simulating the water uptake ratio were achieved after repeated trials of different topology and transfer function. 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. 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 optimal ANN model for water uptake ratio was terminated when low mean square error (MSE) and high correlation coefficient (R) values were obtained as shown in Figure 4.32a and b.

The Figure 4.32 represents ANN performance with network validation, number of epochs and regression analysis for training and validation datasets for water uptake ratio. The regression analysis between ANN predicted outputs and experimental data for water uptake ratio indicated a precise and effective prediction capability of ANN model for value with R of 0.8032, 0.9264, 0.9163 and 0.8367 for training, validation, testing and all data respectively (Fig. 4.32). The MSE value was found to be 0.032133 at 0 epochs for the optimal architecture of the ANN model for water uptake ratio.

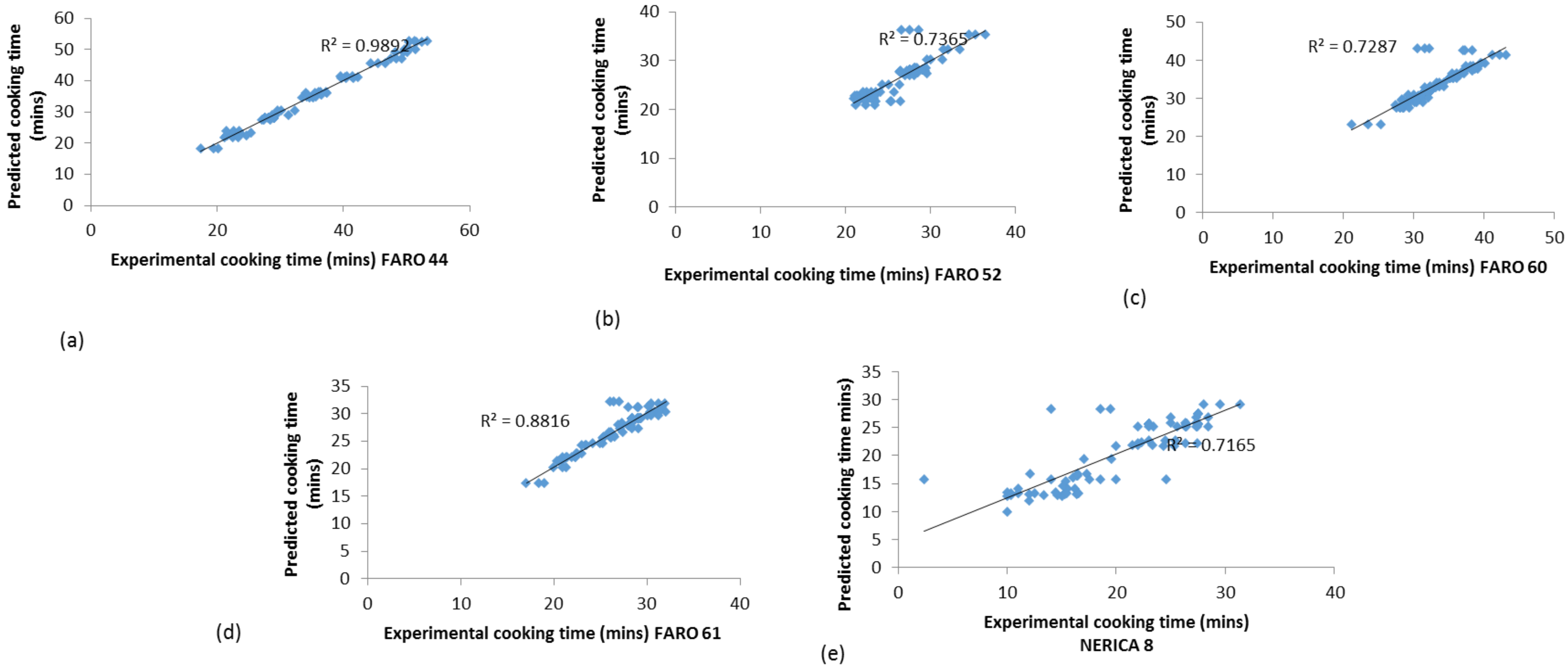


Fig. 4.30. Comparison between the experimental cooking time and predicted cooking time using ANN

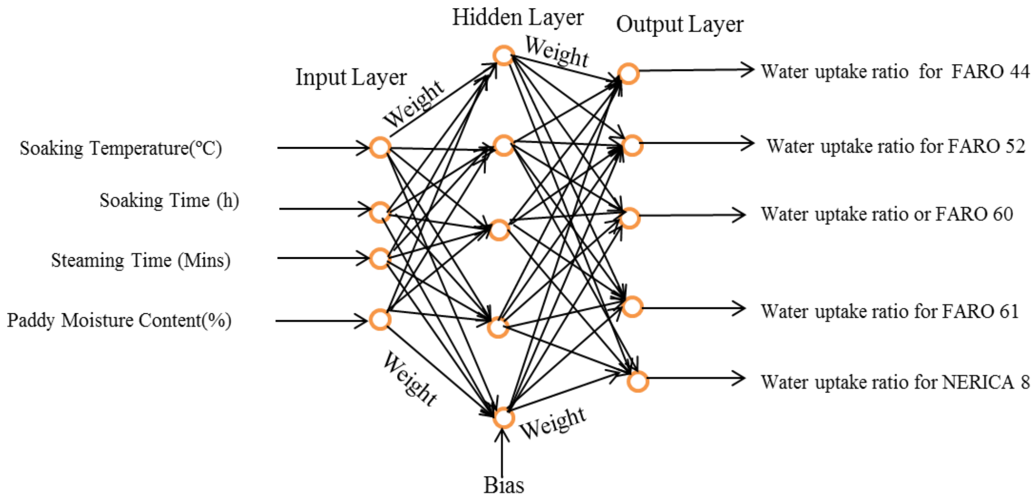


Fig. 4.31. The optimum architecture of the developed ANN model for water uptake ratio

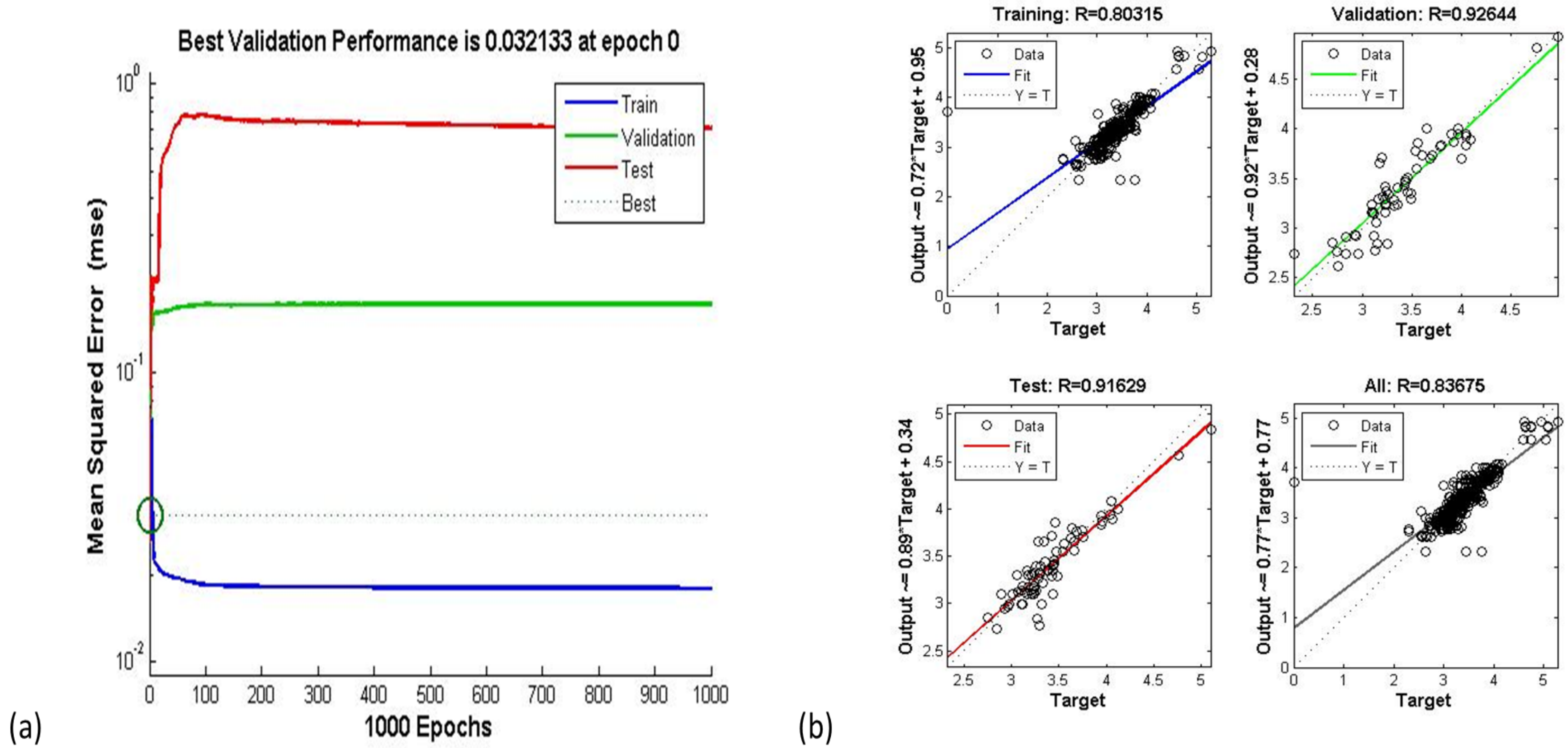


Fig. 4.32. Artificial neural network simulation for water uptake ratio

The predictive capability of the generated ANN model for water uptake ratio was tested using unknown set of inputs data and the ANN predicted values versus experimental values were plotted for each variety as depicted in Fig. 4.33 a, b, c, d, e. The coefficient of determination (R^2) between the ANN experimental and predicted data were 0.901, 0.704, 0.874, 0.864, and 0.751 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 while the mean square error between the predicted values and experimental values were 0.041, 0.056, 0.023, 0.028, and 0.024 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44, respectively. This results show that the predictive accuracy of the ANN model for water uptake ratio was high.

