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Evaluating the thermodynamic efficiency of the cement grate clinker cooler process using artificial neural networks and ANFIS

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ABSTRACT

The energy recovery of the grate cooler is a significant part of reducing production costs and tackling the environmental challenges of the cement industry. ASPEN Plus and neural networks predictive model were used to model, simulate and predict the grate clinker cooler in this paper. First, the process flow model and thermodynamic efficiency assessment were carried out. A predictive model of neural networks was then initiated to evaluate the optimal thermodynamic efficiency using plant operating data, which includes clinker cooling airflow, clinker mass flow, ambient and clinker temperature. The energy efficiency was 86.04, 86.1, and 86.5% respectively using the Aspen Plus process model, artificial neural network (ANN), and Adaptive neural inference systems (ANFIS). Therefore, based on the energy efficiency achieved, bootstrap aggregated neural network (BANN) was used to search for optimal operating parameters with the lowest mean square error (MSE) of the model in view. The MSE for the BANN training, testing, and validation data sets were 2.0×10^{-4}, 1.5×10^{-4}, and 1.0×10^{-4}. The final optimal clinker cooling air, clinker mass flow, ambient air, and kiln clinker discharge temperature are chosen from the ANFIS optimal solutions and validated on-site. When compared to actual operating data, the total clinker cooling air decreases by 5%, the energetic efficiency increases by 0.5%, and the ex-clinker cooler discharge temperature decreases to 120 °C, resulting in a significant reduction in energy consumption.

For the different equations used to achieve the objectives of this study, several notations are used to present mathematical expressions. In this study, some of the major notations used are listed as follows:

1. Introduction

Cement production is one of the highly energy-intensive sectors and uses about 5 % of global industrial energy with an estimated 30–40 % share of production costs [1,2]. A standard cement plant with a daily output of around 3000 tons of clinker requires around 2500–4000 kJ/kg of clinker of energy [3]. As a result, different energy efficiency strategies have been used for this sector, with marginal reductions in energy use and cost effects [1,4,5]. Clinker cooler plays a key role in cement production, such as clinker cooling and energy recovery. The units for the cement production consist of a calciner, a rotary kiln, and a grate clinker cooler [1]. Clinker cooling systems are of various types, subject to technology, and are grates (most recent technology), planetary coolers (attachment to the wet or dry long rotary kiln), shafts, and rotary coolers. The grate cooler has been shown to recover more heat than other forms of cooling systems and therefore saves energy.

These circumstances offer a prospect of minimizing energy consumption through optimization of operating parameters in a grate clinker cooler operations. Numerous energetic and exergetic studies have already been conducted on the individual subsystem, such

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Nomenclature

in	Inlet stream	y	Predicted model performance
out	stream	$\underline{x}$	Vector of neural network inputs
Δ	Change in	$\bar{y}_B$	BANN model's vector prediction
o	Ambient	MSE	Mean square error
H_m^E	Excess solid enthalpy	*AARE*	Absolute average relative error
R	Universal gas constant	GCC	Grate clinker cooler
$\dot{m}$	Mass flowrate	BANN	Bootstrap artificial neural network
G	Gibbs free energy	$f(x)$	Predictor of the aggregated neural network
PV	Energy per unit mass (Flow energy)	SSE	Sum of squared error
γ_i	mole fraction of species i	MF	Gaussian membership functions
H_i	Pure component solid enthalpy	n	Number of neural networks
η	Energy efficiency	w_i	Aggregating weight
ANN	Artificial neural network	*RMSE*	Root mean square error
ANFIS	Adaptive neural inference systems	R^2	Coefficient of determination
CFD	Computational fluid dynamics	R	correlation

as the raw mill, the rotary kiln, the rotary burner and the entire cement production process system [6–8].

Efficient cost measures Potential and thirty energy efficiency technology measures in the US cement industry were identified by Worrell, Martin and Price [9]. The estimated amount of investment costs for energy-saving measures has been investigated by the US EPA sector [10]. In addition, despite several studies by the clinker cooler system to calculate thermal efficiency, there have been a limited comprehensive analysis effects on thermodynamic efficiency with process simulator software and neural networks using plant operating parameters.

Various studies have been carried out over the past twenty years to improve the efficiency of the grate clinker cooler; however, analyses in Europe [11], China [12–15], Ethiopia [16], Morocco [17], and Columbia [18] have shown that significant energy-saving and emissions reduction opportunities still exist. The grate clinker cooler system was investigated in both numerical and experimental studies. Ahamed, Madlool, Saidur, Shahinuddin, Kamyar and Masjuki [19] developed a mathematical model for the energy, and energy recovery efficiency of the clinker cooling system using experimental operating parameters. Using the theory of convection of heat transfer, Touil, Belabed, Frances and Belaadi [20] developed a heat transfer clinker model that was compared to experimental data.

In order to establish and validate a heat transfer cooler model using published experimental data, Ahmad, Khan and Agarwal [21] used the initial thermodynamic and gas–solid convective heat transfer theory. Rasul, Widianto and Mohanty [2] introduced a simple model for thermal power assessment and obtained data from the cement cooler grate plant. Rasul, Widianto and Mohanty [22], Atmaca and Yumrutaş [23], Atmaca and Yumrutaş [24] and Mujumdar, Ganesh, Kulkarni and Ranade [25] established integrated real plant models, Shao, Cui and Ma [26] investigated the application of experimental approach and numerical simulation on grate clinker cooler system; however, operating parameters of the grate clinker cooler have not been discussed extensively, which are important for the performance and thermal utilization assessment, which guide thermal recovery and energy conservation.. However, the utilization of plant operational data combined with soft computing technologies to predict the energy efficiency of a grate clinker cooler system is limited in detail and resources.

Soft computing techniques consist of various computational models, algorithms and artificial intelligence methods used in science and engineering optimizations. Soft computing techniques involve but are not limited to fuzzy logic, an artificial neural network (ANN), adaptive neuronal inference systems (ANFIS), systems experts, algorithms for progressive development, other naturally optimizing algorithms.

Mechanistic models were used for energy efficiency studies. However, the development of such a model for complex processes can be complicated and time consuming, particularly with a view to incorporating energy efficiency into the second thermodynamics legislation. Data-based models such as Aspen Plus, the artificial neural network (ANN) and the BANN models could help to solve these problems [27,28].

