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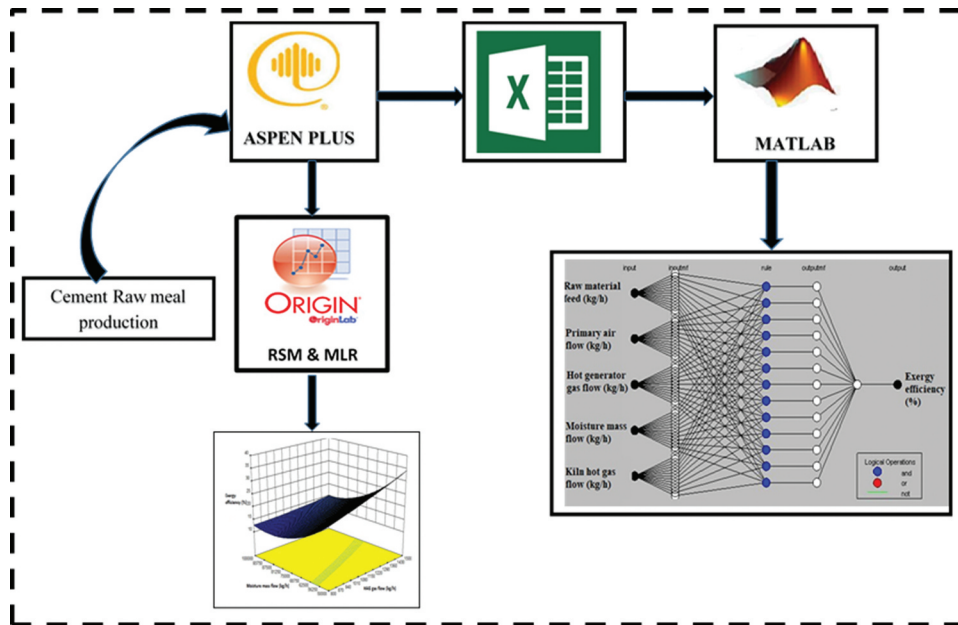
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CHEMICAL ENGINEERING | RESEARCH ARTICLE

Evaluation of optimization techniques for predicting exergy efficiency of the cement raw meal production process

Anthony I. Okoji^{1,2,3,4*}, Ambrose N. Anozie⁵ and James A. Omoleye⁴

Abstract: In cement production, raw meal preparation and energy consumption are extremely important for cost reduction. However, few studies have examined the relationship between operational process parameters and exergy efficiency. For this comparative study on predicting exergy efficiency of raw meal production, adaptive neuro-fuzzy inference systems (ANFIS), multiple linear regression (MLR), and response surface methodology (RSM) were used for a comparison of the predictive accuracy of these parameters. The study also suggests a routine for selecting the best predictive model, which includes considering raw materials, primary air, moisture content, and kiln hot gas flow. The established model was tested against different indicators of predictive performance and found to be consistent. The developed ANFIS, MLR, and RSM models accurately described the process (coefficient of determination, $R^2 > 0.9000$), and in each case, the absolute relative errors (AARE) are 0.000692, 0.00422, and 0.00135. The current study has found that both ANFIS and RSM predicted correctly and consistently better than MLR, but while ANFIS and RSM produced similar results, ANFIS performed slightly better than RSM.

Subjects: Artificial Intelligence; Thermodynamics; Sustainable Engineering & Manufacturing; Chemical Engineering

Keywords: Exergy efficiency; raw meal production; cement production; adaptive neuro-fuzzy inference systems; multiple linear regression; response surface methodology

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PUBLIC OF INTEREST STATEMENT

The exergy efficiency of the cement raw meal manufacturing process is investigated in this study. The Aspen Plus process model was used for plant modeling and evaluating the system's exergy efficiency using plant operational data. It is worth noting that a mechanistic approach takes time, so prediction models based on plant operational data were created to overcome this limitation. When the ANFIS, MLR, and RSM predictive models are compared, it is clear that the ANFIS models have higher predictive capacities than the RSM models, which are followed by the MLR models. This could be due to the non-linearity of the independent and dependent variables. However, the proposed models' performances.

1. Introduction

Cement manufacturers face economic and environmental challenges due to their high-energy consumption. Periodic data collection on industry and other energy-consuming industries is crucial to setting objectives for energy-saving studies (Madloul, Saidur et al., 2013). Atmaca and Yumrutaş (2014) suggested that an estimates of 54% thermal efficiency could be achieved by the cement industry. This ultimately means that enormous amounts of energy are underutilized in cement manufacturing which invariably makes the greenhouse gas emissions generated as a waste that could be managed for sustainability goal. The large losses should not be regarded as an impossible hurdle but as an opportunity for achieving technological improvements (Boyd & Zhang, 2013). The cement raw mill is the primary piece of equipment used in the modern cement industry for the raw meal production process. As a result, it is critical to investigate the exergy efficiency in a cement raw mill in order to satisfy the need for the design and optimization of the cement plant manufacturing process. Because of its significance, exergy as a tool offers excellent assistance to all fields, particularly science and engineering, in the pursuit of sustainable development. A system with a higher exergetic performance saves energy and benefits the environment .

The first law of thermodynamics helps quantify energy conversion in a phase; however, the second law provides theoretical explanations for these conversions. It places constraints on the energy quality and energy transformation direction (Smith et al., 2018). The concept of exergy, which is based on the second thermodynamic law, has been widely applied to energy systems (Han et al., 2018), resource economics performance (Mirhosseini et al., 2019; Mirzaei et al., 2018; Song et al., 2019), and environmental impact assessment (Oni et al., 2017; Sogut et al., 2009). The system can detect the location and magnitude of energy destruction in low-efficiency transformation sectors and provide data for accurate design, simulation, and optimization of rotary kilns and grinding plants used in cement production. Fellaou and Bounahmidi (2017) applied an advanced exergy analysis tool to assess the real potential for energy system thermodynamic changes by separating exergy destruction into inevitable and avoidable parts. Taweel et al. (2018) presented a temperature profile-based analysis of clinker in the grate clinker cooler. Shao et al. (2020) investigated the heat distribution in the entire grate cooler system using experimental research and numerical simulation. Shao et al. (2016) proposed an air distribution model using multi-objective optimization techniques developed to address the issue of heat recovery in a cement grate clinker cooler. Okoji et al. (2018) examined the thermodynamic efficiency of a cement raw mill using the Aspen Plus software. Utlu et al. (2006) also assessed the energy and exergy efficiency of a cement raw mill in the sector. Atmaca and Atmaca (2016) summarised the cement production process in terms of exergy balance, illustrating that increasing energy efficiency can help reduce energy consumption.