4.11 Comparison of Taguchi, RSM and ANN models

In order to compare the effectiveness of Taguchi, RSM and ANN models in predicting total energy consumption and quality attributes during processing, comparative values of their coefficient of regression (R^2) and Mean Square Error (MSE) were presented in Table 4.43 and Table 4.44. Betiku and Taiwo (2015) and Yadav *et al.* (2017) reported that R^2 and MSE can be used to evaluate the effectiveness of modelling techniques. Table 4.43 shows the comparative results of the obtained coefficient of determination (R^2) for Taguchi, RSM and ANN models in fitting the experimental data of total energy consumption and quality attributes. Taguchi model was observed to have highest R^2 values and lowest MSE for total energy consumption than RSM 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. However, Taguchi models were found not to be fit to predict brown rice recovery, head brown rice, milling recovery, head milled rice, chalkiness and water uptake ratio for the rice varieties due to the low R^2 values obtained. Taguchi model was also found to have $R^2 > 0.70$ and low MSE in lightness value, colour value and cooking time of some varieties (FARO 61, FARO 60, FARO 52 and FARO 44), therefore indicating its predicting capability. RSM was observed to have high R^2 and low MSE values that are fitted to predict total energy consumption, brown rice recovery, head brown rice, milling recovery, head milled rice and chalkiness except for lightness value, colour value, water uptake ratio and cooking time. This might be due the RSM ability to establish linear, quadratic and interaction effects that exist in the process.

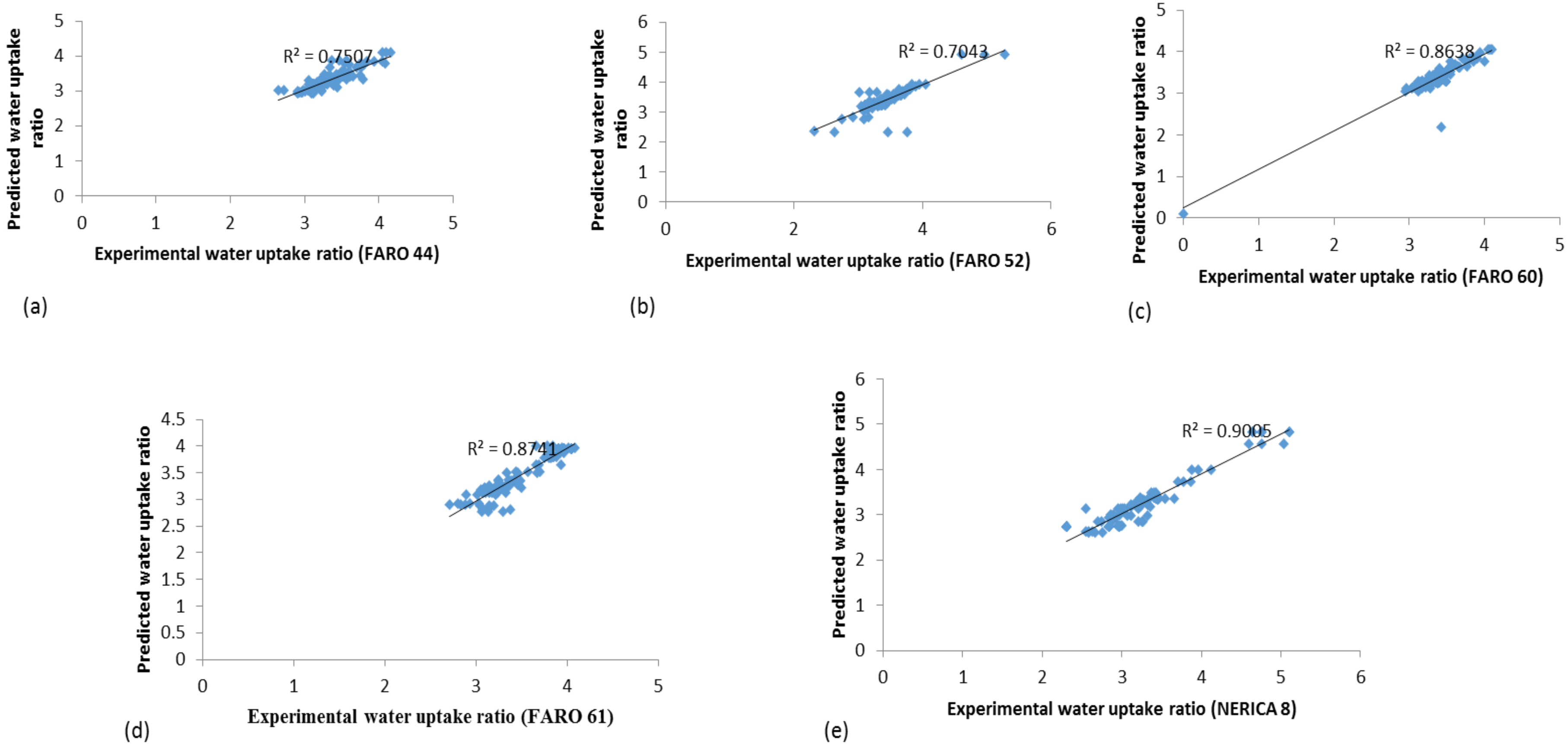


Fig. 4.33. Comparison between the experimental water uptake ratio and predicted water uptake ratio using ANN

Table 4.43. Comparison of Taguchi, RSM and ANN coefficient of determination (R^2)

VARIETY	RESPONSES	TAGUCHI MODEL	RSM MODEL	ANN MODEL
FARO 44	Total energy consumption	**0.959***	0.915	0.941
FARO 52	Total energy consumption	**0.947***	0.911	0.935
FARO 60	Total energy consumption	**0.966***	0.915	0.937
FARO 61	Total energy consumption	**0.949***	0.913	0.938
NERICA 8	Total energy consumption	**0.945***	0.914	0.937
FARO 44	Brown rice recovery	0.689	0.901	**0.932***
FARO 52	Brown rice recovery	0.596	0.920	**0.965***
FARO 60	Brown rice recovery	0.416	**0.992***	0.988
FARO 61	Brown rice recovery	0.506	**0.897***	0.896
NERICA 8	Brown rice recovery	0.567	**0.984***	0.979
FARO 44	Head brown rice	0.640	**0.897***	0.867
FARO 52	Head brown rice	0.619	0.944	**0.965***
FARO 60	Head brown rice	0.161	**0.994***	0.954
FARO 61	Head brown rice	0.288	**0.861***	0.813
NERICA 8	Head brown rice	0.743	0.970	**0.972***
FARO 44	Milling recovery	0.528	0.928	**0.939***
FARO 52	Milling recovery	0.479	0.869	**0.942***
FARO 60	Milling recovery	0.236	0.787	**0.891***
FARO 61	Milling recovery	0.413	0.885	**0.944***
NERICA 8	Milling recovery	0.746	0.928	**0.954***
FARO 44	Head milled rice	0.448	**0.928***	0.916
FARO 52	Head milled rice	0.436	0.882	**0.982***
FARO 60	Head milled rice	0.565	0.809	**0.846***
FARO 61	Head milled rice	0.336	0.931	**0.955***
NERICA 8	Head milled rice	0.641	0.966	**0.982***
FÁRO 44	Chalkiness	0.705	0.968	**0.986***
FÁRO 52	Chalkiness	0.145	0.950	**0.976***
FÁRO 60	Chalkiness	0.317	0.950	**0.976***
FÁRO 61	Chalkiness	0.213	**0.937***	0.815
NERICA 8	Chalkiness	0.233	0.967	**0.985***

Comparison of Taguchi, RSM and ANN Coefficient of Determination

VARIETY	RESPONSES	TAGUCHI MODEL	RSM MODEL	ANN MODEL
FARO 44	Colour value	0.646	0.456	**0.748***
FARO 52	Colour value	**0.803***	0.219	0.753
FARO 60	Colour value	**0.803***	0.241	0.753
FARO 61	Colour value	0.211	0.351	**0.766***
NERICA 8	Colour value	0.499	0.379	**0.751***
FARO 44	Lightness value	0.665	0.363	**0.744***
FARO 52	Lightness value	0.733	0.310	**0.778***
FARO 60	Lightness value	0.733	0.530	**0.754***
FARO 61	Lightness value	0.708	0.455	**0.712***
NERICA 8	Lightness value	0.657	0.289	**0.795***
FARO 44	Cooking time	0.848	0.786	**0.989***
FARO 52	Cooking time	0.416	0.708	**0.737***
FARO 60	Cooking time	0.729	0.521	**0.729***
FARO 61	Cooking time	0.363	0.679	**0.882***
NERICA 8	Cooking time	0.638	0.612	**0.717***
FÁRO 44	Water uptake ratio	0.627	0.615	**0.751***
FÁRO 52	Water uptake ratio	0.627	0.319	**0.704***
FÁRO 60	Water uptake ratio	0.627	0.292	**0.864***
FÁRO 61	Water uptake ratio	0.627	0.809	**0.874***
NERICA 8	Water uptake ratio	0.627	0.674	**0.901***

Table 4.44. Comparison of the Mean Square Error (MSE) of Taguchi, RSM and ANN

VARIETY	RESPONSES	TAGUCHI MODEL	RSM MODEL	ANN MODEL
FARO 44	Total energy consumption	**1.555***	4.716	3.345
FARO 52	Total energy consumption	**1.959***	4.690	3.522
FARO 60	Total energy consumption	**1.240***	4.306	3.212
FARO 61	Total energy consumption	**1.838***	4.519	3.327
NERICA 8	Total energy consumption	**1.814***	4.370	3.305
FARO 44	Brown rice recovery	4.294	0.024	**0.019***
FARO 52	Brown rice recovery	0.091	0.106	**0.049***
FARO 60	Brown rice recovery	0.111	**0.005***	0.009
FARO 61	Brown rice recovery	0.106	**0.015***	0.017
NERICA 8	Brown rice recovery	0.313	**0.026***	0.034
FARO 44	Head brown rice	0.682	**0.035***	0.046
FARO 52	Head brown rice	0.202	0.101	**0.064***
FARO 60	Head brown rice	2.050	0.004	**0.030***
FARO 61	Head brown rice	0.646	**0.036***	0.049
NERICA 8	Head brown rice	0.436	0.053	**0.051***
FARO 44	Milling recovery	0.806	0.078	**0.067***
FARO 52	Milling recovery	7.915	0.62	**0.280***
FARO 60	Milling recovery	1.375	0.127	**0.066***
FARO 61	Milling recovery	2.931	0.179	**0.087***
NERICA 8	Milling recovery	1.520	0.507	**0.336***
FARO 44	Head milled rice	0.631	**0.094***	0.111
FARO 52	Head milled rice	10.549	0.652	**0.107***
FARO 60	Head milled rice	0.814	0.121	**0.099***
FARO 61	Head milled rice	4.748	0.202	**0.132***
NERICA 8	Head milled rice	6.848	0.613	**0.327***

