

Modeling operational cement rotary kiln variables with explainable artificial intelligence methods – a “conscious lab” development

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ABSTRACT

Digitalizing cement production plants to improve operation parameters' control might reduce energy consumption and increase process sustainabilities. Cement production plants are one of the extremest CO₂ emissions, and the rotary kiln is a cement plant's most energy-consuming and energy-wasting unit. Thus, enhancing its operation assessments adsorb attention. Since many factors would affect the clinker production quality and rotary kiln efficiency, controlling those variables is beyond operator capabilities. Constructing a conscious-lab “CL” (developing an explainable artificial intelligence “EAI” model based on the industrial operating dataset) can potentially tackle those critical issues, reduce laboratory costs, save time, improve process maintenance and help for better training operators. As a novel approach, this investigation examined extreme gradient boosting (XGBoost) coupled with SHAP (SHapley Additive exPlanations) “SHAP-XGBoost” for the modeling and prediction of the rotary kiln factors (feed rate and induced draft fan current) based on over 3,000 records collected from the Ilam cement plant. SHAP illustrated the relationships between each record and variables with the rotary kiln factors, demonstrated their correlation magnitude, and ranked them based on their importance. XGBoost accurately (R-square 0.96) could predict the rotary kiln factors where results showed higher exactness than typical EAI models.

KEYWORDS

Rotary kiln; cement industry; machine learning; digitalization

1. Introduction

Although the cement industry globally is one of the most important parts of the economic sector, cement production is an extremely CO₂ emission process. Several investigations have been conducted to reduce cement production issues (Chipakwe et al. 2020). They were focused mainly on cement chemistry, and few studies have been conducted on process control and equipment assessments (Söğüt 2012; Sui et al. 2014; Gaurav and Khanam 2016; Coskun 2019). Therefore, many rooms are left open for exploring and understanding relationships between various cement product factors, where cement plants are also one of the most energy-intensive industries. In modern cement manufacture as a dry method process, a rotary kiln is one of the primary units (S. Wang, Dong, and Yuan 2007). As a central unit, the rotary kiln is the most energy-consuming and energy-wasting unit throughout cement production. Thus, the rotary kiln is the most expensive part of a cement plant, which significantly consumes fuel and directly affects the final product price (Bui, Tarasiewicz, and Charette 1982;

Radwan 2012). All these aspects have highlighted the importance of understanding interactions among rotary kiln variables essentially on the industrial scale.

In cement production, the rotary kiln is a rotating furnace tube for baking and turning the raw material into cement clinker (Sharabiany, Fatehi, and Araabi 2011). This long cylinder (based on the plant capacity, the length could be 70 m with around 5 m diameter) can produce over 2,000 tons of clinker per day. It uses a powerful electrical motor, and its temperature can be up to 1,400 °C (Makaremi et al. 2009). The cylinder, based on specific slop, turns around its axis, and the raw materials stick adhesively to its walls, gradually mixed, burned, and baked to produce clinker. Controlling the feed rate would have an essential role in smooth kiln performance. If the flow of feed into the kiln is suddenly interrupted, the heat normally absorbed by the slurry concentrates in the chains, causing serious damage if not quickly corrected. Small, controlled increases or decreases in the feed rate may cause a significant variation in the kiln temperature profile (Delong and Aitken 1981).

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These variations can be managed by understanding correlations among kiln variables. A powerful fan, called induced draft or “ID fan,” is installed at the end of the pre-heater in a kiln rotary. It develops necessary suction through the kiln and controls the gas flow in the kiln (Sharabiany, Fatehi, and Araabi 2011). The ID fan sucks the kiln air out of it, and consequently, new air is blown into the kiln. Rotational kiln speed can be adjusted by feed rate (Fallahpour et al. 2007). ID fans (typically assessed with its current (A)) induce the total flow inside the kiln. Thus, they may also be called dirty fans since they handle the gases generated by combustion, dust that cannot be taken into the bag filter, excess air, and any infiltration air that arises to the fan inlet (Boateng 2015). In other words, numerous factors could affect the ID fan performance and kiln feed rate, exhibiting complex nonlinear interactions among them (Akulp, Dominguez, and Longchamp 1994; Fallahpour et al. 2007; Boateng 2008). However, it was reported that controlling these two critical variables is beyond the operator’s capabilities (DeLong and Aitken 1981).