Previous works on energy efficiency have made use of mechanistic models, however, developing such a model for complex processes, particularly integrating exergy efficiency as the second law of thermodynamics may be complicated and time-consuming (Li et al., 2019). Data-driven models such as Aspen plus, adaptive neural network and a fuzzy inference system (ANFIS), multiple linear regression (MLR) and response surface methodology (RSM) models may be able to assist in resolving these issues (Li et al., 2019)

RSM is a powerful mathematical tool for designing, modeling, and optimizing experimental materials. It is an empirical modeling technique that is related to one or more responses to individual variables. It is distinctive in that it provides information on the various models and their interactions (Maddah et al., 2019). RSM has been used for the optimization, such as extraction of *Terminalia catappa* L and Kernel oil (Agu et al., 2020); prediction of parameters of optimum processes for activated rice husk carbon production (Mansour Ghaffari & Mostafa, 2011). MLR, on the other hand, involves more than one input variable, which can contribute to a “multiple linear regression” in many regression analysis applications. In this case, by modifying the linear equation to the observed data, the MLR tests the correlation between two or more input variables to give a desired output (Khademi & Behfarnia, 2016; Sadrmomtazi et al., 2013). While Jang and Sun

(1995) developed adaptive neuro-fuzzy inference system (ANFIS) as a technique that combines the capabilities of an adaptive neural network and a fuzzy inference system (ANFIS). This is an example of neural networks, fuzzy system has a simple learning procedures with a good computational strength, and ability to describe uncertainty (Malik & Rashid, 2000). Although the technique has been used to model a variety of systems, there is little evidence of its use in cement raw meal preparation processes.

Consider the following references for more in-depth discussion of other solutions, Awasthi and Omrani (2019) applied a goal-oriented approach based on fuzzy axiomatic design for prioritising sustainable mobility projects. Gharaei, Karimi et al. (2019) proposed an integrated multi-product and multi-buyer SC under penalty policies, quality management practices, and a VMI with consignment stock agreement. They explored the impact of augmented penalty algorithms using the outer approximation including equality relaxation. The multi-objective, integrated economic production quantity model by Gharaei, Hoseini Shekarabi et al. (2019) was based on quality assurance and green policy considerations as well as stochastic constraints. As part of an integrated approach, Sayyadi and Awasthi (2020) studied sustainable transportation policy evaluation using system dynamics simulation and analytic network model. A stochastic maintenance quality model for multi-component systems is investigated in Duan et al. (2018), which uses a simulated annealing algorithm to solve a complicated optimisation problem. Gharaei et al. (2020) addressed joint economic lot-sizing problem in the context of integrated four-level SC planning, utilizing generalised benders decomposition to optimize the MINLP model. Hoseini Shekarabi et al. (2019) evaluated integrated multilevel multi-wholesaler supply chains under the shortage and limited warehouse space using generalized outer approximations (GOA) to determine the optimal lot-sizing. Kazemi et al. (2018) analysed how defects affect order quantities and the impact of emission costs on replenishment order sizes as well as the total profit of a retailer. Rabbani et al. (2019) applied a decision model based on interval-valued fuzzy sets and probabilistic statistical reference point systems for sustainable supplier selection under uncertainty to evaluate the sustainability performance of suppliers. Rabbani et al. (2020) used a hybrid robust possibilistic approach for a sustainable supply chain location-allocation network, and the AUGMECON2 method for solving the model and gaining Pareto solutions. A simulation-based optimization approach developed by Sayyadi and Awasthi (2018) for identifying key sustainability determinants assists with identifying critical variables for meeting sustainability objectives in transportation. Tsao (2015) used nonlinear optimization to solve a piecewise nonlinear problem in a carbon-efficient supply chain network through trade credits. A non-cooperative game is used to model the relationship between a single manufacturer and multiple suppliers with quality variations under uncertain demands, according to Yin et al. (2016).

Most researches are focusing on the exergy efficiency and parametric study analysis of the raw meal production process. However, there are little research on using the Aspen plus to evaluate the exergy efficiency with the selected plant operational data which have influence on the intensive property of the process and in addition, incorporating the predictive model to obtain the optimal solution by validating with the plant operating data. In most cases, Aspen Plus must generate the mass, enthalpies, and exergy of all the streams involved in order to evaluate exergy efficiency, whereas ANFIS, MLR, and RSM brings to board improvement through predictive approach because they do not require the rigors of measuring stream mass, enthalpies, and exergy.

In this study, ANFIS, RSM, and MLR models are trained by using a large number of actual production data to obtain the relationship between the exergy efficiency and the plant operational parameters, and Minitab 17 software is employed to find the optimal input parameters to achieve the maximum exergy efficiency. A set of Pareto optimal solutions is achieved with the selected design operational variables, which are raw material feed flow (kg/h), HAG gas flow (kg/h), primary airflow (kg/h), feed moisture mass flow (kg/h), Kiln hot gas flow (kg/h). The model can predict the exergy efficiency and provide a reference for implementing optimum efficiency in enterprises

through simulations specific to existing data. The proposed approach is capable of generating training data, enabling a network to be trained, and, in addition, for an early stop in prediction. Early stopping of ANFIS means that their predictions are continuously monitored during training, so that they are terminated when their predictions on testing data do not further reduce. A model's prediction accuracy is enhanced if the predicted target values are closer to the actual experimental values.