Asterisk (*) numbers are desirable

Comparison of the Mean Square Error (MSE) of TAGUCHI, RSM and ANN

VARIETY	RESPONSES	TAGUCHI MODEL	RSM MODEL	ANN MODEL
FARO 44	Chalkiness	0.082	0.450	**0.193***
FARO 52	Chalkiness	0.878	0.063	**0.032***
FARO 60	Chalkiness	**0.016***	0.063	0.032
FARO 61	Chalkiness	1.524	**0.035***	0.103
NERICA 8	Chalkiness	15.576	0.488	**0.228***
FARO 44	Colour value	**0.630***	2.515	1.039
FARO 52	Colour value	**0.411***	1.681	0.550
FARO 60	Colour value	**0.411***	2.753	1.440
FARO 61	Colour value	**0.354***	1.144	0.609
NERICA 8	Colour value	**0.713***	3.651	1.187
FARO 44	Lightness value	**2.302***	16.730	7.963
FARO 52	Lightness value	**0.309***	8.107	2.595
FARO 60	Lightness value	**0.309***	8.858	3.497
FARO 61	Lightness value	**1.750***	6.571	2.420
NERICA 8	Lightness value	8.618	12.274	**4.977***
FARO 44	Cooking time	8.732	20.185	**1.052***
FARO 52	Cooking time	9.814	3.375	**3.838***
FARO 60	Cooking time	**2.233***	7.649	5.881
FARO 61	Cooking time	8.114	3.886	**1.601***
NERICA 8	Cooking time	13.324	14.546	**10.873***
FARO 44	Water uptake ratio	0.040	0.036	**0.024***
FARO 52	Water uptake ratio	0.040	0.108	**0.056***
FARO 60	Water uptake ratio	0.040	0.138	**0.028***
FARO 61	Water uptake ratio	0.040	0.028	**0.023***
NERICA 8	Water uptake ratio	0.040	0.135	**0.040***

Asterisk (*) numbers are desirable

However, its inability to have a fit model that can predict the lightness value, colour value, cooking time and water uptake ratio might be as a result of the high non-linear relationship that exists between the independent variables and the responses. ANN models were observed to be superior than Taguchi and RSM models because the generated R^2 values and Mean Square Error (MSE) values for total energy consumption and quality attributes were high ($R^2 > 0.70$) and low respectively. Table 4.44 showed that the RSM models have a greater deviation of mean square error (MSE) than the ANN models. Therefore, it can be deduced from Table 4.42 and 4.43 that ANN models could predict total energy consumption than RSM due to higher R^2 and lower MSE than RSM. ANN was also found to have high precision accuracy for predicting the quality attributes of the rice varieties than Taguchi and RSM. Patel and Brahmbhatt (2016), findings also reported that ANN has higher prediction capability than RSM.

4.12 Optimization of the Processing Conditions

Optimization of the processing conditions for the rice varieties was carried out in order to determine the optimal conditions that would resulted in minimum energy consumption, maximum brown rice recovery, maximum head brown rice, maximum milling recovery, maximum head milled rice, minimum chalkiness, maximum lightness value, minimum colour value, minimum cooking time and maximum water uptake ratio. Table 4.45, 4.46, 4.47, 4.48 and 4.49, shows the optimum processing condition for FARO 44, FARO 52, FARO 60, FARO 61 and NERICA 8, respectively. The optimum processing conditions obtained for FARO 44 occurred at 74ºC soaking temperature, 11 h soaking time, 15 min steaming time and 10% paddy moisture content with composite desirability of 0.82. For FARO 52, the optimum processing conditions were obtained at 79ºC soaking temperature, 14 h soaking time, 23 min steaming time and 16% paddy moisture content with the composite desirability of 0.82. FARO 60 optimum processing conditions were obtained at 65ºC soaking temperature, 11 h soaking time, 35 min steaming time and 17% paddy moisture content with composite desirability of 0.80. FARO 61 optimum processing conditions was obtained at 78ºC soaking temperature, 18 h soaking time, 15 min steaming time and 15% paddy moisture content with composite desirability of 0.84. NERICA 8 optimum processing conditions was obtained at 69ºC soaking temperature, 19 h soaking time, 22 min steaming time and 15% paddy moisture content with composite desirability of 0.76, respectively.

Table 4.45. Optimum processing conditions at 74ºC soaking temperature, 11 h soaking time, 15 min steaming time and 10% paddy moisture content for FARO 44

Optimum Goal	Minimum values	Maximum values	Predicted optimum values	Desirability values	Experimental values	Percentage deviation (%)
Minimum total energy Consumption (MJ)	46.10	75.60	58.85	0.57	62.20	5.69
Maximum brown rice recovery (%)	77.62	79.50	79.56	1.00	79.54	0.03
Maximum head brown rice (%)	76.75	79.26	78.60	0.74	78.55	0.06
Maximum milling recovery (%)	67.99	72.63	72.40	0.95	72.47	0.10
Maximum head milled rice (%)	67.81	71.60	71.87	1.00	71.76	0.15
Minimum chalkiness (%)	0.70	13.55	0.79	1.00	0.80	1.27
Maximum lightness value	23.73	46.80	38.43	0.64	40.39	5.10
Minimum colour value	20.41	26.34	17.64	1.00	18.68	5.90
Minimum cooking time (min)	22.32	51.58	33.21	0.63	34.27	3.19
Maximum water uptake ratio	2.95	4.10	3.88	0.81	3.91	0.77

Table 4.46. Optimum processing conditions at 79ºC soaking temperature, 14 h soaking time, 23 min steaming time and 16% paddy moisture content for FARO 52

Optimum Goal	Minimum values	Maximum values	Predicted optimum values	Desirability values	Experimental values	Percentage deviation (%)
Minimum total energy Consumption (MJ)	44.88	76.83	55.51	0.67	59.03	6.34
Maximum brown rice recovery (%)	76.57	82.40	82.21	0.97	82.17	0.05
Maximum head brown rice (%)	75.18	82.19	82.16	1.00	82.10	0.07
Maximum milling recovery (%)	63.51	73.03	73.26	1.00	73.54	0.38
Maximum head milled rice (%)	61.57	72.58	72.58	1.00	72.47	0.15
Minimum chalkiness (%)	0.50	4.30	2.17	0.56	2.20	1.38
Maximum lightness value	27.77	33.33	30.89	0.56	33.49	8.42
Minimum colour value	21.33	26.53	23.44	0.59	23.99	2.35
Minimum cooking time (min)	21.51	35.44	25.65	0.70	27.48	7.13
Maximum water uptake ratio	2.72	4.95	3.42	0.31	3.47	1.46

Table 4.47. Optimum processing conditions at 65ºC soaking temperature, 11 h soaking time, 35 min steaming time and 17% paddy moisture content for FARO 60

Optimum Goal	Minimum values	Maximum values	Predicted optimum values	Desirability values	Experimental values	Percentage deviation (%)
Minimum total energy Consumption (MJ)	45.27	73.68	53.69	0.70	56.90	5.98
Maximum brown rice recovery (%)	77.34	78.33	79.54	1.00	79.53	0.01
Maximum head brown rice (%)	75.62	77.95	79.36	1.00	79.33	0.04
Maximum milling recovery (%)	68.46	72.34	71.36	0.75	71.43	0.10
Maximum head milled rice (%)	69.36	71.42	71.42	1.00	71.33	0.13
Minimum chalkiness (%)	0.50	4.30	1.29	0.79	1.32	2.33
Maximum lightness value	24.2	31.00	31.03	1.00	32.53	4.83
Minimum colour value	14.1	21.21	14.16	0.99	14.60	3.11
Minimum cooking time (min)	23.3	37.52	30.61	0.49	33.49	9.41
Maximum water uptake ratio	2.21	4.07	3.18	0.52	3.20	0.63

Table 4.48. Optimum processing conditions at 78ºC soaking temperature, 18 h soaking time, 15 min steaming time and 15% paddy moisture content for FARO 61

Optimum Goal	Minimum values	Maximum values	Predicted optimum values	Desirability values	Experimental values	Percentage deviation (%)
Minimum total energy consumption (MJ)	47.45	76.11	56.41	0.69	59.74	5.90
Maximum brown rice recovery (%)	76.79	78.45	78.28	0.90	78.27	0.01
Maximum head brown rice (%)	75.59	77.61	76.85	0.62	76.80	0.07
Maximum milling recovery (%)	67.34	71.97	73.76	1.00	73.85	0.12
Maximum head milled rice (%)	63.35	70.11	70.18	1.00	69.85	0.47
Minimum chalkiness (%)	1.25	4.52	1.18	1.00	1.21	2.54
Maximum lightness value	28.17	35.50	39.21	1.00	41.63	6.17
Minimum colour value	21.38	25.58	21.28	0.99	21.89	2.87
Minimum cooking time (min)	20.67	31.28	19.12	1.00	20.72	8.37
Maximum water uptake ratio	2.80	4.01	3.39	0.48	3.41	0.59

Table 4.49. Optimum processing conditions at 69ºC soaking temperature, 19 h soaking time, 22 min steaming time and 15% paddy moisture content for NERICA 8

Optimum Goal	Minimum values	Maximum values	Predicted optimum values	Desirability values	Experimental values	Percentage deviation (%)
Minimum total energy Consumption (MJ)	48.35	76.90	59.07	0.62	62.37	5.59
Maximum brown rice recovery (%)	78.65	81.65	80.81	0.72	80.78	0.04
Maximum head brown rice (%)	77.86	81.76	80.26	0.62	80.21	0.06
Maximum milling recovery (%)	63.11	72.00	67.99	0.55	68.32	0.49
Maximum head milled rice (%)	48.54	69.38	68.3	0.95	68.17	0.19
Minimum chalkiness (%)	1.75	19.19	5.77	0.77	6.00	3.99
Maximum lightness value	23.13	33.00	32.45	0.94	33.43	3.02
Minimum colour value	26.98	31.95	28.32	0.73	29.51	4.20
Minimum cooking time (min)	13.25	26.93	13.87	0.95	15.04	8.44
Maximum water uptake ratio	2.59	4.83	4.65	0.92	4.69	0.86

The variations observed in the optimum conditions of the rice varieties could be traced to the differences in the intrinsic behaviour and microscopic structures of the rice varieties. The obtained results are similar to the findings of Uyeh e*t al.* (2016) who stated that only a right combination of processing conditions can guarantee a good outcome from parboiling process. The optimum processing conditions values obtained were also within the ranges reported by Nasirahmadi *et al.* (2014) and Leethanapanich *et al.* (2016). Therefore, according to the presented Tables 4.45 -4.49, it can be adduced that there is a good agreement between the optimum predicted values and experimental values, thereby, validating the reliability of the proposed optimum conditions for the rice varieties.