For cement plants, modeling such complicated inter-correlations among rotary kiln operating variables could significantly improve the level of process understanding and control. However, few published investigations examined relationships among cement equipment variables (none around rotary kiln operational parameters) (DeLong and Aitken 1981; L.-X. Wang 1994). Using the conscious lab (CL) concept as a novel methodology would potentially tackle this challenge. CL as a new concept means using industrial monitoring datasets for developing explainable artificial intelligence (EAI) models to understand and predict interactions among full-scale operating variables (Chelgani, Nasiri, and Alidokht 2021; Chelgani, Nasiri, and Tohry 2021; Alidokht et al. 2021; Tohry et al. 2021). EAI methods are not black-box systems (Jorjani, Mesroghli, and Chelgani 2008) and can highlight the interaction among each record of variables with their representative responses within the dataset, evaluate their individual record and variable importance, rank them based on their effectiveness, and illustrate their relationship magnitudes. In other words, EAI models would translate the dataset to a human-basis understanding level, exponentially improving the unit’s reasoning and planning. This strategic methodology can generate a systematic approach toward digitalizing the whole plant. It would be markedly decreased laboratory costs, prohibiting the scale-up complexes, saving time, and converting decisions based on the process’s real operational properties (not according to some ideal solid aspects).

This study, for the first time, as a novel perception, is going to use extreme gradient boosting (XGBoost), which is coupled with SHAP (SHapley Additive exPlanations) “SHAP-XGBoost” as an EAI system for modeling of “ID fan current” and rotary kiln “feed rate” by using an industrial dataset (monitored operating variables). This investigation will launch a CL for accessing critical variables of a rotary kiln in a short sentence. XGBoost, as a newly constructed machine learning model, would be able to handle missing data, regularize the prediction by parallel processing, prune

a non-greedy tree, and set an objective function (Gómez-Ríos, Luengo, and Herrera 2017; X. Zhang et al. 2020; K. Zhou, Li, et al. 2021). SHAP would translate the relationships by simultaneously assessing multivariable inter-correlations linearly and non-linearly and increasing the XGBoost process transparency (Chelgani 2021; Mangalathu et al. 2021; Bussmann et al. 2021). For comparison and verification purposes, Pearson correlation, random forest, and support vector regression, as common machine learning tools, were also considered for the modeling and accuracy assessments. These EAI modeling approaches could be key for better controlling the cement plants, improving their process efficiencies, and reducing environmental issues.

2. Materials and methods

2.1. Dataset

For exploring the relationships between kiln feed rate, and ID fan speed, and other operating variables, a dataset was collected from one of the pre-heater and rotary kiln (Clinker Baking unit) circuits (line 1) in the Ilam cement plant (Figure 1). The Ilam plant has two lines for cement production (5,300 t/d). The clinker baking circuit includes a pre-heater unit, five air cyclones, and one calcinator) up to 900 °C for calcination (and rotary kiln (62 m length, 4.2 m diameter) with 2,000 t/d capacity (made by O&K Company from Germany). The maximum kiln’s rotation speed is 3 rpm. The plant has approximately a fixed one-year period for the overhaul. The pre-heater and rotary kiln key operating parameters are summarized in Table 1. Variables were monitored hourly and were taken into account. In general, over 3,000 records from 2020 to 2021 were prepared and used for the modeling. In the plant, before the introduction in the rotary kiln, the raw meal is pre-heated through a suspension pre-heater. The pre-heated material is up in the air with the combustion exhaust gas from the kiln. In the suspension pre-heater, composed of five cyclones stages, the heat transfer rate increases, which enhances the heat exchange efficiency combustion from the kiln, which flows through the cyclones from the bottom upwards. Raw meal, finely milled, is mixed with the exhaust gas upstream. A rotary kiln is a steel cylinder that rotates around its axis. The kiln is horizontally sloped at about 2.5–4.5%, letting the processed mixture move along with it. The kiln fuel is introduced through a burner placed at the end of the kiln. After its entry into the furnace, Raw meal is subjected to calcination, solid-phase reactions, and clinkering.

2.2. Shapley Additive exPlanations (SHAP)

The Shapley Additive exPlanations (SHAP) developed by Lundberg and Lee (Lundberg and Lee 2017) in 2017 originates from the game theory (Feng et al. 2021). SHAP employs Shapley values to explain the model’s output. Shapley value was first introduced by Lloyd Shapley, who received the Nobel Prize in Economics for that in 2012 (Ungari and Benhamou 2021). Shapley value is the average