Most recently, ANN and ANFIS have been used extensively for several processes as a predictive models but more still need to be done in cement production processes. Considering the following references for more in-depth discussion of other solutions, Priyadarshi, Padmanaban, Holm-Nielsen, Blaabjerg and Bhaskar [29] examined the effectiveness of ANFIS-based hybrid multipoint power metering via particle swarm optimization (MPPT) to achieve rapid and maximal PV power with zero oscillations. The proposed hybrid ANFIS–PSO training technique was able to track PV power more effectively, has the lowest RMSE execution period, and is free from constraints for determining antecedent parameters under uniform, non-uniform, and partial shading conditions compared to other training techniques. On the dSPACE platform, Priyadarshi, Padmanaban, Mihet-Popa, Blaabjerg and Azam [30] showed BLDC-driven PV pumping with ANFIS-FPA MPPT using Luo converters under varying conditions. The results of the performed experiments suggested that the ANFIS-FPA had superior power tracking capability, rapid convergence velocity and accurate system response compared to other bio-inspired, swarm-intelligent and classical MPPT techniques. In addition, the study by Priyadarshi, Azam, Sharma and Vardia [31] showed that the use of an adaptive neuro-fuzzy inference system based algorithm for photovoltaic (PV) applications allows rapid convergence velocity with low implementation costs. Using a back propagation supervised learning algorithm, Priyadarshi, Ramachandaramurthy, kumar Padmanaban, Azam, Sharma and Kesari [32] applied artificial neural networks (ANNs) to an energy conversion system with water pumping. Induction motor coupled centrifugal pumping applications requiring sensor less ANN were found to provide accurate influenced with acceptable estimation.

Priyadarshi, Ramachandaramurthy, Padmanaban, Azam, Sharma and Kesari [33] conducted an experimental analysis of a 200 W standalone PV system controlled by an ANFIS system. Based on an assessment of the analyzed system, it was found to be efficient and to possess excellent steady-state and dynamic performance, which confirms the validity of the proposed system. Furthermore, ANFIS (Adaptive Neuro-Fuzzy Inference System) was used by Priyadarshi, Padmanaban, Holm-Nielsen, Ramachandaramurthy and Bhaskar [34] to achieve peak solar power output. ANFIS produces robust, rapid, and precise results under various operating circumstances, while classical methods suffer from oscillatory behavior and a long settling period to maximize PV power.

Artificial Neural network (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) have proven capable of approximating continuous non-linear functions. Both ANN and ANFIS helps in solving complex nonlinear problems and for applications in automation control, pattern recognition, signal processing prediction, modeling, optimization [35]. Osuolale and Zhang [27], have reported that bootstrap aggregated neural network (BANN) is a good search engine for determining optimal plant operational parameters in achieving the lowest mean square error (MSE) of the energy efficiency in a process plant. This present work was aimed at evaluating the energy performance of cement grate clinker cooler using the steady operating data using Aspen Plus process model and neural networks as a predictive model with optimization intents. This will help to eliminate the mechanistic approach to energy assessment of cement plant. In addition, manual calculation or estimates are bound to be error prone. Several experimental data were used to validate and improved the clinker grate cooling model presented in this study. The proposed approach provides both the ability to generate training data, which helps train a network, and to make early predictions. The early stopping of ANN and ANFIS means that the results are constantly monitored during training. As a result, their predictions on testing data are stopped when the predictions do not further decline. Predicted target values close to experimental values enhance a model's prediction accuracy.

2. The grate clinker cooler operations

Fig. 1 shows the experimental data acquisition position with a simple two-dimensional cooler for a 3000 t/d cement plant. The operating functions of the grate clinker cooler include: on the inclined fixed grid plate, the clinker in the rotary kiln is dropped and the moving grate plate moved the clinker forward with the aid of the moving bar. The cooling air passes through the clinker layer to cool it and this is supplied in stages to five air chambers numbered one to five, along the direction of clinker motion to improve the cooling effect and reduce the energy power consumption. The exhaust air is recovered after exchange of heat with the clinker in order for efficiencies to be improved. The heat recovered is supplied to the rotary kiln as secondary air, while the tertiary air duct moves directly to the lower part of the calciner to support the heat required for the process.

3. Methodology and theoretical analysis

ASPEN Plus V10.0 was the process simulator used in the study. It is capable of assessing mass and heat, quantifying material and energy balance, and determining phase and chemical balances, among other things. Solid mixture of enthalpy is expressed as:

$$H_m = \sum_{i=1}^{K} n_i H_i + H_m^E \tag{1}$$

Excess solid enthalpy, H_m^E , H_i, Pure component solid enthalpy at T is related to the activity coefficient through the expression:

$$H_m^E = -RT^2 \sum_{i=1}^{K} n_i \frac{\partial In\gamma_i}{\partial T} \tag{2}$$

To find this solution, ASPEN Plus uses a non-stoichiometric approach. When assuming mass balance, the term Eq. (3), the Gibbs energy, known as objective function, is written as:

$$G = \sum_{i=1}^{K} n_i \Delta G_i^0 + RT \sum_{i=1}^{K} n_i In\gamma_i + RT \sum_{l=1}^{K} n_i InP \tag{3}$$

where G is the Gibbs free energy, n_i is number of moles of species i, K is the total number of chemical species in the reaction mixture, and γ_i is the chemical potential of species i. The objective is to find the set of n_i values that minimizes the value of G. where T is the temperature, P is the pressure, ΔG_i^0 is the standard Gibbs free energy of the formation of species i and γ_i is mole fraction of species i. The software uses this as a framework for computing to determine thermodynamically feasible results.