4.13 Quantitative Descriptive Analysis of Sensory Attributes

Table 4.50 depicted the sensory attributes of cooked rice of the varieties based on trained panelist assessment. The uniform appearance of FARO 44, FARO 52, FARO 60 and FARO 61 were not significantly different ($p<0.05$) except for NERICA 8. Highest black specks (0.58±0.43) were observed in NERICA 8 while the least were observed in FARO 60 and FARO 61. FARO 60 was observed to have the highest score for whitish appearance (8.86±0.22) although there was no statistical difference in the whitish appearance of the varieties. Yellow colour and brown colour observed in the rice varieties were rated low and ranged from 0.13± 0.12 to 0.34±0.69. NERICA 8 was rated to have the highest cream flavour 8.77±0.34 while the least was observed in FARO 44 (7.17±2.65). The rice odour of the rice varieties was not statistically different but FARO 61 was scored highest in terms of having the highest rice odour. The cooked rice varieties were scored high in sweet taste with no significant difference in their sweet taste.

NERICA 8 was observed to have the highest sticky texture 8.34±1.54 while the least were observed in FARO 52, FARO 61, FARO 60 and FARO 44 with no significant difference. The reason for the sticky texture of NERICA 8 could be as a result of high breakdown viscosity of the starch granule. The tendency of swollen starch granules to rupture when held at continuous shearing and high temperatures could be used to measure breakdown viscosity (Patindol *et al*., 2005). Also, bursting starch granules absorb a lot of water, thus, that making them into very good paste that set very well with good adhesive (sticky) properties (Oduro-Yeboah *et al*., 2007).

Table 4.50. Sensory attributes of cooked rice of the varieties

	NERICA 8	FARO 52	FARO 61	FARO 60	FARO 44
Uniform appearance	8.63±0.24^{b}	8.95±0.12^{a}	8.93±0.14^{a}	8.96±0.11^{a}	8.98±0.17^{a}
Black speck	0.58±0.43^{a}	0.23±0.12^{ab}	0.23±0.15^{b}	0.18±0.12^{b}	0.38±0.14^{ab}
Whitish appearance	8.00±2.43^{a}	8.80±0.29^{a}	8.82±0.22^{a}	8.86±0.17^{a}	8.83±0.25^{a}
Yellow colour	0.15±0.19^{a}	0.18±0.14^{a}	0.13±0.12^{a}	0.34±0.69^{a}	0.18±0.13^{a}
Brown colour	0.28±0.30^{a}	0.18±0.15^{a}	0.13±0.06^{a}	0.19±0.17^{a}	0.22±0.19^{a}
Cream flavour	8.77±0.34^{a}	7.82±2.31^{a}	7.69±2.42^{a}	7.58±2.48^{a}	7.17±2.65^{a}
Rice odour	8.80±0.37^{a}	8.78±0.32^{a}	8.84±0.21^{a}	8.63±0.48^{a}	8.74±0.38^{a}
Sweet taste	8.43±0.53^{a}	8.73±0.19^{a}	8.60±0.37^{a}	8.45±0.59^{a}	8.74±0.21^{a}
Sticky texture	8.34±1.54^{a}	0.28±0.21^{b}	0.23±0.20^{b}	0.23±0.17^{b}	0.20±0.18^{b}
Hard texture	0.64±0.39^{b}	5.88±3.75^{a}	6.11±3.26^{a}	5.48±3.67^{a}	7.27±3.14^{a}
Grainy texture	0.21±0.20^{b}	8.82±0.25^{a}	8.80±0.26^{a}	8.78±0.25^{a}	8.99±0.36^{a}

The values of mean in the same row with the same superscript do not differ significantly ($p<0.05$)

Gayin *et al.* (2009) reported similar findings for Ex-Baika rice variety. Also, NERICA 8 can be referred to as low amylose rice due to Cruz and Khush (2002) reports, that low amylose rice is usually moist and sticky. NERICA 8 rice variety could be useful for dishes involving boiled rice grains that do stick together such as rice balls eaten with soup. FARO 44 was scored highest for hard texture (7.27±3.14) and grainy texture (8.99±0.36) while the least score was for NERICA 8 which was 0.64±0.39 and 0.21±0.20 for hard texture and grainy texture respectively. The hard texture may be due to the high setback. Retrogradation tendency of the rice starch is defined by the setback. The hard texture could also be due to high amylose content. Usually, high amylose content rice varieties have hard texture when they are cooked. According to Cruz and Khush (2002), rice that shows a high volume of expansion, a high degree of flakiness, less tender and becomes hard upon cooling could be referred to as high amylose rice.

4.14 Principal Component Analysis (PCA) of the Sensory Attributes

Principal component analysis was applied to the QDA data of the eleven sensory attributes cooked rice of the rice varieties with the aim of establishing and interpreting the principal sensory attributes of the five rice varieties. Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) for FARO 44, FARO 52, FARO 60 and FARO 61 has a significance of 0.000 which indicates that sufficient correlation exists among the eleven sensory attributes and the high value of KMO (0.606), indicates a good sampling adequacy. Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) for NERICA 8, it has a significance of 0.002 which indicates that sufficient correlation exists among the eleven sensory attributes but a low value of KMO (0.150) which indicates a sampling adequacy that is not too good.

According to Vilela *et al.* (2015) reported that KMO must exceed 0.5. Two dimensional models for the two main principal components for FARO 61, FARO 60, FARO 52 and FARO 44 yields an eigenvalue of 3.571 for the first principal component, indicating that 32.47% of total variability is explained by this component and the eigenvalue of 1.691 for the second principal component, indicating that its proportion of variance is 15.38%. Thus, the two components explained 47.85% of the total amount of initial variance (Table 4.51). Figure 4.34 illustrated the principal components of FARO 61, FARO 60, FARO 52 and FARO 44. The Figure 4.34 shows that only eight sensory attributes contributed to the two dimensional model in a meaningful way.

Table 4.51. Total variance explained in FARO 44, FARO 52, FARO 60 and FARO 61

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.571	32.466	32.466	3.571	32.466	32.466	3.550
2	1.691	15.375	47.841	1.691	15.375	47.841	1.705

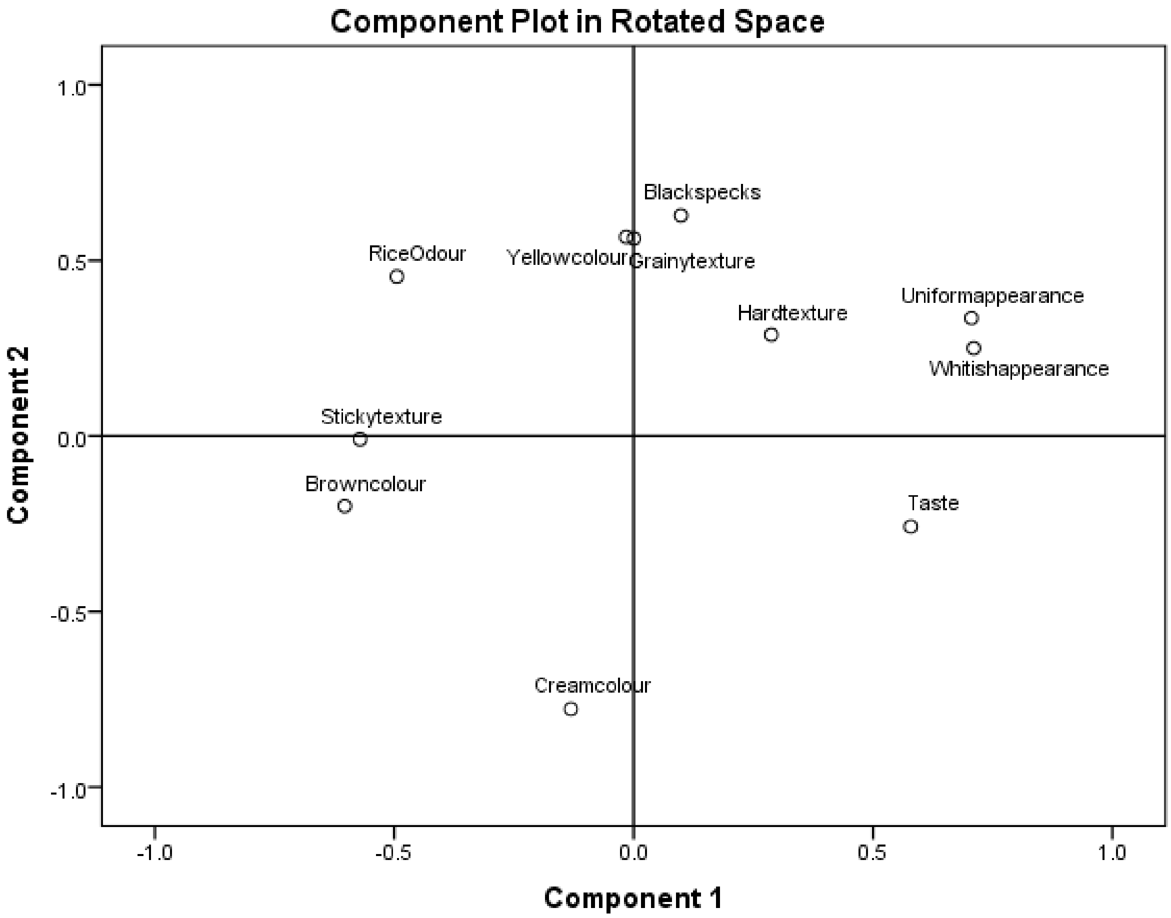


Figure 4.34. The principal components of FARO 44, FARO 52, FARO 60 and FARO 61.