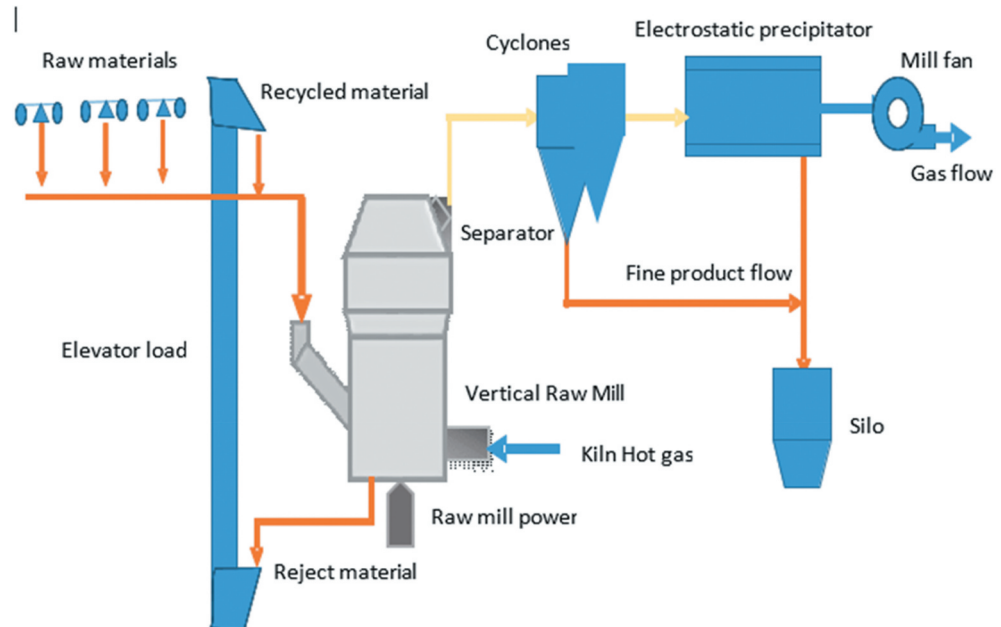
2. Raw meal production process

The raw material used to produce clinkers is some naturally occurring minerals and some waste materials available from other industries. Limestone (for calcium) mixed with much smaller amounts of clay, shale, and sand are the most common mixture of ingredients (as a source of silica, aluminum, and iron) as shown in Figure 1. The various raw material components are moved by a standard belt conveyor directly through the rotary sluice into the mill with a capacity of 240,000 kg/h on a dry basis. The material was spinned by the table and found its way in between the lowered rollers and the table for proper size reduction to take place. The spills material from the table comes in contact with the upward movement of the hot gases through the dam rings caused the ground material to be entrained in the hot air at a temperature of 430°C for proper drying and transport into the classifier forming the upper part of the mill by the air stream. Fine particles exit the separator at a temperature of about 85°C, while coarser particles are rejected and recycled for subsequent grinding. Those parts that leave the mill with the exhaust gases are precipitated in cyclones. The precipitate is transferred to a raw meals storage silo. A filter fan sends the now cleaned gases to the atmosphere, but the residual fine dust, which is not precipitated in cyclones, is transferred to the electrostatic precipitator, where dust trapped takes place. The raw meal with the right chemical balance is a milled fine powder made from the raw materials. The chemistry of the raw materials and the raw meal is very closely regulated to ensure a high cement quality. Material homogenization is important for ensuring consistency in product quality.

Mass balance:

$$\sum_{i=1}^n \dot{m}_{in} - \sum_{i=1}^n \dot{m}_{out} = 0 \tag{1}$$

Figure 1. Raw Meal Preparation Flowsheet, source: .Okoji et al. Okoji et al. (2018)



Where \dot{m} is the mass flow rate of streams, *in* is the inlet condition, *out* is the outlet condition, *i* is the *i*th stream, and *n* is the *n*th stream.

Energy balance:

$$\sum_{i=1}^n \dot{Q}_i + \sum_{i=1}^n \dot{W}_s = \sum_{i=1}^n \dot{m}_{out} \Delta h_{out} - \sum_{i=1}^n \dot{m}_{in} \Delta h_{in} \quad (2)$$

Where \dot{Q}_i is the heat crossing the boundary of the plant's component unit, \dot{W}_s is the shaft work required or produced by the unit, Δh is the change specific in enthalpy of a stream for the ambient condition.

Exergy balance:

$$\sum_{i=1}^n \dot{Q}_i \left(1 - \frac{T_o}{T_i}\right) + \sum_{i=1}^n \dot{W}_s + \sum_{i=1}^n \dot{m}_{in} ex_{in} - \sum_{i=1}^n \dot{m}_{out} ex_{out} = I \quad (3)$$

$$ex_i = \Delta h - T_o \Delta s = (h_i - h_o) - T_o (s_i - s_o) \quad (4)$$

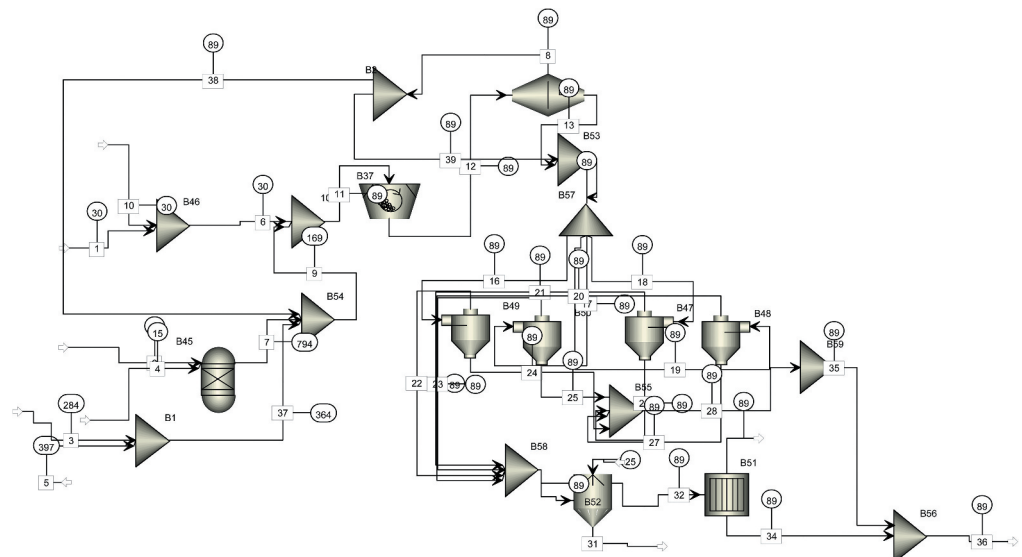
Where ex_i is the specific exergy of a stream, T_o is the ambient temperature, Δs is the change in specific entropy concerning the ambient condition, s_o is the stream-specific entropy at ambient condition, s_i is the specific entropy of a stream at the current state, *I* is the irreversibility of the process (Utlu et al., 2006). The plant design and process input data obtained for the Aspen plus process model simulation are presented in the Table 1 and 2.