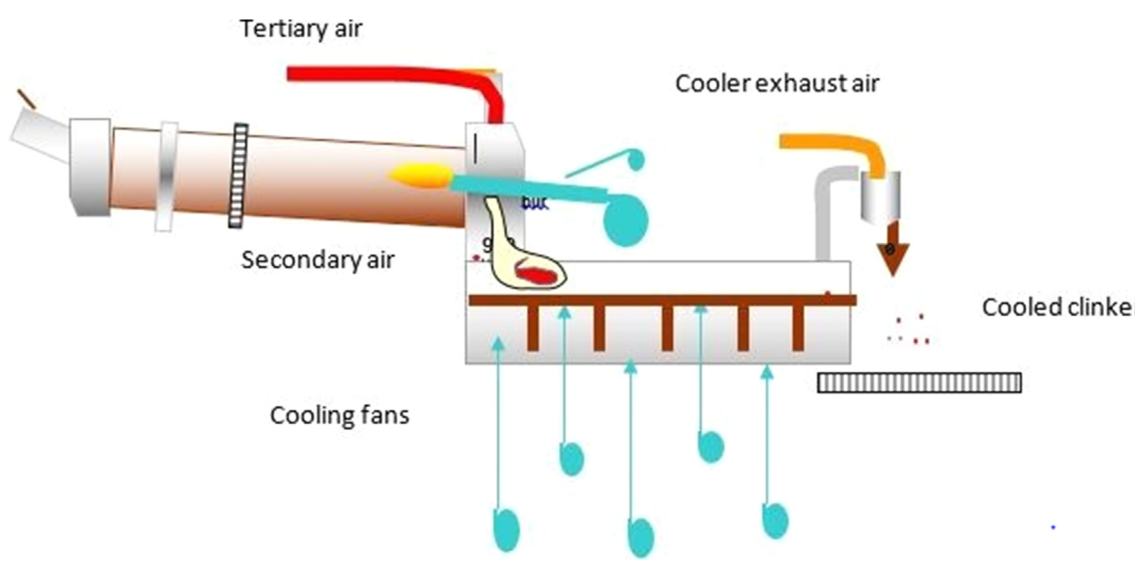

Fig. 1. Schematic diagram of rotary kiln and Grate cooler [36].

3.1. First law of thermodynamics performance of clinker cooler

The energy balance of the system, for which the sum of energy input of the system should be equal to the sum of the energy output of the process

$$\sum \dot{E}_{in} - \sum \dot{E}_{out} \tag{4}$$

Regarding Fig. 2, the total sum of the input energy is defined as:

$$\sum \dot{E}_{in} = \dot{E}_{hotclinkerfeedin} + \dot{E}_{coolingair} \tag{5}$$

A total sum of the output energy is defined as:

$$\sum \dot{E}_{out} = \dot{E}_{clinkerfeedout} + \dot{E}_{Tertiaryair} + \dot{E}_{Secondaryair} + \dot{E}_{coolerexhaust} \tag{6}$$

The following calculations are used to estimate the performance of the cooler and the amount of energy that can be extracted from the cooler. Energy efficiency is the ratio of system energy output to input, which can be expressed as [16,21]:

$$\eta_1 = \frac{\sum \dot{E}_{out}}{\sum \dot{E}_{in}} \tag{7}$$

Secondary and tertiary air recovery energetic efficiency can be expressed as [2]:

$$\eta_{recovery,cooler} = \frac{\dot{E}_{Tertiaryair} + \dot{E}_{Secondaryair}}{\dot{E}_{hotclinkerfeedin}} \tag{9}$$

The cooling efficiency of a cooler can be expressed as:

$$\eta_{coolingefficiency} = \frac{\dot{E}_{Hotclinkerin} - \dot{E}_{Hotclinkerout}}{\dot{E}_{Hotclinkerfeedin}} \tag{10}$$

3.2. Process model

The process model using Aspen Plus simulator is described in detail below and represented using a process flow sheet in Fig. 2.

3.2.1. Grate clinker cooler process

The grate clinker cooler was simulated as a set of five heat exchangers. The first two heat exchangers represent secondary and tertiary air to 950 °C and 805 °C, respectively, while the last three heat-exchanger cool the clinker to 125 °C and the heat recuperated is used for the drying of raw meal in vertical roller mill. Before each heat exchanger, a part of the solid split out from the mainstream as recuperated hot gas rotary kiln operation while the noodle-like clinker; a combination of this four-component ($2CaO * SiO_2$, $3CaO * Al_2O_3$, $CaO * Al_2O_3 * Fe$ and $3CaO * SiO_2$) as finished products.

3.3. Modeling of the grate clinker cooler process

Table 1 shows the design parameters used for the Aspen Plus process modeling, while the plant's operating data was used to simulate the energy efficiency of the cooler clinker grate. Based on the thirty (30) days steady state plant operating data simulated in Aspen Plus, a steady state energy analysis of the streams was performed using Eqs. (1), (2) and (2). (3). The energy efficiency of the cement grate clinker cooler was evaluated with Eq.4. The temperature, pressure, enthalpy and internal energy of each stream was generated in Aspen Plus. In both the basic working conditions and the references, the energy was evaluated from each stream via the Aspen Plus process simulator. Maximum energy was measured for the network input and output by Eq. (2) and (3) and the energy efficiency estimate by Eq. (4).

3.4. Artificial neural network modeling

The artificial neural network (ANN) was used to model and predict the energy efficiency of the grate clinker cooler of the cement plant. The information was shown through the neurons of the input layer and the results. As input data for Aspen plus, thirty