According to Sivakumar *et al.* (2007), factor loadings with an absolute value greater than 0.56 represent a strong influence on sensory attributes. The first principal component (PC1) was best described by the following attributes: uniform appearance, whitish appearance, brown colour and sticky texture. The second principal component (PC2) was characterized by attributes: cream colour, black specks, grainy texture and yellow colour attribute (Figure 4.34). Two dimensional model for the two main principal components for NERICA 8 yields an eigenvalue of 3.332 for the first principal component, indicating that 30.29% of total variability is explained by this component and the eigenvalue of 2.314 for the second principal components, indicating that's its proportion of variance is 21.04%. Thus, the two components explained 51.34% of the total amount of initial variance (Table 4.52). Figure 4.35 illustrated the principal components of NERICA 8. The Figure 4.35 shows that only eight sensory attributes contributed to the two dimensional model in a meaningful way. The first principal component (PC1) was best described by attributes: grainy texture, whitish appearance, sticky texture and brown colour. The second principal component (PC2) was characterized by yellow colour, black specks, cream colour and hard texture.

Table 4.52. Total variance explained in NERICA 8

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.332	30.287	30.287	3.332	30.287	30.287	2.877
2	2.314	21.039	51.325	2.314	21.039	51.325	2.803

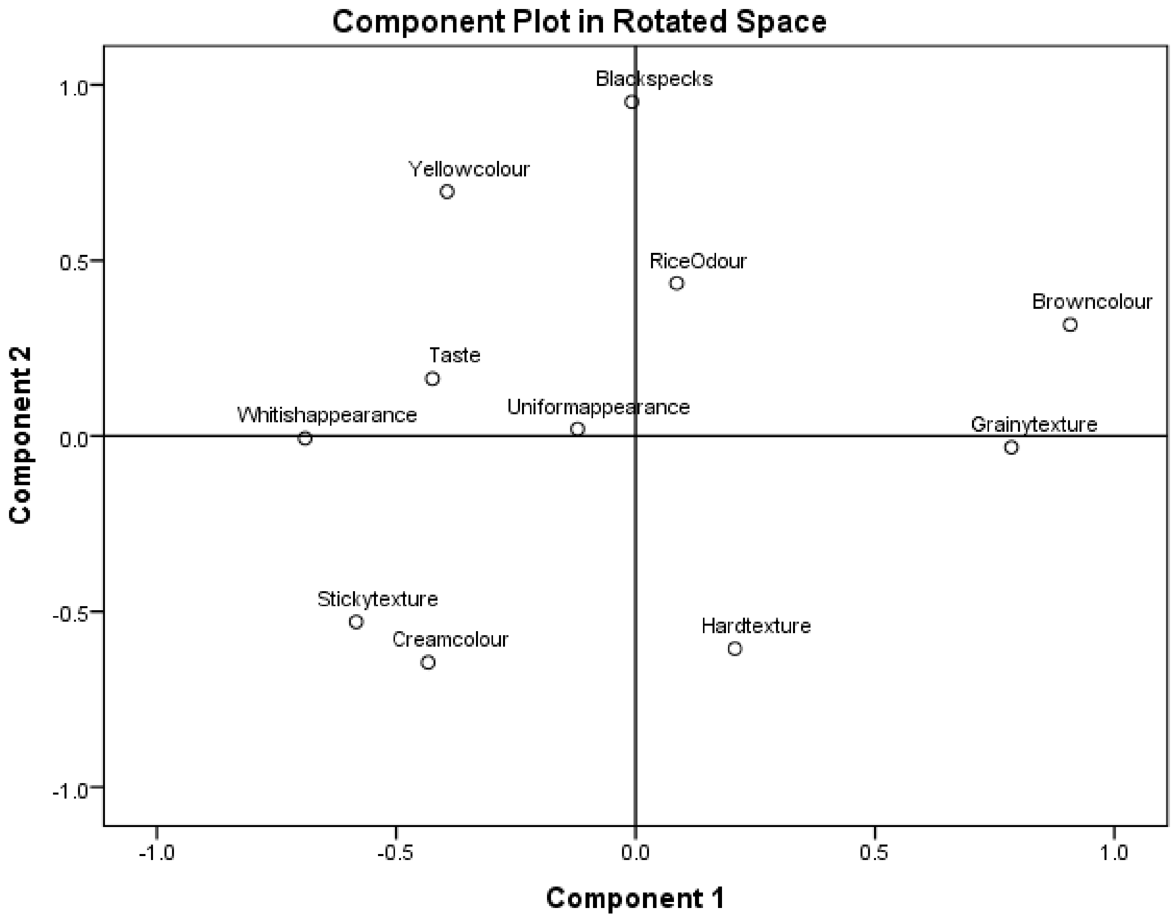


Figure 4.35. The principal components of NERICA 8

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The rice varieties (NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44) thousand paddy mass, sphericity, equivalent diameter, aspect ratio, cooking time, water uptake ratio, colour (L*, a*, b*) varied significantly with the varieties but no significant difference was observed in the surface area and bulk density of the paddies. The head milled rice and milling recovery of white rice of the varieties varied significantly and also has high broken milled rice and chalkiness which signifies poor quality attributes that would have low market value. Polishing operation was the highest energy consuming unit operation in processing paddy to white rice and electrical energy accounted for 96.42% of total energy consumption. Drying, 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 most. However, the significance of soaking temperature, soaking time, steaming time and paddy moisture content on brown rice recovery, head brown rice, milling recovery, head milled rice, chalkiness, lightness values, colour values, cooking time and water uptake ratio varied significantly with the rice varieties. Therefore, the rating of the most significant processing parameter on quality attributes depends on the rice variety. Parboiling resulted in brown rice recovery that ranged from 75.93 to 82.66%, head brown rice (74.55-82.19%), milling recovery (56.49–73.54%), head milled rice (48.54–72.67%), chalkiness (0.32–19.19%), lightness value (22.92–46.80), colour value (14.10–32.03), cooking time (10-51.58 min) and (2.21-4.95) in water uptake ratio, respectively.

Taguchi model showed most predictive accuracy for total energy consumption with coefficient of determination (R^2) that ranged from 0.947-0.966, and mean square error

(MSE) from 1.240 – 1.959 for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44. Taguchi model's predictive accuracy for quality attributes was low with an exception to cooking time, colour value and lightness value of some variety. RSM-CCD models showed the capability to predict total energy consumption, brown rice recovery, head brown rice, milling recovery, head milled rice and chalkiness with accuracy regardless of variety. Artificial neural network model have the high capability of simulating total energy consumption of the rice varieties with R^2 that ranged from 0.935 to 0.941 and 3.212 to 3.522 in MSE. However, Taguchi model has more predictive accuracy than ANN and RSM in predicting total energy consumption.

Artificial neural network models proved precise than Taguchi and RSM in predicting quality attribute with R^2 (0.704 – 0.988) and MSE (0.009 – 10.873). The optimum processing conditions that can guarantee minimum total energy consumption and acceptable quality attributes were 74ºC soaking temperature, 11 h soaking time, 15 min steaming time and 10% paddy moisture content for FARO 44, 79ºC soaking temperature, 14 h soaking time, 23 min steaming time and 16% paddy moisture content for FARO 52, 65ºC soaking temperature, 11 h soaking time, 35 min steaming time and 17% paddy moisture content for FARO 60, 78ºC soaking temperature, 18 h soaking time, 15 min steaming time and 15% paddy moisture content for FARO 61 while 69ºC soaking temperature, 19 h soaking time, 22 min steaming time and 15% paddy moisture content for NERICA 8 respectively. Composite desirability of the optimum conditions for the rice varieties ranged from 0.76 – 0.84. The percentage deviation between the predicted optimum values and the experimental values for total energy consumption and quality attributes ranged from 0.01 - 9.41%.

Therefore, applying the established optimum processing conditions would guarantee acceptable quality attributes and minimal energy consumption for the rice varieties and this would improve local rice production. Based on quantitative descriptive analysis (QDA), whitish appearance, sweet taste, creamy flavour and rice odour were not significantly different in the cooked rice of the varieties. However, difference was observed in the uniform appearance, black specks, grainy texture, sticky texture and hard texture of the cooked rice of the varieties. Principal component analysis (PCA) characterised sensory attribute of FARO 61, FARO 60, FARO 52 and FARO 44 as uniform appearance, whitish appearance, black specks, grainy texture, cream colour, brown colour and yellow colour. Sticky texture, cream colour, grainy texture, black specks, yellow colour and brown colour and hard texture are the principal sensory attributes that characterised NERICA 8. This information on sensory attributes will aid in understanding the culinary profile of the rice varieties.

5.2 Recommendations

i. Adopting the optimum processing conditions for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44 are needed to minimize total energy consumption and maximize the quality attributes.
ii. Artificial neural network model is recommended for predicting rice quality attributes due to its ability to establish the complex and non-linear relationship that exist in processing system while Taguchi model is recommended for total energy consumption prediction due to its ability to establish a linear or homogenous relationship among the process parameters.
iii. Further studies could be carried out on the application of ANN to model storage properties of rice.

5.3 Contributions to Knowledge

The following are the contributions of this research to body of knowledge:

i. The study established appropriate processing conditions for NERICA 8, FARO 52, FARO 61, FARO 60 and FARO 44. These conditions produced acceptable quality attributes with minimum energy consumption.
ii. Taguchi, RSM and Artificial Neural Network (ANN) modelling techniques were successfully used to predict total energy consumption of the rice varieties under different processing parameters.
iii. ANN modelling technique was successfully used to simulate the quality attributes of the rice varieties under different processing parameters.
iv. It was revealed that optimum processing conditions that can guarantee minimum total energy consumption and optimum quality attributes differs among the rice varieties.
v. Culinary profiles of the rice varieties were provided.