3. Models development

3.1. Multiple linear regression model (MLR)

Finding a correlation between two or more variables involves many engineering challenges. The quest of addressing this challenges birthed a simple statistical method called regression analysis and ever since the scientists have always been interested in its application. It is generally possible

Figure 2. Cement raw meal production flow sheet represented with Aspen Plus process model.



to consider regression models as a method for fitting models to data. Using multiple linear regression, the relationship between variables is explored as well as the summary of data. The general form of multiple models of linear regression is expressed in Equation. (5) below:

$$\hat{Y} = b_0 + \sum_{i=1}^n b_i X_i \tag{5}$$

where \hat{Y} is the model's output, X_i 's are the independent input variables to the model, and $b_1, b_2, b_i, \dots, b_n$ are partial regression coefficients. To make the model's performance comparable with that of the training set, the parameters are set to minimize variability. This study's multiple linear regression model demonstrates the relationship between operational data and the exergy efficiency of the raw meal production process.

3.2. Response surface methods model (RSM)

Box-Behnken, central composite design (CCD), and factorial design are the three most widely used RSM methods. The main composite design is a five-level design that combines axial points while constructing the experimental runs, whereas the three-level designs include the Box-Behnken and factorial design. By applying both ORIGINPRO 2019 and Minitab 17 software, the RSM modeling was completed. This was also done to evaluate the interactive impacts on the exergy efficiency of raw meal output of the independent input variables. The independent input variables were raw material feed flow (kg/h), HAG gas flow (kg/h), primary airflow (kg/h), feed moisture mass flow (kg/h), Kiln hot gas flow (kg/h).

The quadratic model has been used to express the behavior of the exergy efficiency (Y) system response as a function of the independent input variables in Equation. (6).

The input variables were raw material feed flow (x_1), HAG gas flow (x_2), primary airflow (x_3), moisture mass flow(x_4), Kiln hot gas flow(x_5).

$$Y = \delta_0 + \delta_1 X_1 + \delta_2 X_2 + \delta_3 X_3 + \delta_4 X_4 + \delta_5 X_5 + \delta_{11} X_1^2 + \delta_{22} X_2^2 + \delta_{33} X_3^2 + \delta_{44} X_4^2 + \delta_{55} X_5^2 + \delta_{12} X_1 X_2 + \delta_{13} X_1 X_3 + \delta_{14} X_1 X_4 + \delta_{15} X_1 X_5 + \delta_{23} X_2 X_3 + \delta_{24} X_2 X_4 + \delta_{25} X_2 X_5 + \delta_{34} X_3 X_4 + \delta_{35} X_3 X_5 + \delta_{45} X_4 X_5 + \epsilon \tag{6}$$

where δ_0 is the offset term or model constant; $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5$ are the linear or first-order terms; $\delta_{11}, \delta_{22}, \delta_{33}, \delta_{44}, \delta_{55}$ are the pure quadratic or squared terms; $\delta_{12}, \delta_{13}, \delta_{14}, \delta_{15}, \delta_{23}, \delta_{24}, \delta_{25}, \delta_{34}, \delta_{35}, \delta_{45}$. These are the quadratic function's interactive terms; ϵ is the random error term that makes uncertainties between the values that are experimental and predicted. The acceptability of the quadratic model was based on the p-value of the variance analysis and the coefficient of correlation (R^2) value.

In evaluating the significance of the obtained regression model, the discrepancy between the operational data and the expected values was used.

3.3. Adaptive neuro-fuzzy inference system model (ANFIS)

ANFIS was used to create a multi-input single-output (MISO) fuzzy model with five input variables and one output variable to predict the energy efficiency of a raw meal production process. Furthermore, Figure 3 depicts the architecture of the proposed ANFIS model, which is comprised of five distinct layers: fuzzification, product, norm or standardization, defuzzification, and layers of total production summation (Naderpour et al., 2010). The first-order Sugeno-type model, which has five input variables with both Takagi and Sugeno's fuzzy IF-THEN law, was used for this investigation. Assuming there are two inputs (x, y) and one output (f) for the fuzzy inference method (FIS) under consideration, the fuzzy rules apply as follows (Jang & Sun, 1995):

Rule 1 → if x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$.

Rule 2 → if x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$.

As Figure 2 shows, the ANFIS model architecture comprises 5 separate layers defined as follows, each of them (Jang & Sun, 1995):

- (1) Layer 1: This is the fuzzification layer, and any node i in this layer is transformed to membership values by using the Membership function, as shown in Equation. (7):

$$O_i^1 = \mu_{A_i}(x) \tag{7}$$

in which the input to node i is x , and the linguistic label associated with this node function A_i .

- 2) Layer 2: Every node in this layer reproduces the input and sends out the results. Furthermore, the firing power of each rule can be determined by each specific node in the same layer. This layer is shown as an example in Equation (8) (Jang & Sun, 1995; Sadrmomtazi et al., 2013).

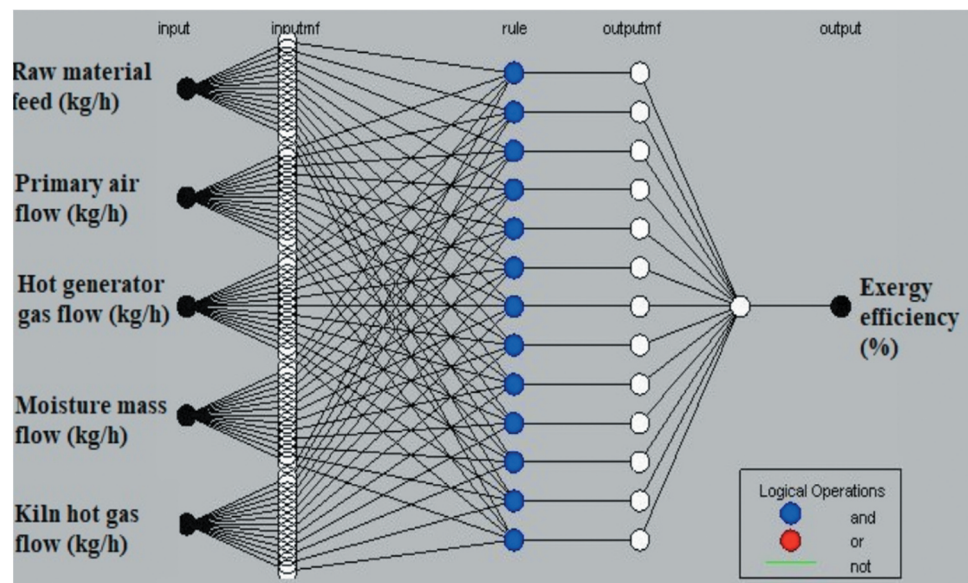
$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), i = 1, 2, \dots \tag{8}$$