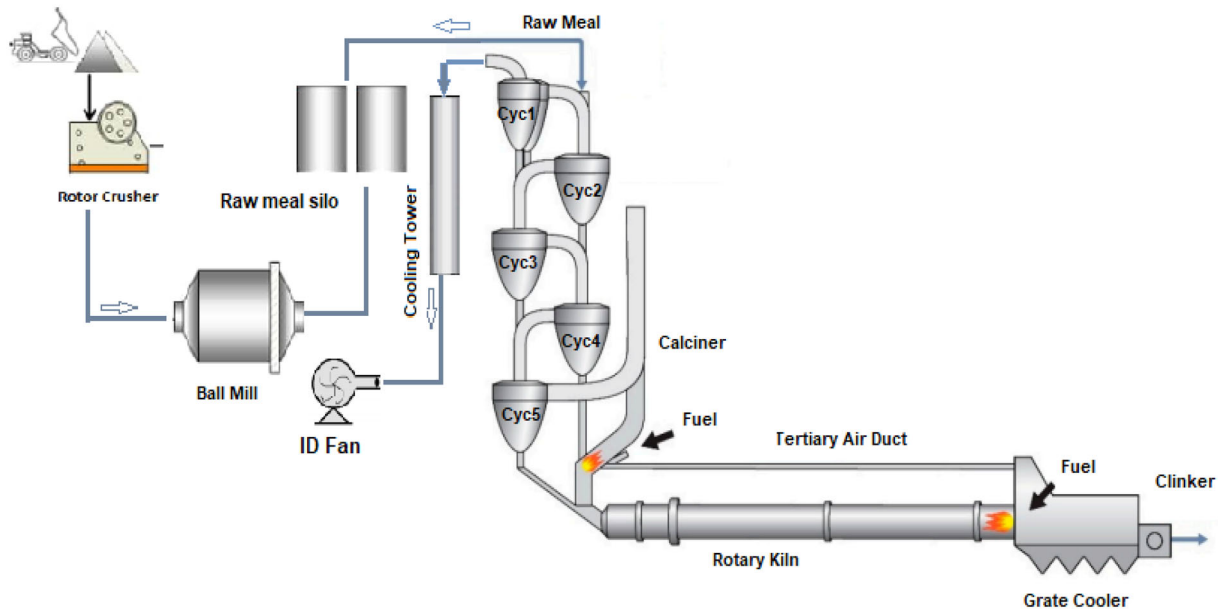


Figure 1. Clinker Baking circuits (line 1) of the Ilam cement plant.

Table 1. The statistical description of operating variables for the pre-heater and rotary kiln of Ilam cement plant.

Description of variables	Variables	Min	Max	Mean	STD
The current of motors ID fan	ID fan current (A)	116	1915	1,214.74	104.09
The load of kiln feed	Feed rate (t/h)	70	225	139.95	11.73
The current of the elevator motor of kiln feed	Elevator 1(A)	0	81	49.90	3.55
The main kiln motor drive current	Kiln drive (A)	21	1288	241.44	65.61
The speed of ID fan	ID fan rotation (rpm)	86	995	879.62	83.68
Total of kiln fuel and pre-calciner	Total fuel(lit/hr)	220	96,047	8,969.66	2,437.51
The temperature of the fuel (mazut)	Fuel (°C)	32	114	35.70	7.06
Ventilation before the ID fan duct	Pressure ID fan (mbar)	37	94	55.00	3.92
Kiln inlet ventilation	Kiln Inlet (mbar)	0.1	5.8	2.26	0.83
Pressure cone in cyclone 5	Cyclone 5 (mbar)	8	22	13.22	1.37
Pressure cone in cyclone 4	Cyclone 4 (mbar)	16	42	23.78	2.07
Pressure cone in cyclone 3	Cyclone 3 (mbar)	2	39	32.26	3.22
Pressure cone in cyclone 2	Cyclone 2 (mbar)	4	52	45.49	3.27
Pressure cone in cyclone 1	Cyclone 1 (mbar)	1	59	52.17	3.78
Temperature cone in cyclone 5	Temp. cyc 5 (°C)	84	998	835.89	45.81
Temperature cone in cyclone 4	Temp. cyc 4 (°C)	79	824	718.96	31.11
Temperature cone in cyclone 3	Temp. cyc 3 (°C)	49	770	516.03	39.61
Temperature cone in cyclone 2	Temp. cyc 2 (°C)	26	541	218.59	24.97
Temperature cone in cyclone 1	Temp. cyc 1 (°C)	28	380	287.38	19.87
The temperature between the ID fan duct and inlet of pre-heater	Temp. pre-heater (°C)	231	310	248.30	9.51
The current of blowers (No. 1) motor	Airlift blower 3(A)	50	165	148.35	5.68
The current of blowers (No. 3) motor	Airlift blower 1(A)	14	166	146.34	6.39
The speed of the kiln	Kiln Rotation(rpm)	0.7	3.2	2.55	0.23

marginal feature contribution, i.e., it measures how much each feature's importance is in the model (Chelgani, Nasiri, and Alidokht 2021; Chelgani, Nasiri, and Tohry 2021; Mangalathu et al. 2021). More formally, Shapley value ϕ_i for the prediction model f is calculated as follows:

$$\phi_i(f, \mathbf{x}) = \sum_{S \subset M} \frac{|S|! (|M| - |S| - 1)!}{|M|!} [f(S \cup \{i\}) - f(S)], \quad (1)$$

where M denotes the set of all variables, S is a subset of M , f is the trained model, and $[f(S \cup \{i\}) - f(S)]$ determines the i th input variable's contribution to the model (Chelgani 2021; Mangalathu et al. 2021; Bussmann et al. 2021).