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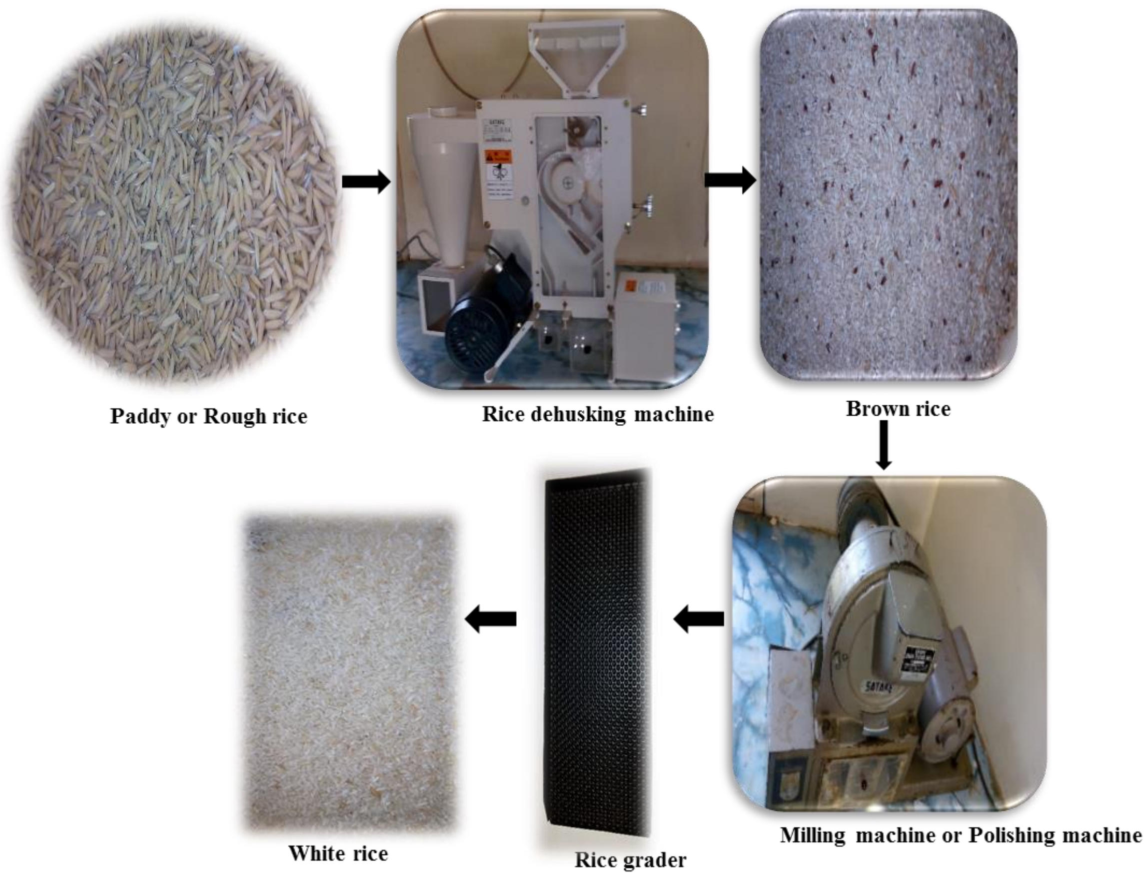
APPENDICES

ONXY RICE MILL, NIGER STATE



Laboratory rice processing equipment

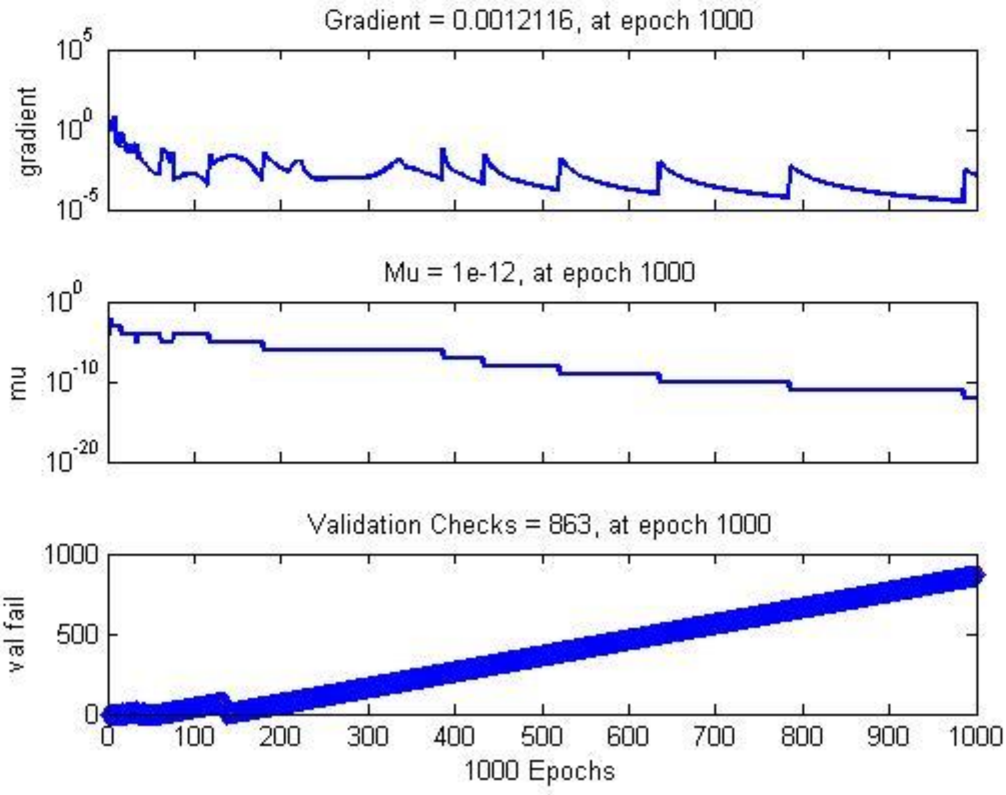
Grain moisture meter

Colour meter

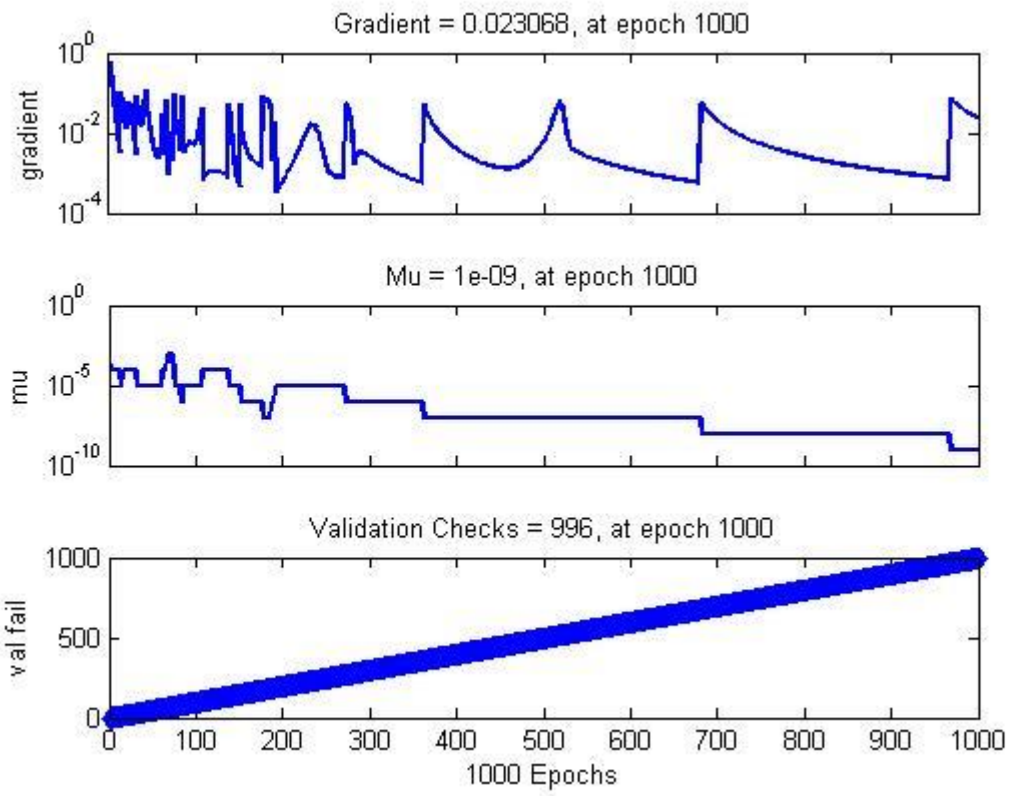
Receiving Rice Paddy at Grain Quality Control Laboratory of National Cereal Research Institute (NCRI)