- 3) Layer 3: This layer is capable of normalizing values for membership. In this layer, the i th node specifies the proportion of the firing power of the i th law to the sum of the firing intensity of all rules. Equation (9) indicates the normalized firing force measurements in this layer for node i th.

$$\bar{w}_i = \frac{w_i}{(w_1 + w_2)}, i = 1, 2, \dots \tag{9}$$

- 4) Layer 4: This layer, also known as the adaptive layer, could define the connection of the input and output values as shown in Equation. (10)

Figure 3. ANFIS model architecture with five input variables.



$$O_i^4 = \overline{w}_i(p_i x + q_i y + r_i) \tag{10}$$

where \overline{w}_i is the output resulted from layer 3, and $\{p_i + q_i + r_i\}$ is the parameter set.

5) Layer 5: This is also known as the de-fuzzification layer. The later signal node is a circle node labeled f^o that computed the total output as the summation of all input signals shown in Equation. (11).

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{11}$$

Using the hybrid learning algorithm, contexts and parameters are determined by combining least squares and gradient descent. Lately, for its predictive purposes, ANFIS has implemented the hybrid algorithm, which is an effective learning process. Many scientists have validated the hybrid algorithm (Vu-Bac et al., 2014).

3.4. Performance criteria

In this analysis, statistical goodness-of-fit parameters were provided to compare the results between the three separate ANFIS, RSM, and MLR models. The best predictor is the coefficient of determination R^2 with Adjusted R^2 to verify the correlation efficiency of the model. Besides, some statistical models have been used to measure the size of the error between the experimental values and expected values. These include mean square error (MSE), root-mean-square error (RMSE), sum square error (SSE), and absolute average relative error (AARE) as shown in equation (Jian et al., 2011; Vu-Bac et al., 2014).

4. Results and discussion

4.1. Development of the model of mathematical regression by RSM

The results of RSM process modeling have provided a mathematical expression that relates to the raw material feed, primary airflow, hot gas generator gas flow, moisture mass flow, and kiln hot gas flow (i.e. independent variables) in terms of exergy efficiency (i.e. response) in terms of the actual values, and are represented by the RSM. Equation. (18).

$$Y = 66.6 - 0.420X_1 - 0.0762X_2 + 20.02X_3 - 0.9082X_4 - 0.0503X_5 - 0.000153X_2^2 + 6.245X_3^2 + 0.008198X_4^2 + 0.000313X_5^2 + 0.000098X_1X_2 - 0.0195X_1X_3 + 0.000967X_1X_4 - 0.000099X_1X_5 - 0.04025X_2X_3 + 0.000911X_2X_4 - 0.27029X_3X_4 + 0.01652X_3X_5 + 0.001888X_4X_5 \tag{18}$$

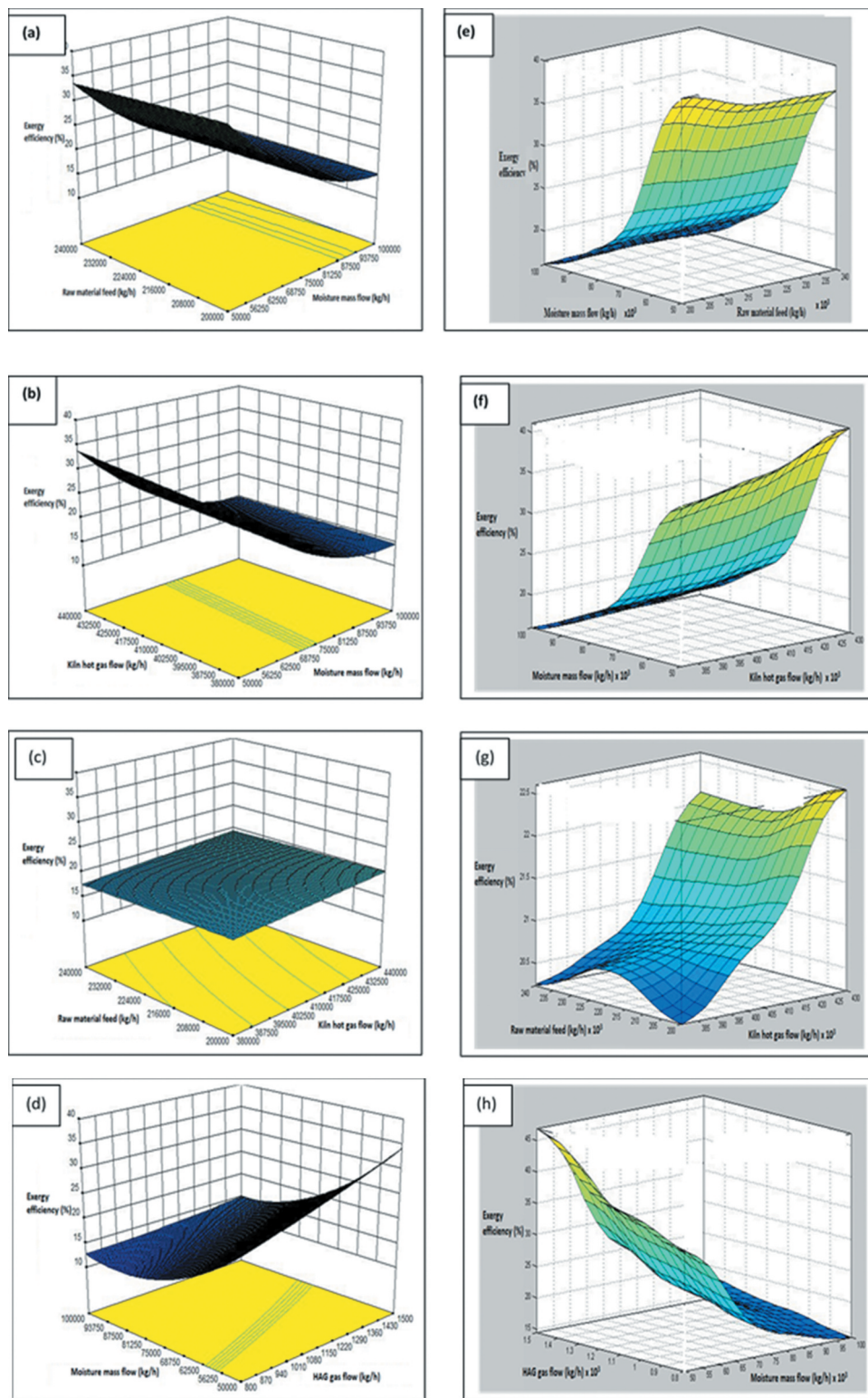
where Y is exergy efficiency (%), X_1 is the raw material feed (kg/h), X_2 is the primary airflow (kg/h), X_3 hot gas generator gas flow (kg/h), X_4 moisture mass flow rate (kg/h) and X_5 kiln hot gas flow (kg/h).