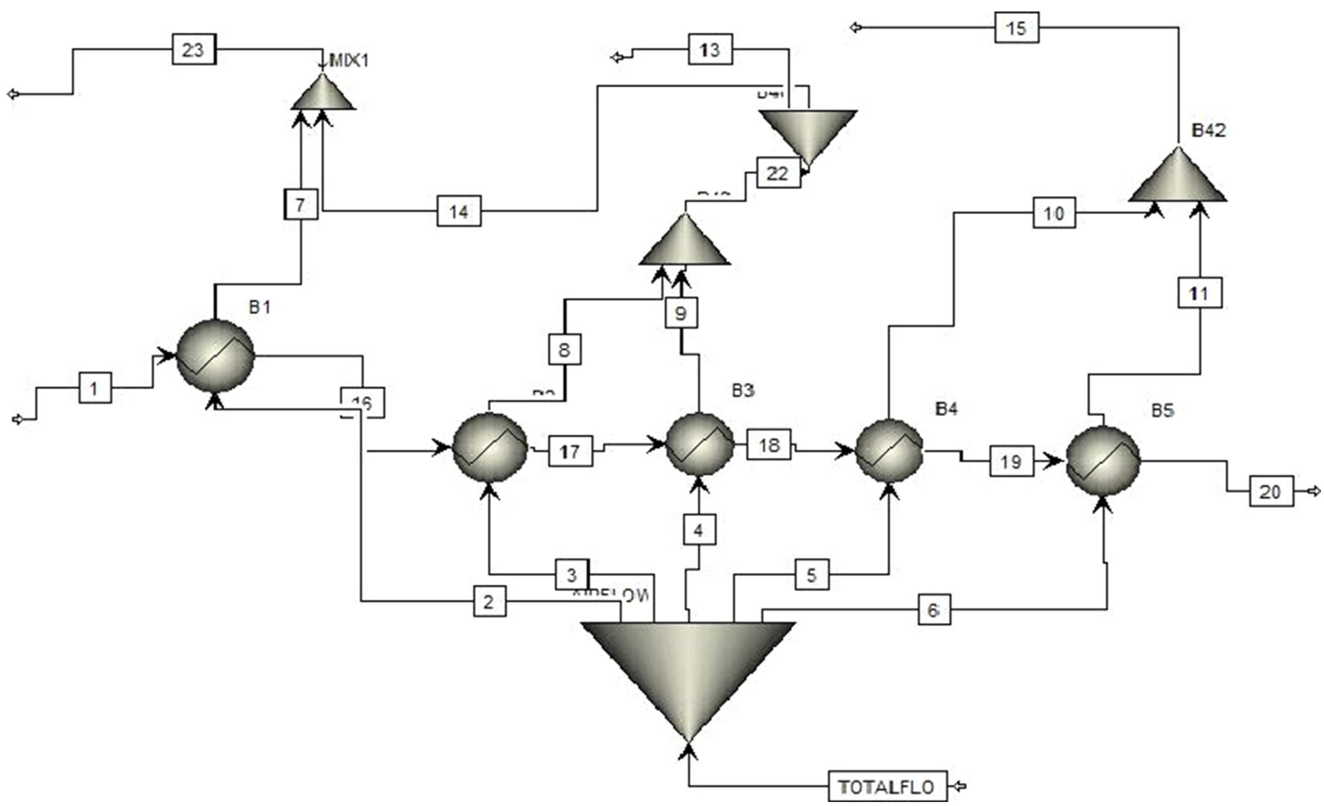

Fig. 2. Cement grate clinker cooler flow sheet represented with Aspen Plus process model [36].

Table 1
Statistical models for evaluation.

Equations	Number
$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{i,pre} - Y_{i,exp}\right)^2}{\sum_{i=1}^{n}\left(Y_{i,exp} - Y_m\right)^2}$	(11)
$AdjustedR^2 = 1 - \lceil\left(1 - R^2\right)x\frac{n-1}{n-k-1}\rceil$	(12)
$MSE = \frac{\sum_{i=1}^{n}(Y_{exp} - Y_{pre})^2}{n}$	(13)
$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_{exp} - Y_{pre})^2}{n}}$	(14)
$SSE = \sum_{i=1}^{n}(Y_{exp} - Y_{pre})^2$	(15)
$AARE = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_{pre} - Y_{exp}}{Y_{exp}}\right]$	(16)

(30) days of steady-state cement plant operating data were used to assess energy efficiency for each data operation. For this work, six hundred and twenty-six (626) plant operating data samples were selected, four hundred and thirty-eight (438) plant data were selected as predictive training models, while ninety-four (94) plant data were collected as a validation data. The training process will then be used to find the best model for prediction. Finally, the accuracy of the predicted model was tested using the remaining ninety-four (94) data from six hundred and twenty-six (626) plant operational data. The neural network model for energy efficiency output is defined using the Eq. (7) expression.

$$y = (x_1, x_2, x_3, x_4, \cdots.., x_n) \quad (7)$$

where y is energy efficiency, $x_1, x_2, x_3, andx_4$ are clinker mass flow, clinker temperature, clinker cooling airflow, and ambient temperature respectively. ANN simulation parameters used in the learning and training are the backpropagation algorithm, four input layers, two hidden layers with nine and six nodes, and one output layer (4–9–6–1), as shown in Fig. 3 [37].

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

Using ANFIS, a multi-input single-output (MISO) fuzzy model was developed using four input variables and one output variable to predict the energy efficiency of the cement grate clinker cooler process. The architecture of the proposed model for ANFIS is described in Fig. 4 [40].

The hybrid learning algorithm combines the least squares with the gradient descent approximation to find a reasonable range of contexts and consequent parameters.

The development of the ANFIS model in MATLAB follows the below steps:

Step 1. Import the training group and test group data using import instruction syntax as follows:

```
Traindata = xlsread("traindata.xlsx")
Testdata = xlsread("testdata.xlsx")
```

Step 2. Create the ANFIS prediction model. This study explores 32 different types of ANFIS prediction models: four membership functions with eight types of membership functions. For the purpose of this study, several membership functions made available by MATLAB were applied including triangles, trapezoids, bells, gausses, bilateral Gausses, double S-shaped, and so on.

Step 3. Model is trained using a hybrid train FIS method with a tolerance of zero errors and an epoch of 5000.

Step 4. As soon as the training model is complete, the prediction value is exported using the following syntax:

```
Out_value = evalfis (testdata, fis1)
```

In this analysis, the ANFIS modeling was performed in MATLAB R2013a to train and test data. For this work, six hundred and twenty-six (626) plant operating data samples were selected, 532 plant operational data were used as training group data (train data) for a fuzzy inference method based on neurons. The best predictive model was defined by model training. In order to calculate the average absolute error percentage, the remaining 94 data were used as test data in the best predict model. The estimated energy efficiency of the grate clinker cooler using the model was compared to the actual energy efficiency from the grate clinker cooler while the plant was in steady operation.

The validation of the model identified with the actual energy efficiency of the grate clinker cooler system while the plant was in steady operation was then carried out. Lately, for its predictive purposes, ANFIS has adapted the hybrid learning process, which is a rapid learning method. Many scientists have established the hybrid algorithm as an effective algorithm [38].