Rice Processing Equipment

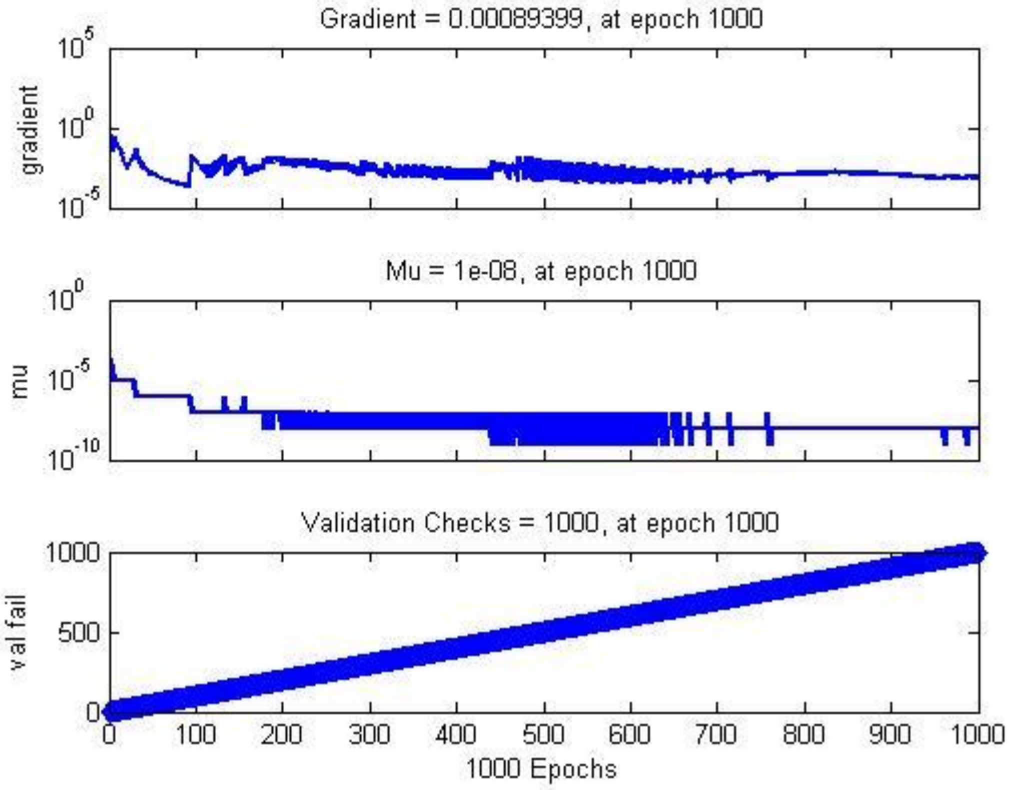
Rice Processing Equipment



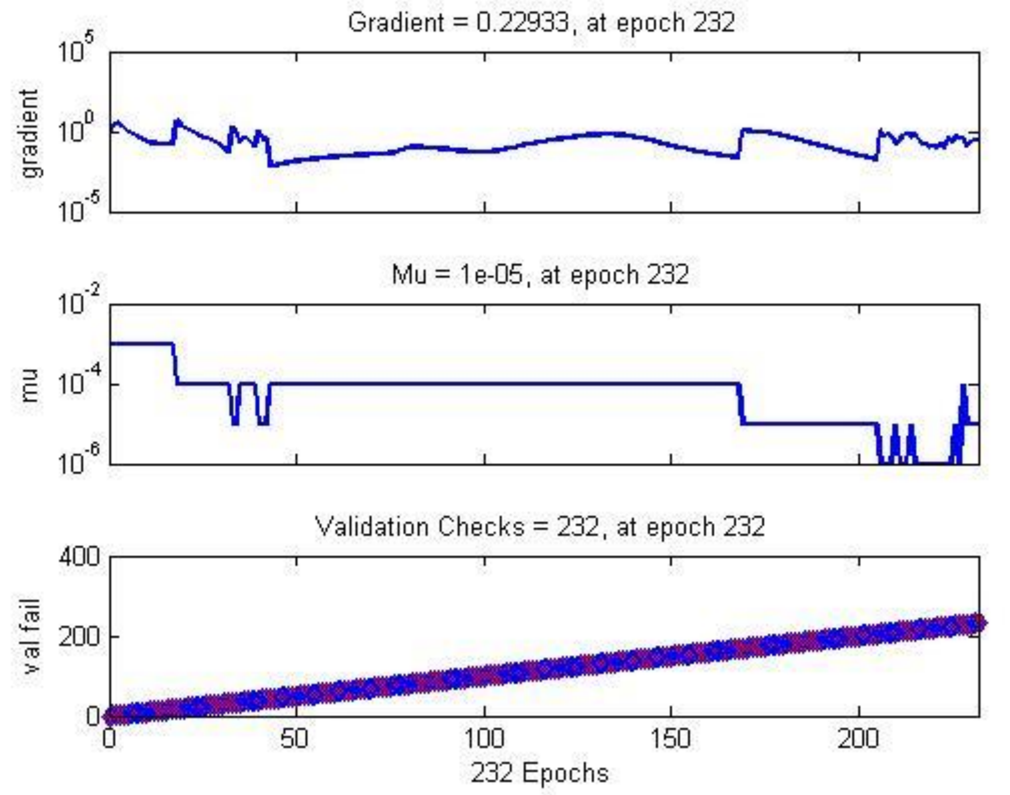
Training state of Brown rice recovery using ANN



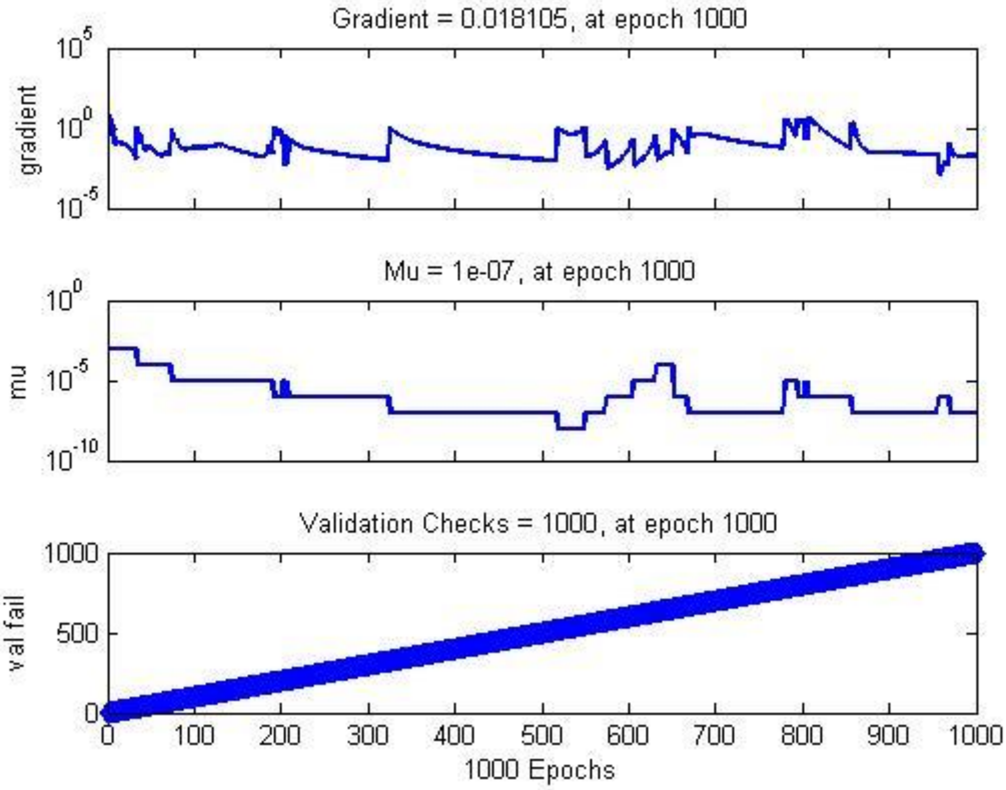
Training state of head brown rice using ANN



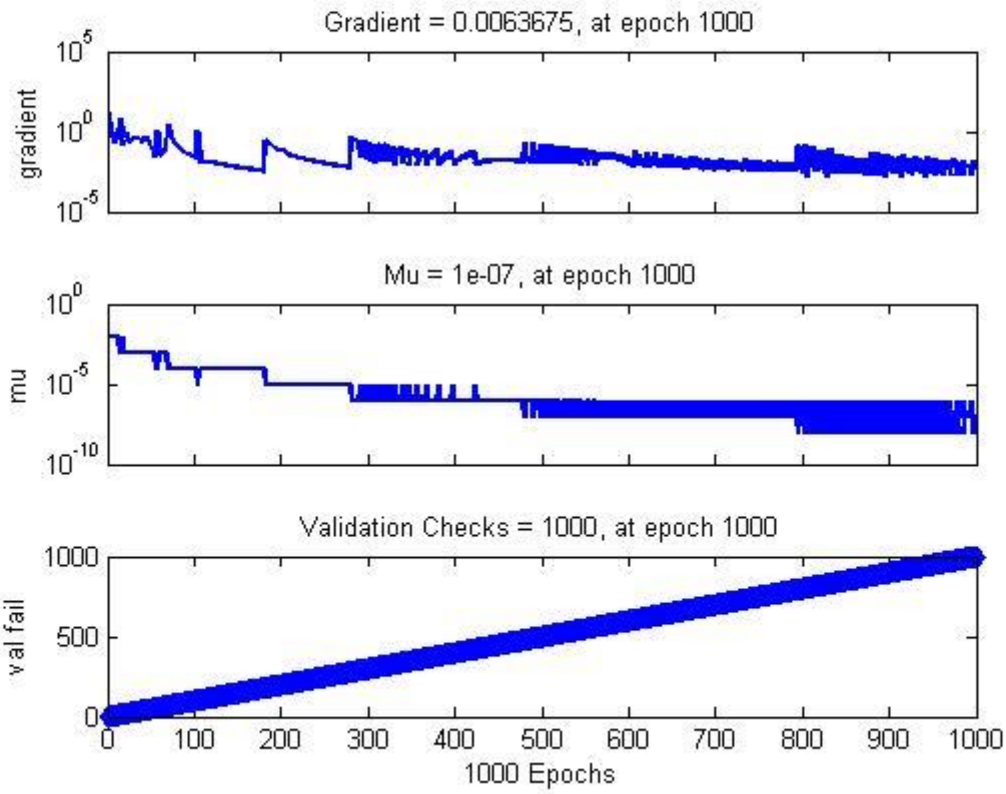
Training state of milling recovery using ANN



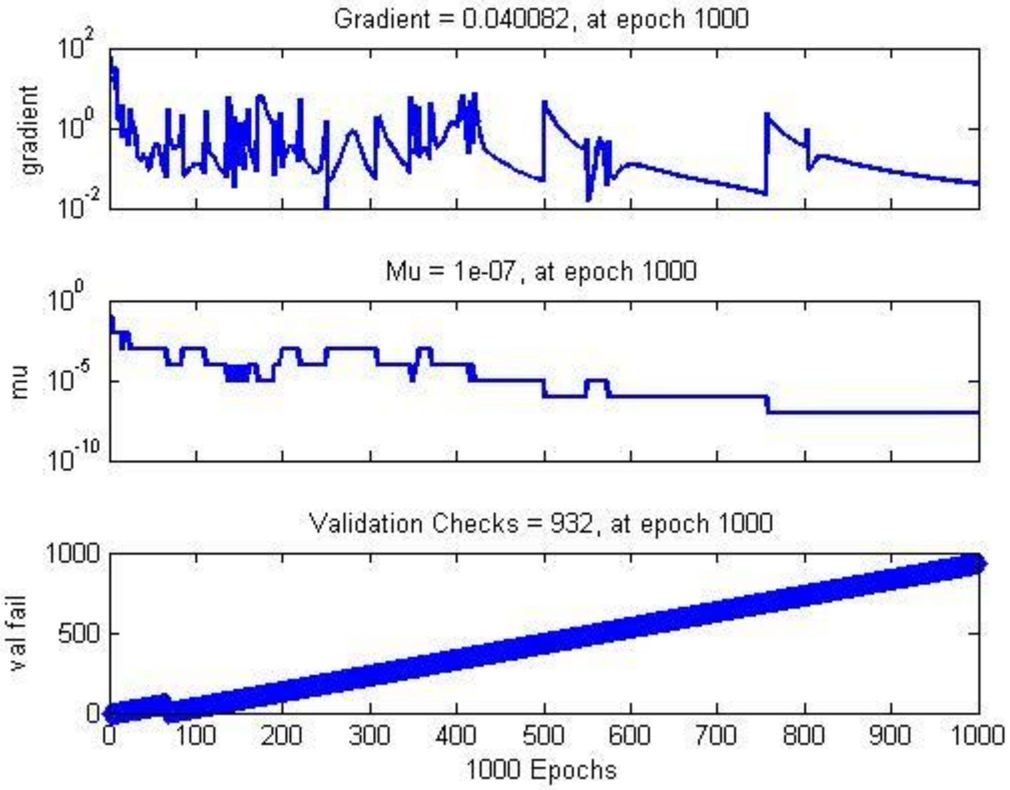
Training state of head milled rice using ANN