2.3. Extreme Gradient Boosting (XGBoost)

XGBoost stands for "Extreme Gradient Boosting," a distributed, decision tree-based ensemble approach developed in 2016 (Chen and Guestrin 2016). XGBoost uses a gradient boosting framework designed to be extremely efficient, adaptable, scalable, and portable (Ogunleye and Wang 2020; Ezzoddin, Nasiri, and Dorrigiv 2022; Hasani and Nasiri 2022; Leng et al. 2022; Nasiri and Hasani 2022). It employs various regularization methods, including L_1 regularization (i.e., Lasso) and L_2 regularization (i.e., Ridge), to smooth the learned weights and avoid overfitting (Gómez-Ríos, Luengo, and Herrera 2017; Chelgani 2021; K. Zhou, Li, et al. 2021). Moreover, it uses first and second-order derivatives

(Abbasniya et al. 2022). XGBoost's objective function includes a convex loss function and a penalty term (X. Zhang et al. 2020), as can be seen in Equation (2):

$$L^{(t)} = \sum_i l(y_{pred}^{(t)}, y_{truth}) + \sum_k \Omega(f_k), \quad (2)$$

where t denotes the t th training iteration, l computes the difference between the ground truth and predicted value, and $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2$ is the penalty term for the k th tree, controlling its complexity of it (Chelgani, Nasiri, and Tohry 2021; X. Zhang et al. 2020; Nasiri and Alavi 2022). In the penalty term, T is the number of leaf nodes, and w represents the score on each leaf. γ and λ are parameters controlling the penalty associated with T and w (Ma et al. 2019; W. Zhang et al. 2021; Zhifen Zhang et al. 2021; J. Zhou, Qiu, et al. 2021; Fatahi et al. 2022).

2.4. Random Forest

Random Forest (RF) is a supervised learning algorithm, which is a decision tree (DT) basis model (Zojaji, Ebadzadeh, and Nasiri 2022). RF, first proposed by Breiman (Breiman 2001) in 2001, can be considered as an improved Bootstrap aggregating (Bagging) algorithm (Hou, Liu, and Yang 2022). The bagging approach combines several learning models to improve the final output. RF employs a random sampling technique when creating trees (Chelgani 2019). The training samples are drawn with replacement; thus, some samples may be used many times in a tree. Training on different samples helps the RF to reduce variance (Matin et al. 2016; Sun et al. 2021). Moreover, RF considers a random subset of input variables when splitting nodes. Modeling by RF has the following advantages: 1) reducing overfitting 2) having a few tunable parameters 3) being robust to outliers 4) having low bias 5) reducing variance compared to DTs (Gong et al. 2018; Ouallouche, Lazri, and Ameer 2018; Chelgani, Nasiri, and Tohry 2021; Nasiri, Homafar, and Chelgani 2021). Formally, RF creates an ensemble of N DT estimators, and its final prediction can be computed as follows:

$$\hat{T}(\mathbf{x}) = \frac{1}{N} \sum_{n=1}^N \hat{T}_n(\mathbf{x}), \quad (3)$$

where $\mathbf{x}$ represents the input feature vector, and $\hat{T}_n(\mathbf{x})$ denotes the n th decision tree's prediction (Wager and Athey 2018; J. Zhou et al. 2019).

2.5. Support vector regression

Support vector regression (SVR) is a supervised machine learning method, similar to support vector machines but for the regression problem. The main idea behind SVR is to minimize the generalization error bound instead of minimizing the training error (Premalatha and Lakshmi 2013). The advantages of using RF for regression tasks include having high generalization capability with high prediction accuracy, being robust to outliers, low computational complexity in high dimensional space (i.e., computational complexity does

not depend on the dimension of the input space), and being capable of obtaining a global solution (Y. Wang, Zhao, and Wang 2013; Awad and Khanna 2015; Parveen, Zaidi, and Danish 2016; Wolff 2017; Lawal and Kwon 2021).

Given a dataset $D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_n, y_n)\}$, $\mathbf{x} \in \mathbb{R}^n$, $y \in \mathbb{R}$, consider the problem of approximating output variable y with a linear function:

$$\begin{aligned} (w, x) + b &= 0 \\ f(x) &= w \cdot x + b \end{aligned} \quad (4)$$

The parameters of the linear function (i.e., w and b) can be determined by minimizing the following objective function:

$$\phi(w, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i^- + \xi_i^+), \quad (5)$$

where C denotes the regularization parameter, ξ_i^- and ξ_i^+ are slack variables, indicating upper and lower bounds on the output variable (Li, Fang, and Liu 2018; Panahi et al. 2020; Premalatha and Vijaya Lakshmi 2013; Zichen Zhang and Hong 2019).