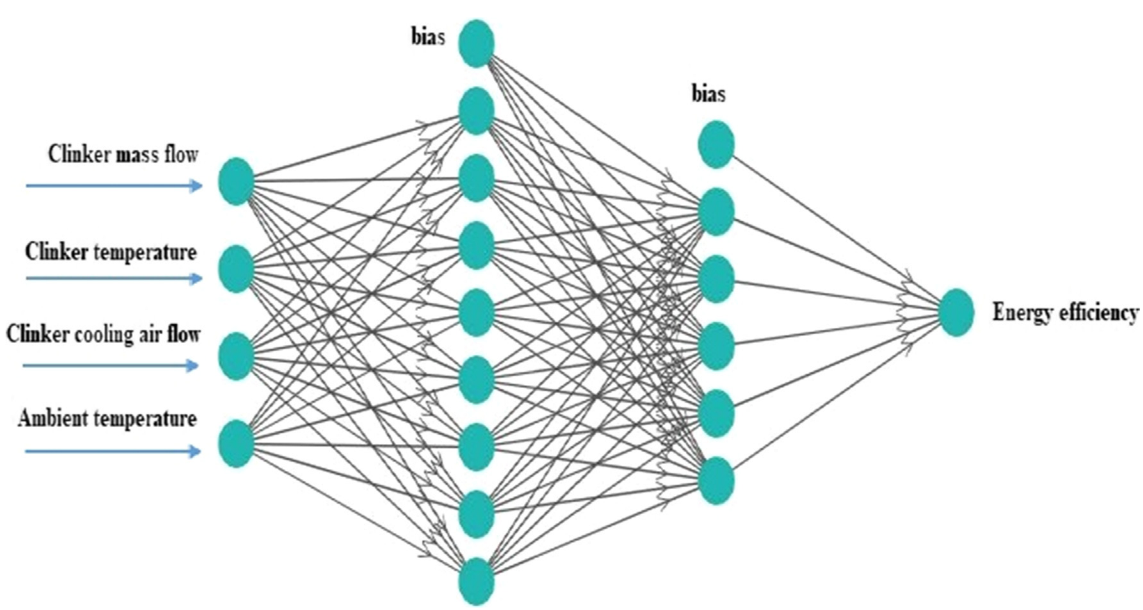

Fig. 3. The ANN architectures used as a predictive model for energy efficiency.

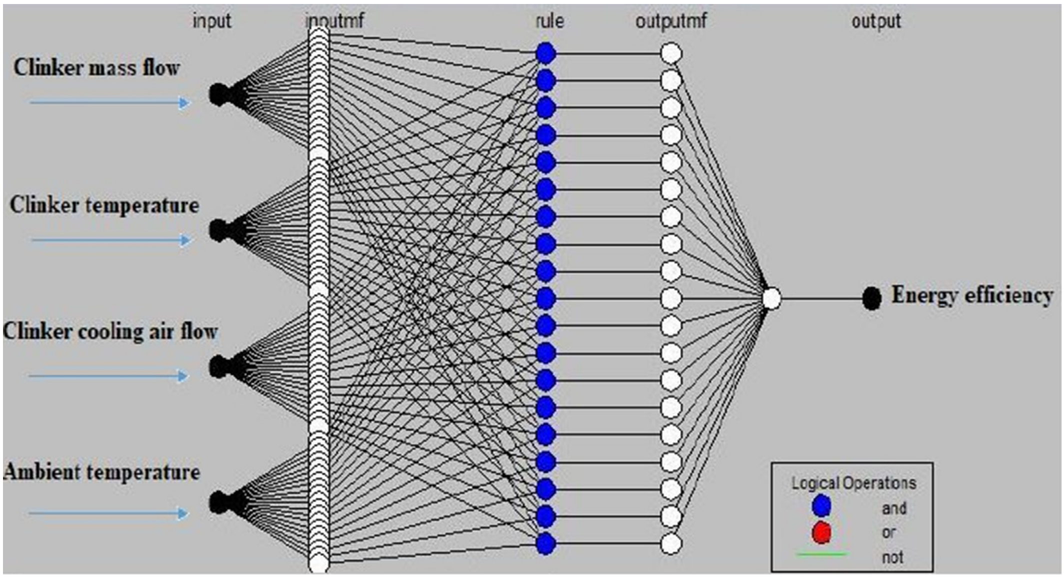

Fig. 4. ANFIS model architecture with four input variables.

The ANFIS model developed in MATLAB R2013a follows the phases below (see Fig. 5):

3.6. Performance criteria

In this analysis, statistical goodness-of-fit parameters were provided to compare the results between the two separate predictor namely, ANN and ANFIS 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 [38,39].

4. Results and discussion

4.1. Process model using Aspen plus

Monthly average operating data from consistent steady-state running conditions of the cement plant were compared with simulation results to validate the process model. This includes the physical and chemical properties of each stream from the thermodynamic data that has been developed. The results of the validation were summarized in Table 2. There is a slight discrepancy between the operating data and the simulation results, which falls