The value of R, which is close to unity, indicates that the operational data and expected values were well correlated. Also, the value of R^2 indicates the model can explain 90.8% of the variance in the operational data and expected values. R^2 , it implies a strong fit of the model that is similar to unity. The description of each model terminology and its interactions have also been examined by drawing up a Pareto map (Figure 5d) using Minitab 17 software. The longer the bar, the greater the importance and the insignificance of every bar. The figure shows that the most important model term was moisture mass flow ratio, followed by hot gas generator gas flow, followed by kiln hot gas flow.

4.2. Parametric effect of using RSM model

The interaction between the five parameters examined for the exergy efficiency of the raw meal production process was considered using three-dimensional surface plots (Figure 4a-e), which

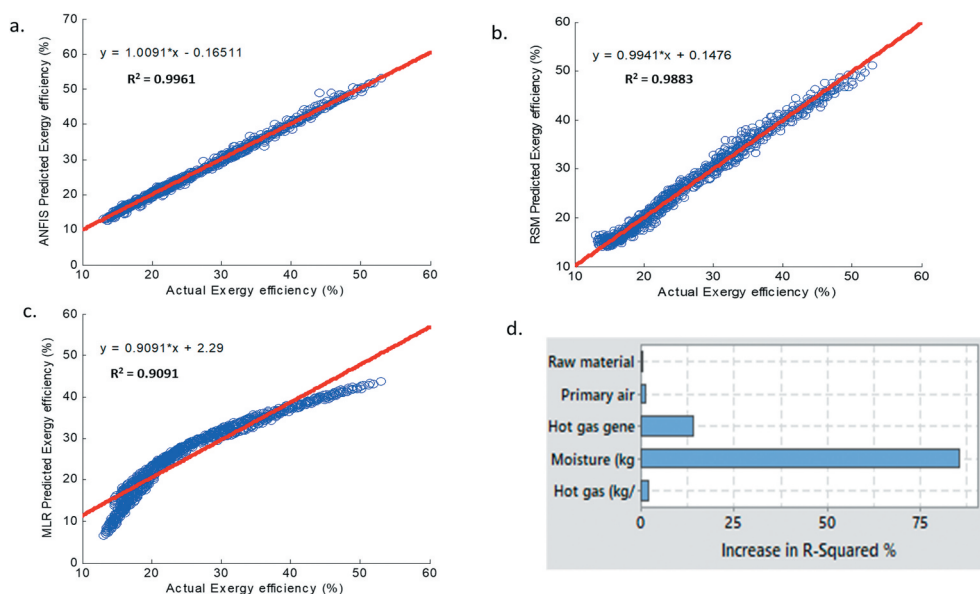
Figure 4. 3D surface plots by RSM (a–d) and ANFIS (e–h).



enabled visual observations to be made. The plots were created with the RSM design of experiment (DOE) and Minitab 17 software.

(1) *Effect of moisture mass flow and raw material feed flow.*

Figure 5. The plots of predicted value versus actual exergy efficiency for ANFIS, RSM, and MLR (a—c), Pareto chart of standardized effects for exergy efficiency (d).



This three-dimensional plot of the parameters in Figure 4a is similar to Figure 3b, and it shows an interaction between moisture mass flow and feed with significant effects on the exergy efficiency of the raw meal production process. The exergy efficiency was highest at the lowest moisture mass flow with high raw material feed. As the raw material feed increases, at a reduced moisture mass flow the exergy efficiency of the system increased as high as greater than 35% at variables which are of the value of 260,000 kg/h for raw material feed and 55,000 kg/h for moisture mass flow. This could only be achieved at 17.5% of the moisture in the raw material feed. The figure suggests moisture mass flow had a more significant effect on the increase of the raw meal exergy efficiency than the raw material feed.

4.2.1. Effect of kiln hot gas flow and moisture mass flow

The surface plot of three-dimension for the parameters in Figure 4b looks similar to Figure 4a and it shows a strong interaction that occurred between the two parameters was more significantly observed when compare to Figure 4a and c. An increase in exergy efficiency is also observed at the lowest moisture mass flow and moderately on the kiln hot gas flow. The exergy efficiency of the raw meal production process is noted at moisture mass flow of 50,000 kg/h and with a consistent increase of kiln hot gas flow until a maximum kiln hot gas flow with temperature increase to affect the drying process in raw mill internals for efficient grinding. The exergy efficiency is affected significantly by moisture mass flow (Atmaca & Kanoglu, 2012).

4.2.2. Effect of raw material feed and kiln hot gas flow

The surface plot of three-dimension in Figure 4c looks similar to Figure 4b and it shows interface occurs between the raw material feed and kiln hot gas flow with a substantial effect on the exergy efficiency of the raw meal production process. The exergy efficiency was highest at the lowest raw material feed with consistently high kiln hot gas flow. As the raw material feed increases, at an increase in the kiln hot flow the exergy efficiency of the system increased as high as greater than 26% at the peak of both variables which are of the value of 260,000 kg/h for raw material feed and 440,000 kg/h for kiln hot gas flow. This could only be achieved at 22% of the moisture in the raw material feed. The figure suggests kiln hot gas flow which is waste heat from the kiln had a more significant effect on the increase of the raw meal exergy efficiency than the raw material feed.