3. Results and discussions

3.1. Inter-correlations

SHAP, and Pearson's correlation have been used for exploring the potential relationships among operating variables and outcomes (ID fan and kiln feed rate), highlighting the importance of monitoring variable importance and ranking them based on their effectiveness in the modeling prediction. These assessments would formulate and lead to constructing a robust and informative *CL* for the unit. SHAP results (Figures 2 and 3) illustrated that ID fan rotation and pressure ID fan have the highest positive correlations with the ID fan current. SHAP outcomes also showed a high positive relationship between the ID fan rotation, total fuel consumption, and kiln feed rate. Generally, kiln speed and kiln feed rate can control with a fixed linear relationship and unilateral variation; however, it was documented that the speed should be kept constant in the upper range of feed rates (Alsop and Post 1995; Arad, Arad, and Bobora 2008; Stadler, Poland, and Gallestey 2011).

Exploring linear inter-correlations among variables by SHAP and Pearson correlation (Figure 4) highlights several interactions between various parameters. A strong positive correlation between ID fan current and kiln feed rate can be observed. In other words, increasing the ID fan current could positively affect its performance when the feed rate increases. A comparison between Pearson correlation and SHAP results indicated that a highly nonlinear model such as SHAP would be required for modeling the rotary kiln parameters since Pearson correlation as a linear method could not accurately illustrate some intercorrelations (Chelgani and Makaremi 2013).

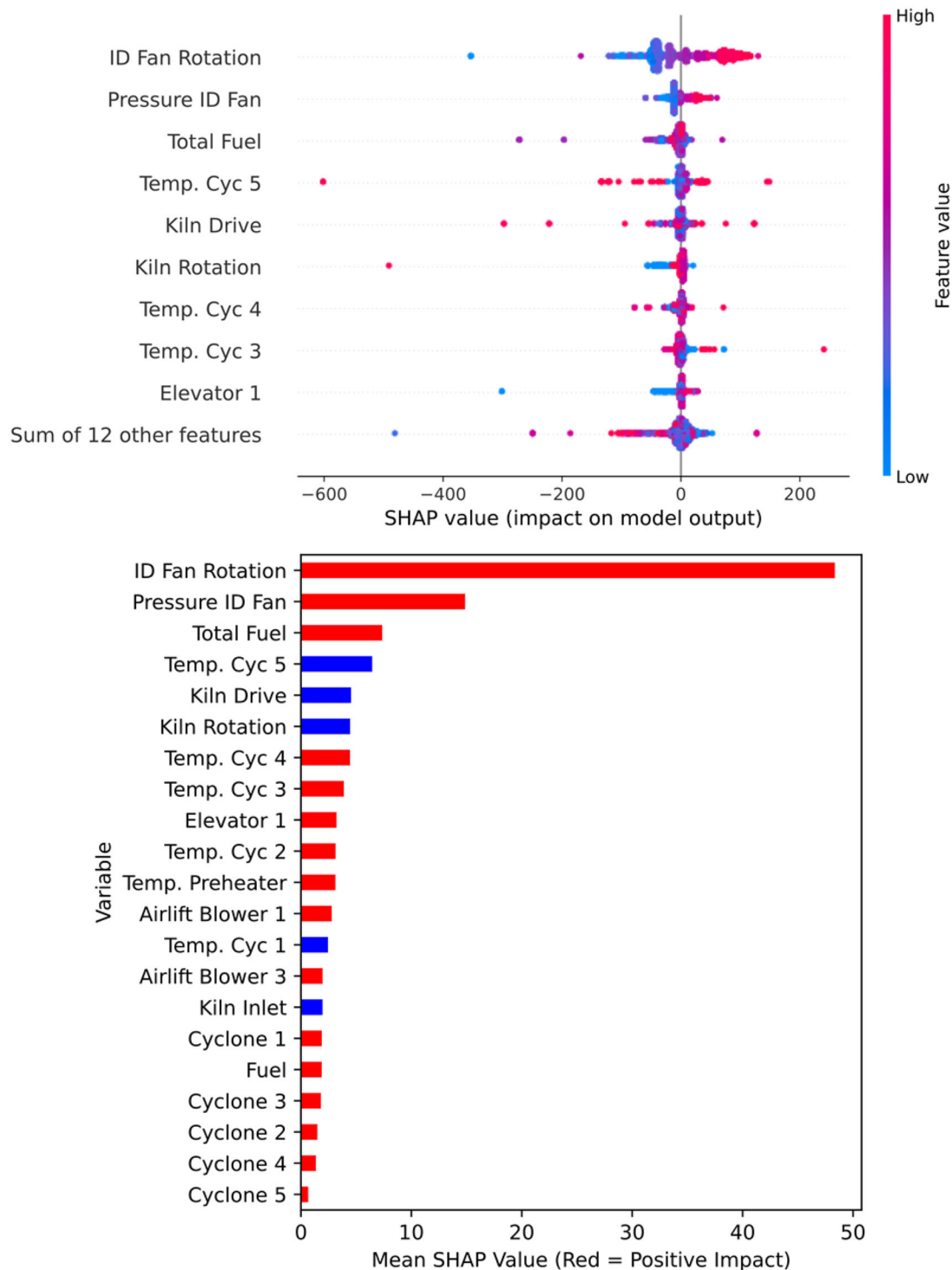


Figure 2. SHAP values of various variables for the prediction of ID fan current.