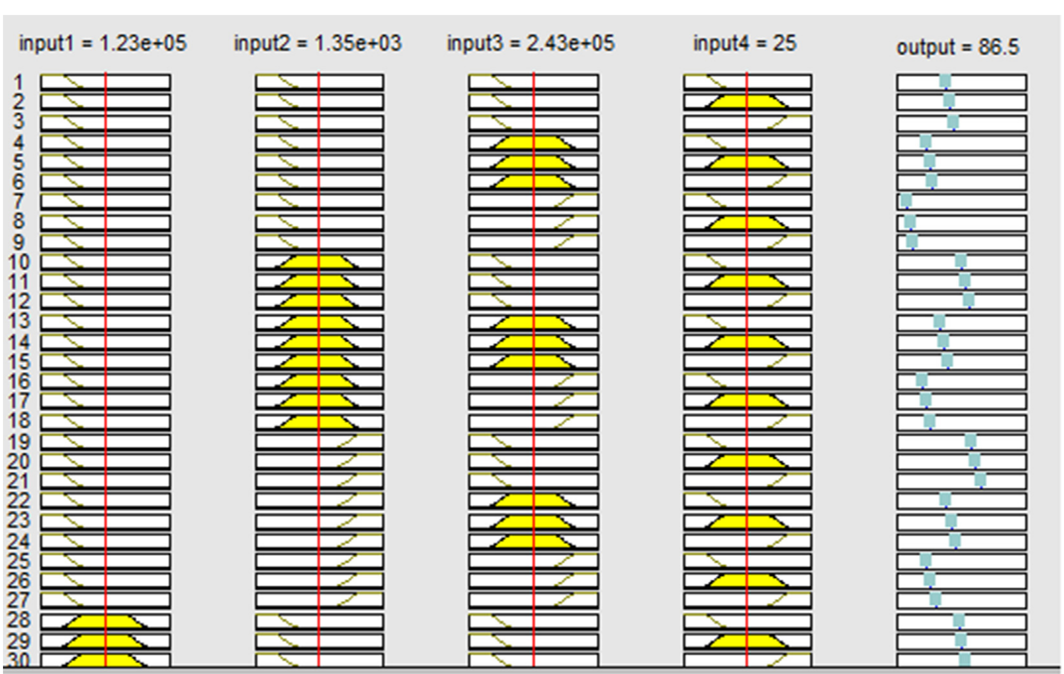

Fig. 5. ANFIS model architecture with four input variables and optimum energy efficiency.

Table 2
Material streams, operational and simulation data of model validation.

Materials	Unit	Operational data	Simulated data
Main stream			
Clinker output	kg/h	125,000	125,500
Clinker cooling air flow	kg/h	255,000	252,500
Gas stream			
Clinker outlet temperature	°C	125	127
Secondary air temperature	°C	905	880
Tertiary air temperature	°C	810	805
Exhaust air temperature	°C	283	289

within an acceptable limit of ±2%. Although the energy efficiency of the plant studied does not in any way affect the expressed results. The results of the model validation showed that the process model is consistent and can be helpful in predicting plant performance with a different set of operating parameters.

The process model was further carried out by reference plant data, which identified an area for improving the energy efficiency of the cement grate clinker cooler. Table 3 shows the mass and energy balance of the process of cement grate clinker cooler which provides information on the input and outlet streams of the grate clinker cooler process. The energy efficiency for the cement grate clinker cooler system as indicated in Table 3 is 86.04%. The percentage of energy efficiency achieved in this study was the same trend with an estimated 70.8 to 87.5 % [19]. Based on the results shown in the Aspen Plus process simulator (Table 3), the exhaust energy can be used either to dry the raw material for grinding process or to generate energy in turbine operation. This could help to minimize a significant source of thermodynamic inefficiency.

4.2. Artificial neural network (ANN) models

The estimation of energy efficiency was based on ANN models. ANN performance depends on the method used to train data sets, network structure and minimal error results. The mean square error (MSE) of the individual power efficiency network sets for training, testing and validation is shown in Fig. 6. It is a useful resource for process engineers and operators to evaluate the effects of the cement grate cooler process on energy performance. Table 4 expresses the model performance indicators for ANN and process model energy efficiency. The Sum of square Error (SSE) on the data sets training, testing, and unseen data (validation) are given in Table 4. Model performance indicators for ANN models achieved a mean square error (MSE) of 0.4×10^{-3} and 0.2×10^{-3} for the training and validation respectively. While the R^2 gives 0.9999 and 0.9899 for both the training and validation respectively. The sum of square error (SSE) is estimated as 0.00126 and 0.00128 for both the training and validation respectively. Aspen Plus generates mass, enthalpy and internal energy from all streams of energy efficiency assessment, while ANN uses data training and tests to predict energy efficiency without first undertaking string mass, enthalpy and internal energy measurement rigor.

4.3. Aggregated neural network in bootstrap

The energy efficiency of each system was modeled, and a bootstrap aggregated neural network (BANN) containing 30 neural networks was created. Every single network has one layer hidden in it. The simulation algorithm Levenberg-Marquardt was used to train the networks. Training data varies for each network. Several nonperfect models combined increase the accuracy of predictions for the entire input space. The actual values obtained from Aspen Plus simulation and Bootstrap aggregated neural network (BANN) model efficiency for training, testing and validation for the cement grate cooler process are shown in Fig. 7. Fig. 8 shows MSE values for aggregated neural networks with different numbers of steady networks. The effectiveness of individual networks on different data sets can be seen to be inconsistent. A low MSE network on training data can have a wide MSE on validation information. It indicates that a single neural network is not robust [20]. The MSE for BANN models on training and testing data sets for the cement grate clinker cooler system energy efficiency is 2.0×10^{-4} and 1.5×10^{-4} respectively, this is an improvement compared to the minimum MSE set out in Table 4 for the single ANN neural network model. Fig. 9. The energy efficiency predicted for the cement grate cooler model BANN is shown. The value of this cannot be overemphasized within a processing plant, especially in the decision-making area for the most energy efficient operating conditions in the system [27]. This can serve as a reference for engineers and process operators.

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

The plots of four inputs (raw material feed, primary airflow, hot gas generator gas flow, moisture mass flow, and kiln hot gas flow) using Gaussian membership functions (MF) are displayed in Fig. 4. Table 4 expresses the model performance indicators for ANFIS and process model energy efficiency. The Sum of square Error (SSE) on the data sets training, testing, and unseen data (validation) are given in Table 4. Model performance indicators for ANFIS models achieved a mean square error (MSE) of 2.6×10^{-2} and 7.4×10^{-2} for the training and validation respectively. While the R^2 gives 0.9996 and 0.9887 for both the training and validation respectively. The sum of square error (SSE) is estimated as 0.0649 and 0.1795 for both the training and validation respectively. The calculated R and R^2 of the ANFIS model were 0.9941 and 0.9884 respectively. The value of R, which is near unity, indicates a strong good agreement between the operational data and predicted values. This is also an indication that a relationship exist between the operational data input and the actual output. Besides, the value of R^2 shows 98.84 % of the variation in the plant operational data and the predicted values can be explained by the model.

Table 3
Simulated data for energy analysis of a cement grate clinker cooler.

Equipment/ N° of input stream	Mass (kg/kg Cl)	Energy (kJ/kg)	Equipment/ N° of output stream	Mass (kg/kgCl)	Energy (kJ/kg)
Clinker feed (1)	1.000	1404.8	Cooler clinker exit (20)	1.000	40.5
			Secondary air (23)	0.235	598.9
			Tertiary air (13)	0.895	533.5
Cooling fans (2, 3, 4, 5, 6)	2.018	86.2	Cooler exhaust (15)	0.888	110.0
Total	3.018	1491.0	Total	3.018	1282.9
Energy Efficiency			86.04%		

Cl-clinker; N°-Number; 1, 2, 3, 4, 5, 6, 13, 15, 20, and 23 are denoted in Fig. 2. Process flow sheet.