4.2.3. Effect of moisture mass flow and hot gas generator gas flow

Figure 4d depicts a three-dimensional surface plot of moisture mass flow and hot gas generator gas flow to the exergy efficiency. The surface plot imitates Figure 4b, and it demonstrates a strong interaction between the two parameters that was more significantly observed when compared to Figure 4a, b, and c.

The highest exergy efficiency is also observed at the lowest moisture mass flow and moderately on the hot gas generator gas flow. The highest exergy efficiency of the raw meal production process is noted at moisture mass flow of 50,000 kg/h and hot gas generator gas flow of 1350 kg/h. The exergy efficiency is affected significantly by moisture mass flow (Atmaca and Atmaca, 2016).

4.3. ANFIS modeling

Figure 3 shows the plots of five inputs (raw material feed, primary airflow, hot gas generator gas flow, moisture mass flow, and kiln hot gas flow) using Gaussian membership functions (MF). Figure 5a depicts a plot of the operation data and expected values. The calculated R and R^2 values were 0.998 and 0.9961, respectively. The value of R^2 which is near unity, indicates a strong good agreement between the operational data and predicted values. Furthermore, the value of R^2 shows that the model can explain 99.61% of the variation in the operational data and the predicted values. The high value of R^2 also indicates the model's fitness (Utlu et al., 2006).

4.4. Effect of parametric analysis using ANFIS model

In order to determine the exergy efficiency of raw meal production, 3D surface plots were used to examine the interactions between five parameters (Figure 4e–h). These plots can be viewed visually, and were produced using the ANFIS model.

4.4.1. Effect of moisture mass flow and raw material feed flow

The relationship between moisture mass flow and raw material feed flow on the exergy efficiency is expressed in Figure 4e. The figure shows that the relationship between the two parameters influenced the exergy efficiency of the process in the production of raw meals considerably. When moisture mass flow and raw material feed were lowest, exergy efficiency was highest. As both factors increased, exergy efficiency decreased (Figure 4e). The exergy efficiency decreased from over 35% to less than 20% for the raw meal production process. Decreasing the moisture mass flow beyond 75,000 kg/h increases the exergy efficiency of the system. Likewise, decreasing the raw material feed below 230,000 kg/h considerably increases the exergy efficiency. It is understood that both parameters are considered to have a major impact on the process exergy efficiency

4.4.2. Effect of kiln hot gas flow and moisture mass flow

Figure 4f shows the three-dimensional surface plot of kiln hot gas flow and moisture mass flow the exergy efficiency of the raw meal production process. The figure showed looks similar to Figure 4e, and the relationship between the two parameters influenced the exergy efficiency of the process in the production of raw meals considerably. The exergy efficiency of the system was highest at the lowest moisture mass flow and highest kiln hot gas flow. As the moisture mass flow and kiln hot gas flow increases, the exergy efficiency of the raw meal production process decreases (Figure 4f). The exergy efficiency decreased from about 40% to less than 20%. The lowest exergy efficiency is observed at moisture mass flow of 100,000 kg/h and kiln hot gas flow of 380,000 kg/h. increasing the kiln hot gas above this value increases the exergy efficiency. Similarly, decreasing the moisture mass flow, significantly increases the exergy efficiency of the raw meal production process.

4.4.3. Effect of raw material feed and kiln hot gas flow

Figure 4g illustrates the relationship between raw materials feed and kiln hot gas flow on exergy efficiency. The figure shows that the relationship between the two parameters influenced the exergy efficiency of the process in the production of raw meals considerably. The exergy efficiency was highest at the lowest raw material feed and highest at the hot gas generator gas flow. As the raw material feed increases at the highest hot gas generator gas flow, the exergy efficiency started decreasing (Figure 4g). The exergy efficiency decreased from over 26% to less than 24%. The lowest exergy efficiency is observed at the raw material feed of 260,000 kg/h and the hot gas generator gas flow of 380,000 kg/h. Increasing the kiln hot gas flow beyond 430,000 kg/h increases the exergy efficiency of the raw meal production process. Likewise, decreasing the raw material feed to 220,000 kg/h considerably increases the exergy efficiency of the process.

4.4.4. Effect of moisture mass flow and hot gas generator gas flow

The relationship between moisture mass flow and hot gas generator gas flow on the exergy efficiency is described in Figure 4h. The figure shows the interaction of the two parameters that significantly influenced the exergy efficiency of the raw meal process. The exergy efficiency was highest at the lowest moisture mass flow and highest at the hot gas generator gas flow. When the moisture mass flow increases at the highest hot gas generator gas flow, the exergy efficiency started decreasing (Figure 4h). The exergy efficiency decreased from over 40% to less than 20%. The lowest exergy efficiency is observed at moisture mass flow of 100,000 kg/h and the hot gas generator gas flow of 800 kg/h. Increasing the hot gas generator gas flow beyond 1500 kg/h increases the exergy efficiency of the raw meal production process. Likewise, decreasing the moisture mass flow to 75,000 kg/h increases significantly the exergy efficiency of the process. It is understood that both parameters are considered to have a major impact on the process exergy efficiency (Atmaca & Kanoglu, 2012).

4.5. Multiple linear regression (MLR) modeling

The values suggested that the operating data were well aligned with the predicted values. The results also checked that the MLR model has been generalized to allow the results to be predicted. Figure 5b depicts a plot of the operation data and expected values and estimated value of R and R^2 for MLR model are, respectively, 0.953 and 0.9091. The value of R , which is nearly unity, indicates that the operational data and expected values were in good agreement. Also, the value of the R^2 shows that the model can explain 90.9% of the variance in the experimental and expected values. For the model, the value of R^2 achieved is a good fit indicative.