3.2. Predictions

From the entire dataset, 70% of recorded variables were used to train the different AI models (i.e., XGBoost, RF, and SVR), 15% of the samples were used for validation, and the remaining 15% were considered for the model's testing phase. For finding XGBoost's optimal hyperparameters through the validation phase, many different values for its hyperparameters were examined in the tuning process (a try

and error procedure) to find its optimal hyperparameters using the validation set. (Table 2). The XGBoost outcomes (Table 3) in the testing phase demonstrated a higher accuracy than two other examined typical machine learning methods (RF and SVR). These differences have been highlighted for both the ID fan current and kiln feed rate predictions in Figure 5.

By comparing different ML algorithms, it could be mentioned that both RF and XGBoost are ensemble methods

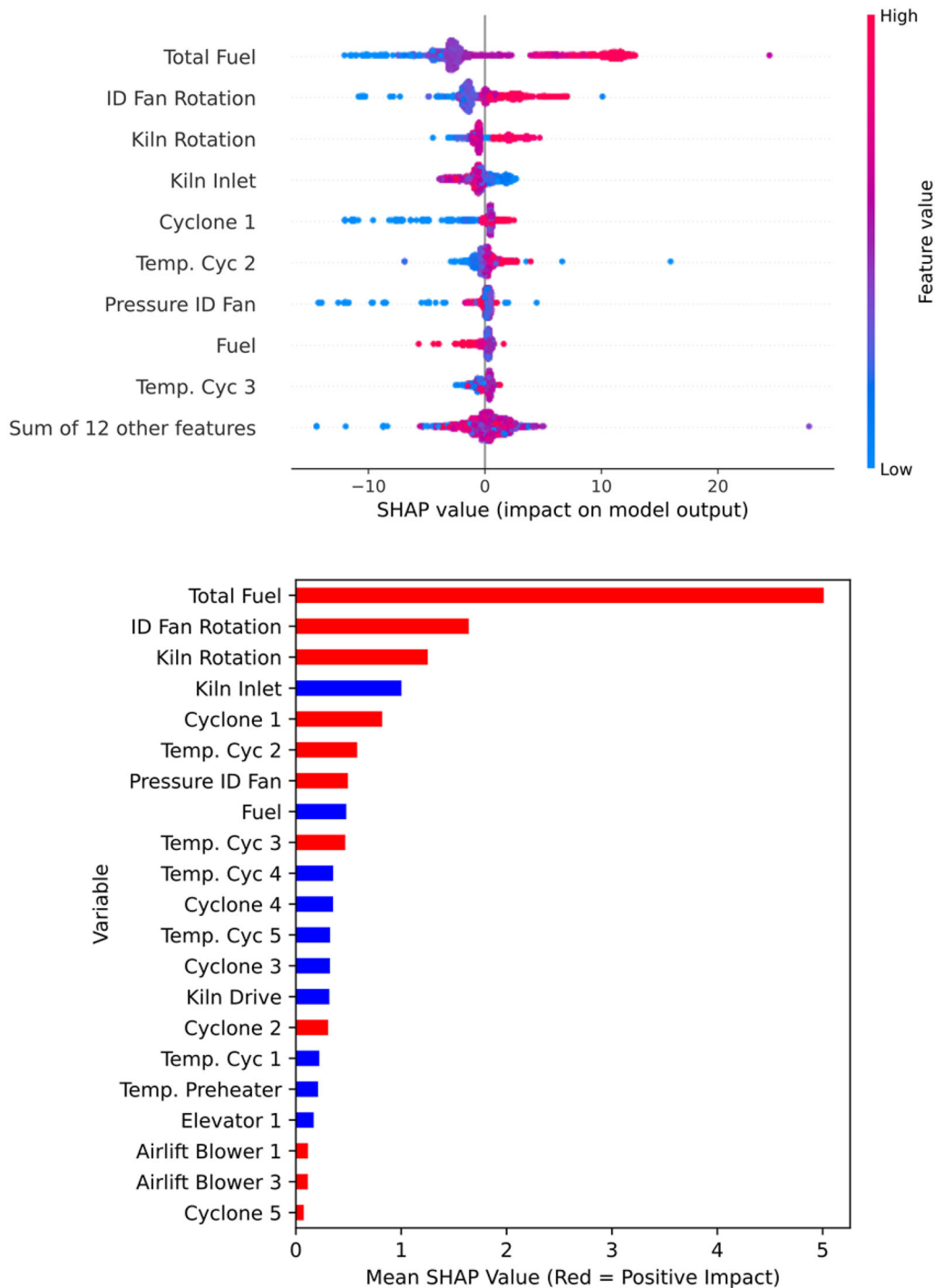


Figure 3. SHAP values of various variables for the prediction of Kiln feed rat.

but not SVR. RF is based on bagging, while XGBoost is a boosting method. SVR has low bias and high variance, whereas XGBoost and RF have low bias and low variance. However, XGBoost is more flexible than the other two methods. It allows the user to customize the objective function. When using SVR, it might be challenging to choose the appropriate kernel function. In terms of computational complexity, XGBoost implements parallel processing, so it is very fast and has low computational complexity. SVR performs well in high dimensional space, but RF requires more computational resources; therefore, it has a high computational cost.