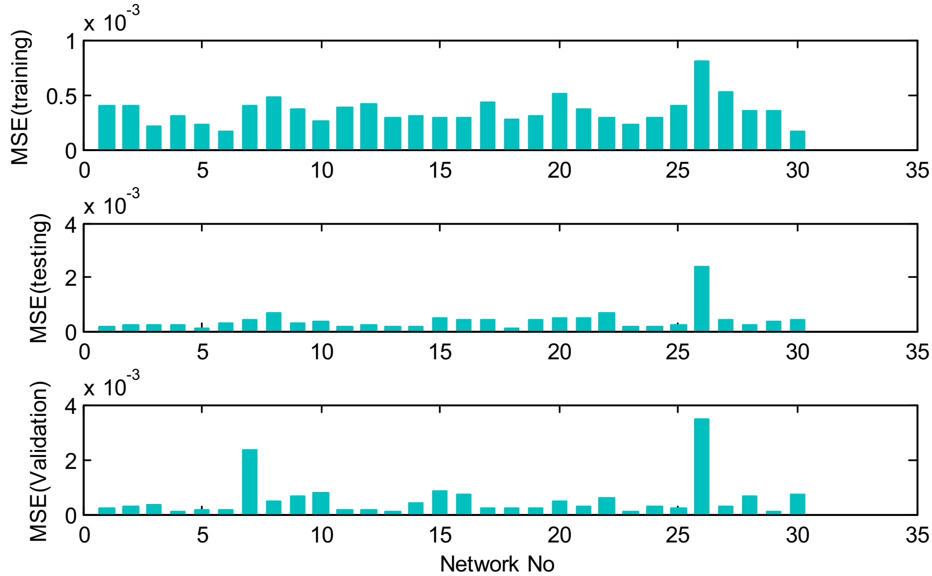

Fig. 6. Model errors of individual networks for energy efficiency of cement grate clinker cooler.

Table 4
ANN and ANFIS model performance assessment.

Model indicators	ANN			ANFIS				
	Training set	Testing set	Validation set	Training set	Testing set	Validation set	Energy efficiency (%)	
R	0.9999	0.9998	0.9949	0.9998	0.9994	0.9887	Process model	86.0
R^2	0.9999	0.9998	0.9899	0.9996	0.9989	0.9775	ANN	86.1
MSE	2.0×10^{-4}	1.5×10^{-4}	1.0×10^{-4}	0.0265	0.0262	0.0748	Optimal	86.5
RSME	0.02	0.0141	0.0122	0.1627	0.1650	0.2735		
SSE	0.00126	0.00126	0.00128	0.0649	0.0295	0.1795		
AARE	0.05×10^{-5}	0.11×10^{-5}	0.02×10^{-5}	1.5×10^{-5}	2.5×10^{-5}	3.1×10^{-5}		

4.5. 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 effectiveness of the ANN and ANFIS models developed to predict the energy efficiency of the cement grate clinker cooler system has been evaluated. Table 4 presents the results obtained. The value of R should

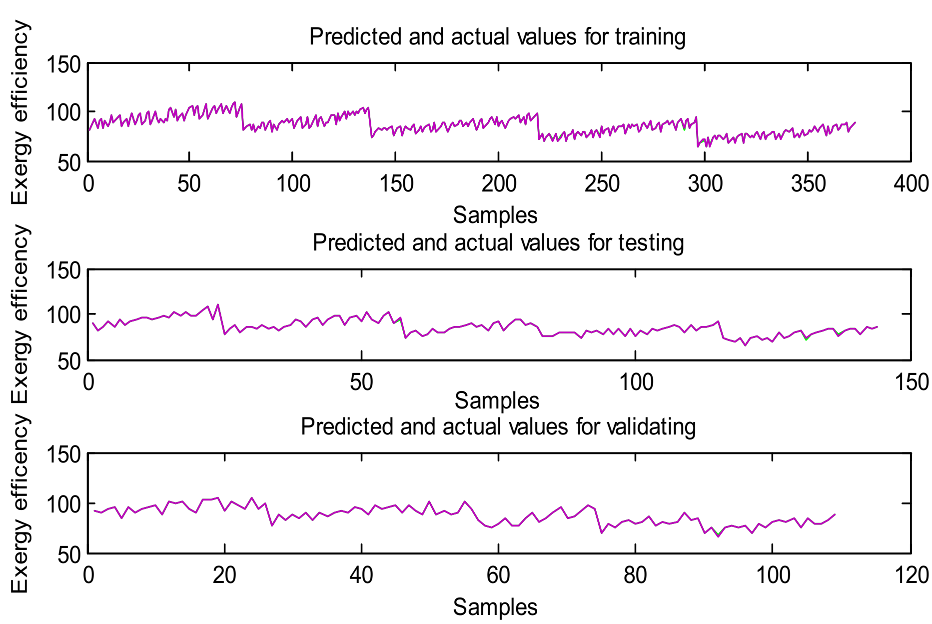

Fig. 7. Actual and BANN model predicted energy efficiency for the cement grate clinker cooler.

be close to unity (1) for a strong correlation between experimental and expected values. The two predictive models, shows high R^2 almost 1, indicating strong compatibility. 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. The lower the values, the higher the model's performance. These were determined for the tested models and their values are shown in Table 4. The model of ANN was more closely followed by ANFIS, based on statistical index results. This current work shows that the findings from the predictions are reliable and accurate. This work showed that the results were similar in terms of prediction accuracy but ANN was better than ANFIS, even though the results obtained by ANN and ANFIS were very similar.