4.6. Evaluation of the predictive potential of the models developed

By determining their R , R^2 , adjusted R^2 mean square error (MSE), root-mean-square error (RMSE), sum square error (SSE), and average absolute relative error (AARE), The efficacy of the ANFIS, MLR, and RSM models developed to predict the exergy efficiency of the raw meal production process has been evaluated. Table 6 presents the results obtained. The parity plots are shown in Figure 5 (a–c) for operational data and expected values, which supports the high observed R values for the three models in Table 6. The value of R should be close to unity (1) for a strong correlation between experimental and expected values. In all the three predictive models, the achieved correlation determination are with indication of good fit having high R^2 almost 1. Moreover, for the models, the RMSE, which is the MSE square root, was also determined. All of the values obtained were low for both MSE and RMSE, confirming the models' good fit. AARE (also known as the average absolute relative error) calculates a model's precision and accuracy. Furthermore, the model's performance improves as the values are reduced. Table 6 shows the values that have been determined for the proven models. ANFIS was more closely followed by RSM and finally by the MLR, based on statistical index results. Operational data with the actual exergy efficiency values were plotted against the predicted exergy efficiency for the three examined model for the study as expressed in Figure 5(a–c). The figure shows the least reliable model to be MLR, backed by its relatively increased SSE. However, this current work shows that the findings from the predictions are reliable and accurate with R^2 almost 1. This work showed that the results of ANFIS and RSM modeling were

Table 1. Specifications of raw meal production equipment

Parameters	Unit	
Inlet material flow	kg/h	240,000
Inlet moisture flow	kg/h	48,000
Inlet hot gas flow	kg/h	440,086
Inlet dust flow	kg/h	19.353
Inlet hot gas temperature		380
HAG temperature		760
Inlet material temperature		30
Operating Pressure	atm	1
Cyclone efficiency	%	96
Separator efficiency	%	86
Electro-static precipitator efficiency	%	84

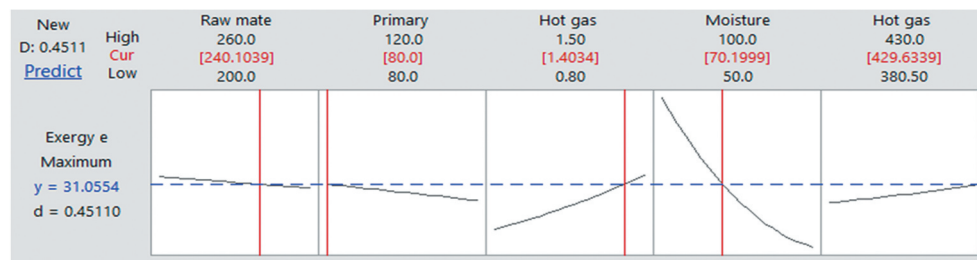
Table 2. Statistical models for evaluation

Equations	Number
$R^2 = 1 - \frac{\sum_{i=1}^n (Y_{i,pre} - Y_{i,exp})^2}{\sum_{i=1}^n (Y_{i,exp} - Y_m)^2}$	(12)
$AdjustedR^2 = 1 - (1 - R^2) \times \frac{n - 1}{n - k - 1}$	(13)
$MSE = \frac{\sum_{i=1}^n (Y_{exp} - Y_{pre})^2}{n}$	(14)
$RMSE = \sqrt{\frac{\sum_{i=1}^n (Y_{exp} - Y_{pre})^2}{n}}$	(15)
$SSE = \sum_{i=1}^n (Y_{exp} - Y_{pre})^2$	(16)
$AARE = \frac{1}{n} \sum_{i=1}^n \left[\frac{Y_{pre} - Y_{exp}}{Y_{exp}} \right]$	(17)

Table 6. ANFIS, MLR, and RSM model performance assessment

Parameter	ANFIS	MLR	RSM
R	0.9980	0.9535	0.9941
R ²	0.9961	0.9091	0.9883
AdjustedR ²	0.9961	0.9086	0.9882
MSE	0.36208	7.9906	1.0298
RSME	0.60173	2.8268	1.0148
SSE	371.132	8190.337	1055.531
AARE	0.000692	0.04215	0.001353

Figure 6. Optimization of exergy efficiency of the raw meal production process of a cement plant.



similar in terms of prediction accuracy but ANFIS was better than RSM, even though the results obtained by RSM and ANFIS were very similar. Using Minitab 17 software for the optimization of the actual exergy efficiency and a Pareto chart (Figure 5d), the significance of each design variables and their interactions was also investigated as it affects the raw meal exergy efficiency. The higher the significance, the longer the bar, and the bar behind the reference line of 50 showed how insignificant the design variables is to affect the raw meal exergy efficiency. According to the graph, moisture was the most influential operational variable which influence the exergy efficiency of the entire process, while others were behind the reference line of 50 with little or no significant.

4.7. Model optimization and validation

Figure 6 shows with the aid of Minitab 17 software the optimum exergy efficiency of the raw meal production process is estimated to be 31.05%, which was predicted at a raw material feed of 240,000 kg/h, primary airflow of 80,000 kg/h, hot gas generator gas flow of 1,400 kg/h, maximum moisture mass flow of 70,000 kg/h, and kiln hot gas mass flow of 430,000 kg/h. The predicted optimal value was validated with the plant operational data using the ASPEN Plus and average exergy efficiency of 31.5% was obtained. There was a good agreement between the predictive optimal model value and the operational plant value.

5. Conclusions

It is difficult and time-consuming to evaluate the exergy performance of a raw meal production process using a mechanistic approach. To overcome this limitation, prediction models were developed using plant operational and experimental data, and ANFIS, MLR, and RSM were used as prediction tools. The developed prediction models are highly predictive and can be used to estimate the exergy efficiency of the cement raw meal production process while in operation.

To evaluate the accuracy of the prediction models, a statistical analysis was performed with a correlation analysis, RMSE, and AARE for prediction error estimation.

When comparing the ANFIS, MLR, and RSM models proposed in this study, it is clear that the ANFIS models outperform the RSM models and are followed by the MLR models. This could be attributed to the non-linearity of the independent and dependent variables.

Finally, the raw meal manufacturing process was optimized with Minitab 17 numerical optimization program in order to improve its exergy efficiency. The maximum exergy efficiency, minimum raw material feeding, and minimum primary air flow, as well as minimum moisture flow, are among the Pareto optimization solutions validated and compared. After comparing the models, the final choice is determined by raw meal maximum exergy efficiency. Although the models perform well in practice, predictive models do not always produce optimal solutions. It is worth noting that in the case study, the exergy efficiency of the raw meal production process of the optimal design point achieved was increased by 20.5% with designed variables of raw material feeding of 240,000 kg/h, primary air flows of 80,000 kg/h, HAG gas flow of 1,403 kg/h, moisture flow of 70,000 kg/h, and hot gas flow of Kiln of 430,000 kg/h, demonstrating a significant impact on exergy efficiency. A further study should be performed on the effect of intensive properties on the overall exergy efficiency of the

process. Even though the electrical and communiton exergy were left out in the final analysis, these effects can also impact the overall energy efficiency of the process.

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Competing Interest

The authors declare no competing interest

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