All the mentioned algorithms can handle outliers and are not easily affected by them (Fan et al. 2018; Lee et al. 2019; Huang et al. 2020). These significant results indicated that the constructed CL based on the SHAP-XGBoost model could be considered as a robust EAI system for controlling and maintaining different cement units in various plants.

4. Conclusions

Since many cement production plants are monitored by the direct knowledge of their operators, developing an accurate

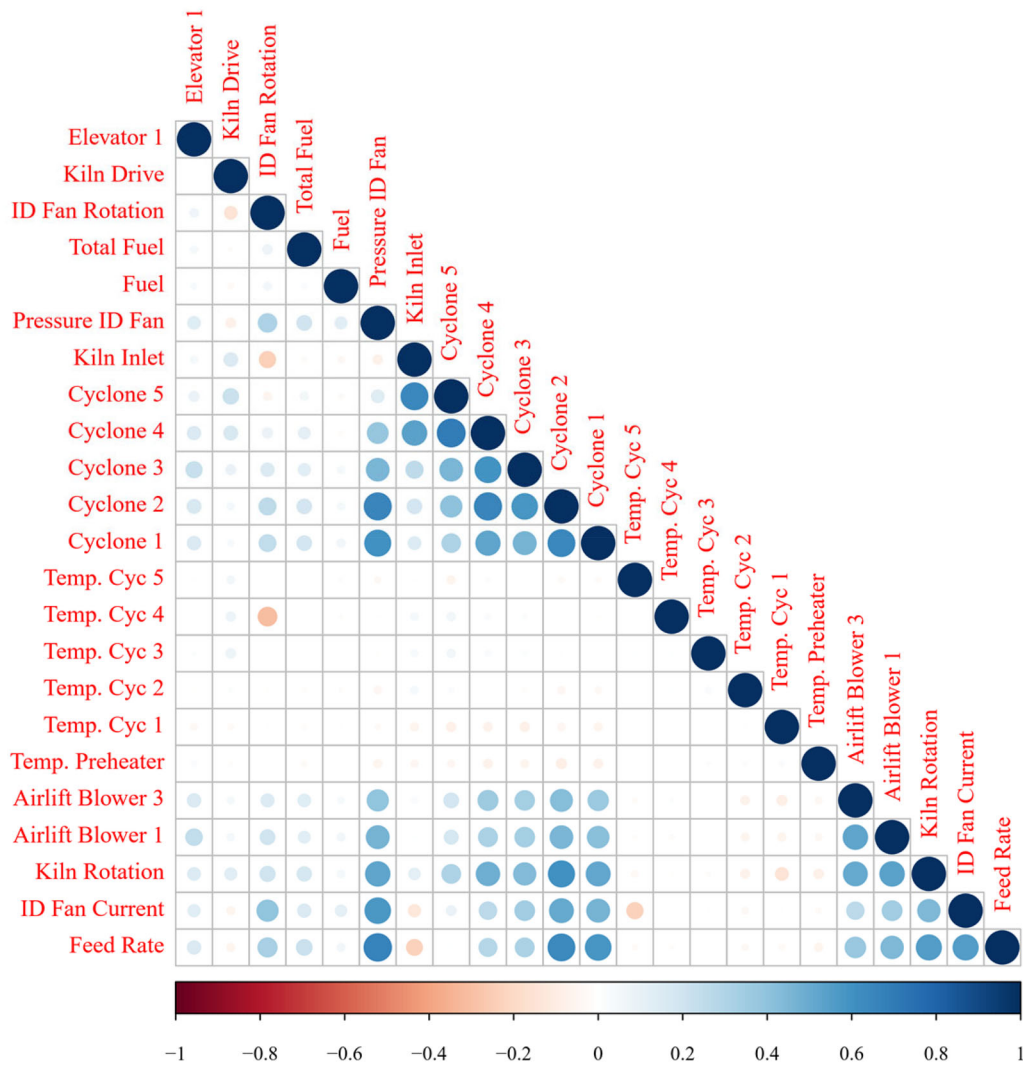


Figure 4. Pearson correlation between operational parameters and their representative rotary kiln indexes.

Table 2. The XGBoost parameter settings for various outputs.