After comparing the models, the final choice is determined by the least calculated error and maximum energy efficiency. The final choice is determined by the maximum energetic efficiency, which is a function of cooler heat recovery and clinker ex-cooler discharge temperature. Although the models perform well in practice,

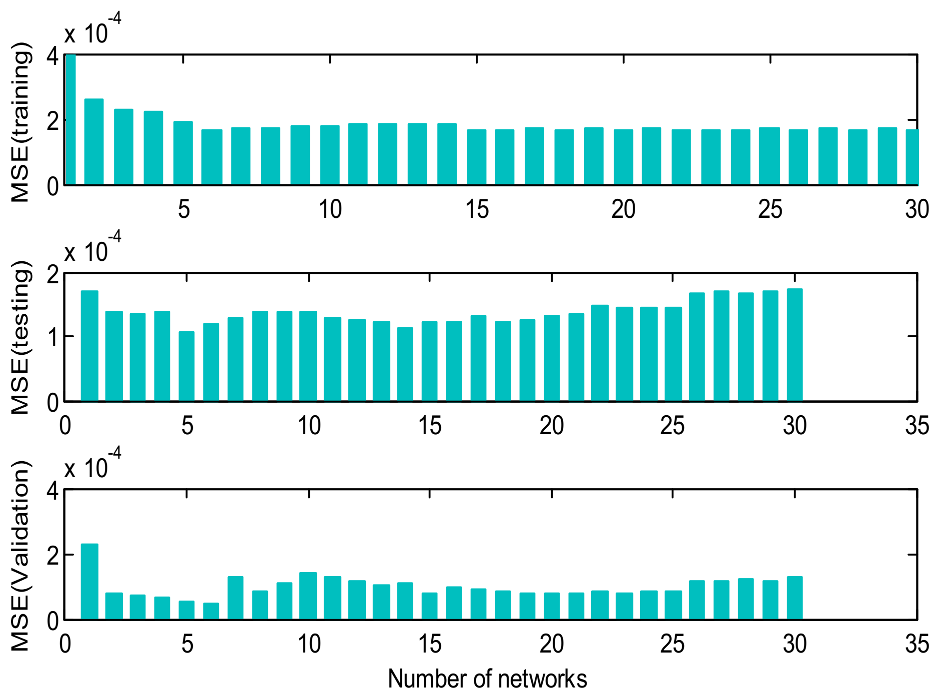

Fig. 8. Model errors of aggregated networks for energy efficiency of cement grate clinker cooler.

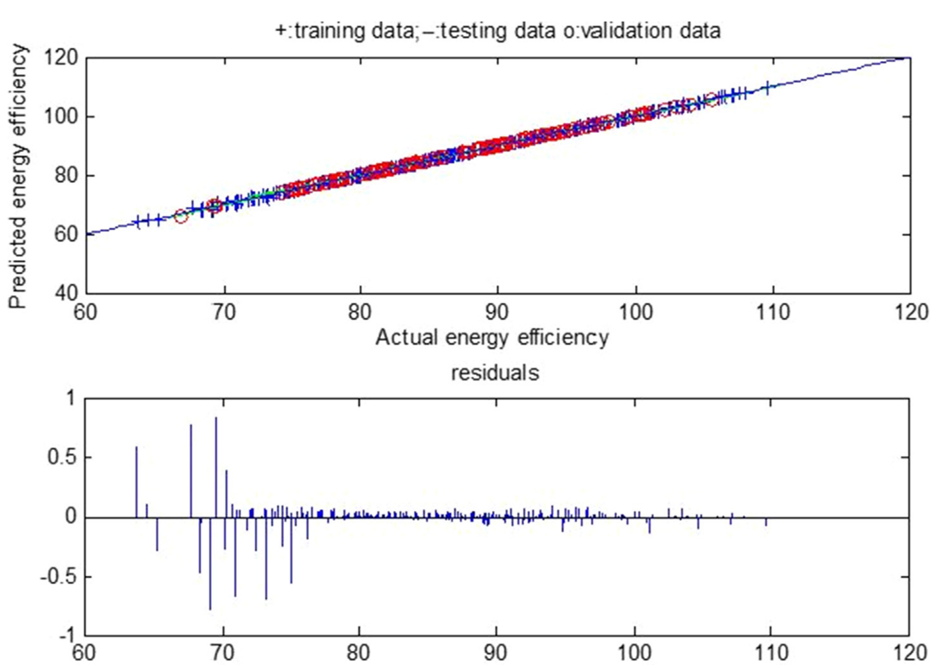

Fig. 9. Predicted and actual energy efficiency for cement grate clinker cooler BANN model.

predictive models by the ANN may not be used to produce optimal solutions of which ANFIS has the advantage in this regards. It is worth noting that in the case study, the energy efficiency of the clinker grate cooler process of the optimal design point achieved was increased by 0.5 % of energy savings

5. Conclusion

This study shows that ANN and ANFIS can accurately model energetic efficiency of grate clinker cooler process in cement manufacturing plant from process operational data. ASPEN plus, ANN, and ANFIS, the proposed process and prediction model, were able to achieve the experimental results faster and more accurately than thermodynamics methods which are typically done by hand or semi-automatically. The excellent relationship between operation parameters and the energetic efficiency using ANN and ANFIS suggests the non-linearity of the process [31]. In addition, ANFIS model predicted optimal energy efficiency of 86.5% with optimal condition of 122500 kg/h of clinker mass flow, clinker temperature of 1350 °C, clinker cooling air flow of 242500 kg/h and ambient temperature of 25 °C. The condition was validated in triplicates and 86.4% was obtained with optimized results indicating 0.5% gain in energy efficiency of the grate clinker cooler. The improvement is based on changing the operating conditions of the system and has no additional capital costs. A reliable strategy based on BANN for improved generalisation of the predicted model is also presented, which enhances model prediction accuracy. However, the predictive error of the ANN model was enhanced by BANN, and this was observed to be lower compared to ANFIS model in terms of error measures, such as RMSE, MSE and AARE [40]. Based on this, it suggests that there is a good correlation between grate clinker cooler operation parameters and energetic efficiency of the systems. The energetic analysis is a much effective way of evaluating the performance of processes and hence the importance of this study to process and design engineers. Furthermore, ANN, ANFIS and BANN predictive based modeling and optimization can aid the decision making of energy efficient operations and control of grate clinker cooler of cement manufacturing process. The optimal energy efficiency can still be validated using different optimization techniques such as genetic algorithm (GA), particle swarm optimization (PSO) and sequential optimization programming which will be the focus of subsequent study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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