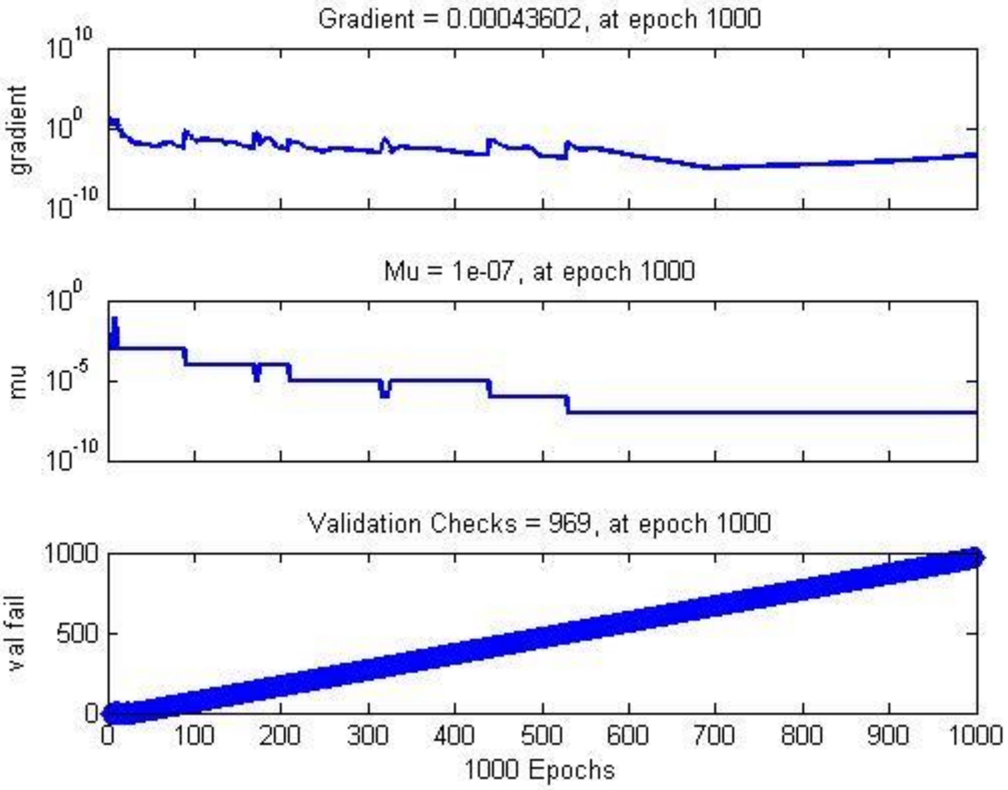
Training state of colour value using ANN



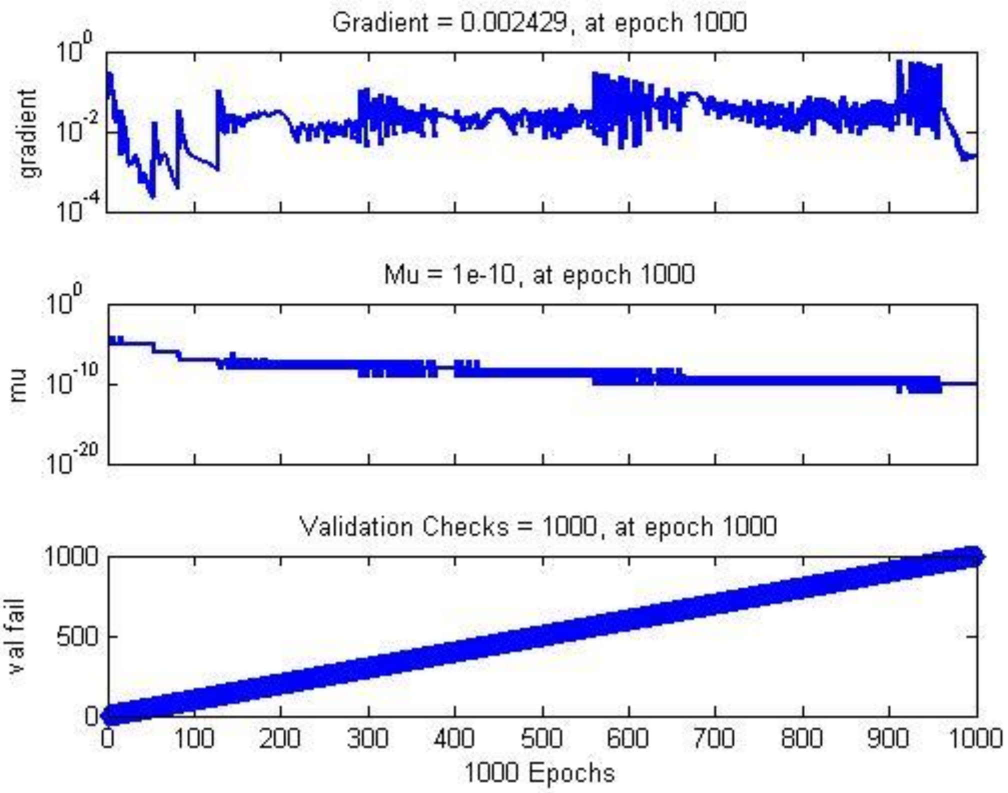
Training state of lightness value using ANN



Training state of cooking time using ANN



Training state of chalkiness using ANN



Training state of water uptake ratio using ANN

PRINCIPAL COMPONENT ANALYSIS OF Correlation Matrix FOR FARO 44, FARO 52, FARO 60 and FARO 61

		Uniform appearance	Black specks	Whitish appearance	Yellow colour	Brown colour	Cream colour	Rice Odour	Taste	Sticky texture	Hard texture	Grainy texture
Correlation	Uniform appearance	1.000	.267	.579	.239	-.500	-.369	-.153	.251	-.373	.218	.328
	Black specks	.267	1.000	.206	.076	-.199	-.492	.140	.033	-.194	.175	.278
	Whitish appearance	.579	.206	1.000	.081	-.524	-.320	-.136	.191	-.166	.564	.123
	Yellow colour	.239	.076	.081	1.000	-.128	-.516	.001	-.078	-.140	.083	.165
	Brown colour	-.500	-.199	-.524	-.128	1.000	.192	.059	-.164	.231	-.014	-.213
	Cream colour	-.369	-.492	-.320	-.516	.192	1.000	-.086	.068	.266	-.238	-.204
	Rice Odour	-.153	.140	-.136	.001	.059	-.086	1.000	-.080	.206	.057	.205
	Taste	.251	.033	.191	-.078	-.164	.068	-.080	1.000	-.279	.117	.026
	Sticky texture	-.373	-.194	-.166	-.140	.231	.266	.206	-.279	1.000	.021	.024
	Hard texture	.218	.175	.564	.083	-.014	-.238	.057	.117	.021	1.000	.045
	Grainy texture	.328	.278	.123	.165	-.213	-.204	.205	.026	.024	.045	1.000

KMO and Bartlett's Test for FARO 44, FARO 52, FARO 60, FARO 61

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.606
Bartlett's Test of Sphericity	Approx. Chi-Square	130.820
	df	55
	Sig.	.000

Structure Matrix for FARO 44, FARO 52, FARO 60, FARO 61

	Component	
	1	2
Uniform appearance	.757	.444
Whitish appearance	.749	.359
Brown colour	-.634	-.292
Sticky texture	-.573	-.096
Taste	.540	-.169
Rice Odour	-.425	.378
Cream colour	-.250	-.798
Black specks	.195	.643
Grainy texture	.072	.565
Yellow colour	.087	.563
Hard texture	.332	.332

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Correlation Matrix for NERICA 8

		Uniform appearance	Black specks	Whitish appearance	Yellow colour	Brown colour	Cream colour	Rice Odour	Taste	Sticky texture	Hard texture	Grainy texture
Correlation	Uniform appearance	1.000	.158	.063	-.104	.012	.098	.049	.114	.025	.127	-.188
	Black specks	.158	1.000	-.063	.671	.362	-.562	.243	.300	-.519	-.528	.064
	Whitish appearance	.063	-.063	1.000	.085	-.703	.115	.025	.442	.057	.220	-.492
	Yellow colour	-.104	.671	.085	1.000	-.113	-.072	.153	.011	-.046	-.489	-.242
	Brown colour	.012	.362	-.703	-.113	1.000	-.584	.102	-.294	-.729	-.029	.660
	Cream colour	.098	-.562	.115	-.072	-.584	1.000	-.326	-.016	.764	.096	-.125
	Rice Odour	.049	.243	.025	.153	.102	-.326	1.000	-.267	-.178	-.318	.104
	Taste	.114	.300	.442	.011	-.294	-.016	-.267	1.000	-.028	.060	-.162
	Sticky texture	.025	-.519	.057	-.046	-.729	.764	-.178	-.028	1.000	-.129	-.398
	Hard texture	.127	-.528	.220	-.489	-.029	.096	-.318	.060	-.129	1.000	.118
	Grainy texture	-.188	.064	-.492	-.242	.660	-.125	.104	-.162	-.398	.118	1.000

KMO and Bartlett's Test for NERICA 8

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.150
Bartlett's Test of Sphericity	Approx. Chi-Square	90.579
	df	55
	Sig.	.002

Structure Matrix for NERICA 8

	Component	
	1	2
Brown colour	.918	.347
Grainy texture	.784	-.006
Whitish appearance	-.691	-.029
Sticky texture	-.601	-.549
Taste	-.419	.149
Uniform appearance	-.121	.016
Black specks	.024	.951
Yellow colour	-.371	.683
Cream colour	-.455	-.660
Hard texture	.187	-.599
Rice Odour	.101	.438

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.