Parameters	ID fan current	Kiln feed rate	Range
N_estimators	700	266	$\{k k \in \{1, 2, \dots, 1000\}\}$
Learning rate (η)	0.257	0.153	$\{0.001k k \in \{1, 2, \dots, 1000\}\}$
Minimum sum of instance weight (hessian) needed in a child	0	0	$\{k k \in \{0, 1, \dots, 10\}\}$
Reg_lambda	0.10	0.27	$\{0.01k k \in \{1, 2, \dots, 100\}\}$
Colsample_bylevel	0.86	0.96	$\{0.01k k \in \{1, 2, \dots, 100\}\}$

Table 3. Model assessments based on accuracy indexes.

Method	Kiln Feed				ID Fan			
	R-Squared		RMSE		R-Squared		RMSE	
	Validation	Test	Validation	Test	Validation	Test	Validation	Test
Random Forest	0.91	0.89	3.61	4.02	0.87	0.90	49.68	42.17
SVR	0.61	0.61	7.64	7.68	0.32	0.29	104.52	112.78
XGBoost	0.96	0.96	2.56	2.47	0.97	0.96	22.31	26.50

knowledge-based system close to human basis understanding could markedly change the process efficiency. Digitalization and using explainable artificial intelligence (EAI) could be key steps of this transformation. As one of the most recent digitalization approaches, construing conscious lab “CL” by using SHAP-XGBoost (a most recent EAI development) for

a rotary kiln has been investigated for the first time based on a cement plant dataset. The developed CL highlighted the correlations among various monitoring variables in the plant and indicated their effectiveness on the rotary kiln representative factors (induced draft (ID) fan current and kiln feed rate). SHAP as an explainable artificial intelligence

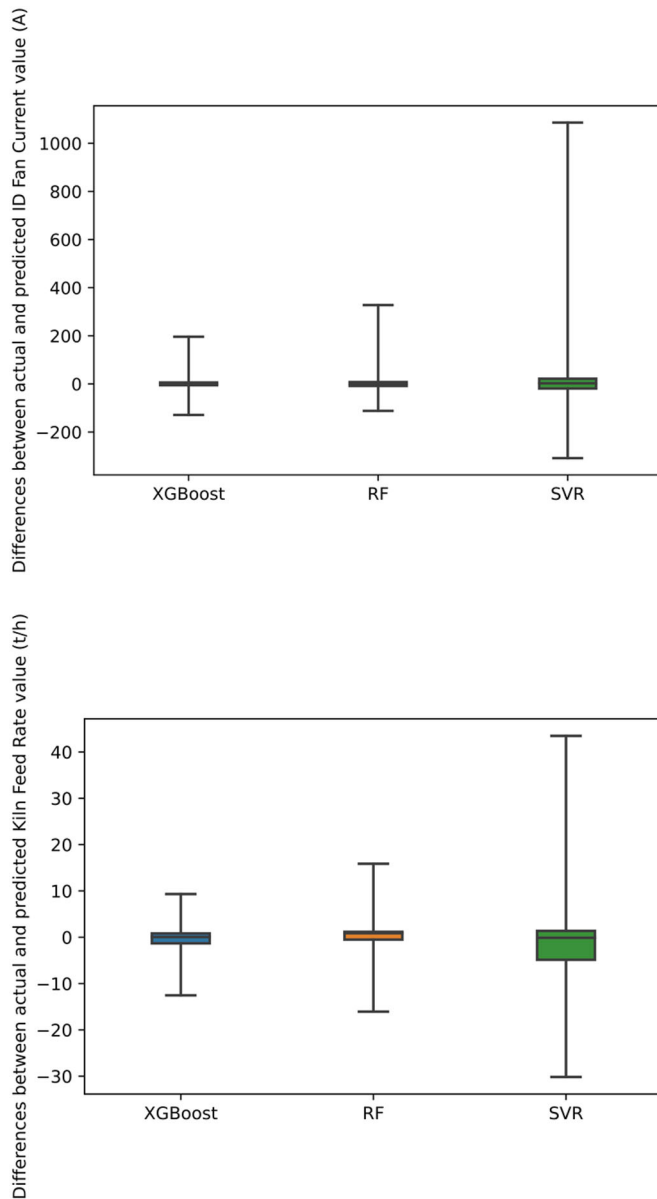


Figure 5. Differences between actual and predicted values by various AI models in the testing phase.

method indicated that ID fan rotation has the highest positive relationship with the ID fan current. In general, increasing the ID fan rotation could increase the ID fan current and kiln feed rate. SHAP analyses demonstrated a significant correlation between the total fuel consumption and kiln feed rate. The XGBoost model has predicted the key rotary kiln representative factors. This model quite accurately could predict these two variables with $R^2 = 0.96$. The estimation accuracy of XGBoost had been challenged with random forest and support vector regression models. The outcomes demonstrated that XGBoost could provide accurate results (root mean square error for kiln feed was XGBoost 2.47, random forest 4.2, and SVR 7.68, and ID fan current 26.49, 42.17, and 112.78, respectively). In general, these outcomes proposed that the developed model could effectively be used as a CL for digitalizing and controlling various units within cement plants.

Disclosure statement

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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