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A conscious lab-based approach for modelling and investigating the impact of influential parameters on feed rate and differential pressure in cement vertical roller mills

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ABSTRACT

Vertical Roller Mills (VRMs) are widely used in energy-intensive industries like cement, steel, and chemicals due to their efficiency in grinding, drying, and material transport. However, two critical aspects remain underexplored: the correlation between operational variables and differential pressure (dp) and the influence of key parameters, such as feed rate, on mill performance. To address these gaps, this study utilized advanced machine learning methods, including Random Forest (RF), LightGBM, and Shapley Additive Explanations (SHAP), integrated within a Conscious Lab-based (CL) framework. The study focused on modelling feed rate as a manipulated and dp as a controlled variable, with SHAP employed to analyze variable interactions. Findings identified operational factors such as working pressure, dp, counter pressure, and mill fan speed as significant determinants of feed rate setpoints. Working pressure emerged as the most influential variable impacting both dp and feed rate, establishing its critical role in stabilizing operations and regulating performance. Key variables, such as working pressure, mill fan speed, and feed rate, were also identified as primary contributors to dp, reflecting the principles of the CL framework for dynamic control. Validation tests revealed LightGBM as the best-performing algorithm, achieving the highest R^2 values (0.98 and 0.97) and lowest RMSE (1.34 and 0.16) for feed rate and dp prediction, respectively, making it the optimal model for predicting feed rate and dp. This study highlighted the potential of combining machine learning with the CL framework to accurately model complex relationships among variables, optimize VRM operations, and advance sustainable energy-efficient practices in the cement industry.

Keywords: *Vertical roller mill, Modelling, Differential pressure.*

1. Introduction

The primary advantage of vertical roller mills (VRM) is their energy efficiency, which is crucial in mineral processing and cement production, where grinding consumes approximately 60% of total electrical energy (Fujimoto, 1993). Grinding processes account for approximately one-third of the total energy consumption in cement production, with an average of 57 kWh of electrical energy used per ton of cement for clinker grinding (Worrell et al., 2000). VRMs are high-capacity grinding equipment widely utilized in energy-intensive industries, including cement, steel, and chemicals (Zhu et al., 2020), combining grinding, drying, conveying, and powder separation functions within a single unit (Harder, 2010). VRMs have become preferred due to their superior grinding efficiency, lower energy consumption, and enhanced drying capabilities (Harder, 2010), offering benefits that can eliminate tertiary and even secondary crushing stages (Fahrland & Zysk, 2013; Schaefer, 2001). These multifunctional systems integrate grinding, drying, conveying, and powder separation (Altun et al., 2017; Harder, 2010), with operational parameters significantly influencing grinding outcomes, energy efficiency, and product quality (Altun et al., 2017). Conventional VRM operation relies heavily on operator experience for manual parameter adjustment (Zhu et al., 2020), and most VRM studies remain theoretical or laboratory-based (Altun, 2017). Process control involves manipulating variables, such as working pressure, feed rate, and differential pressure (Little, 2021), which can lead to operational instability, increased energy consumption, and reduced grinding efficiency (Meng et al., 2015). The variation in operator experience poses risks to mechanical components and process stability. VRMs operate under a negative pressure created by the mill fan to facilitate powder transportation. Enhancing classification efficiency and minimizing pressure differentials are crucial for reducing fan energy consumption. Various studies have examined variables affecting VRM grinding circuits (Liu et al., 2020), including material breakage behavior (Fatahi, Pournazari, et al., 2022), raw meal fineness prediction (Belmajdoub & Abderafi, 2023), material residence time (Barani et al., 2022), and energy consumption reduction (Altun et al., 2015). Research has advanced toward real-time cement fineness estimation (Stanišić et al., 2015), production index prediction (Lin & Zhang, 2016), and intelligent automatic control systems (Yan-yan et al., 2011). Mathematical and numerical modelling studies have analyzed flow field characteristics and blade parameters, revealing their significant impact on classification efficiency, differential pressure, and overall VRM performance (Hu et al., 2024; Liu et al., 2020). The Conscious Lab-based (CL) approach, an artificial intelligence-based framework, leverages operational data to develop dynamic AI systems that can reduce laboratory costs, address scale-up issues, save time, and make decisions based on actual factory conditions rather than theoretical concepts. This AI-based structure utilizes explainable AI

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algorithms based on control room monitoring data, optimizing production through operator training (Chelgani et al., 2024; Fatahi et al., 2025; Fatahi et al., 2021; Fatahi, Nasiri, et al., 2022; Fatahi et al., 2023). VRM stability depends significantly on differential pressure, discharged gas temperature, ventilation rate, and mill inlet negative pressure (Yan-yan et al., 2011; Authenrieth et al., 2012;). Differential pressure, the difference between the mill inlet and outlet pressurereflects the material load inside the mill and correlates with other process variables (Fedoryshyn et al., 2012; Pareek & Sankhla, 2021). Despite extensive VRM research, two critical areas remain understudied: (1) the correlation between operational variables and differential pressure, and (2) the effects and correlation of key parameters like feed rate. This combined research employs machine learning methods, including Random Forest, LightGBM, and Shapley Additive Explanations (SHAP), to predict differential pressure and model feed rate as a manipulated variable and main drive power as a controlled variable. Understanding these complex interactions and relationships will guide optimal VRM operation, performance, and energy efficiency while enabling operators to make more rational decisions across various operational conditions.

2. Material and methods

2.1. Dataset collection

The dataset for modelling vertical roller mill (VRM) processes was systematically gathered through continuous monitoring of operational parameters over an extended period. Data collection occurred in the central control room of Production Line 9 at Tehran Cement Plant (Tehran, Iran), one of Iran's largest cement production complexes with nine production lines and a production capacity of 13800 t/day. Monitoring spanned 1,026 hours under diverse operational conditions, representing actual industrial settings rather than laboratory conditions. The data collection process integrated scientific knowledge with operational expertise from experienced VRM operators. Process data was recorded by applying appropriate set points to manipulable variables and capturing the resulting responses from actuator systems. This comprehensive approach ensured that the dataset reflected real-world operational scenarios, including operator decisions and system responses to programmable logic controller (PLC) commands. Fig. 1 shows the schematic of data collection stages from the VRM cement grinding circuit.

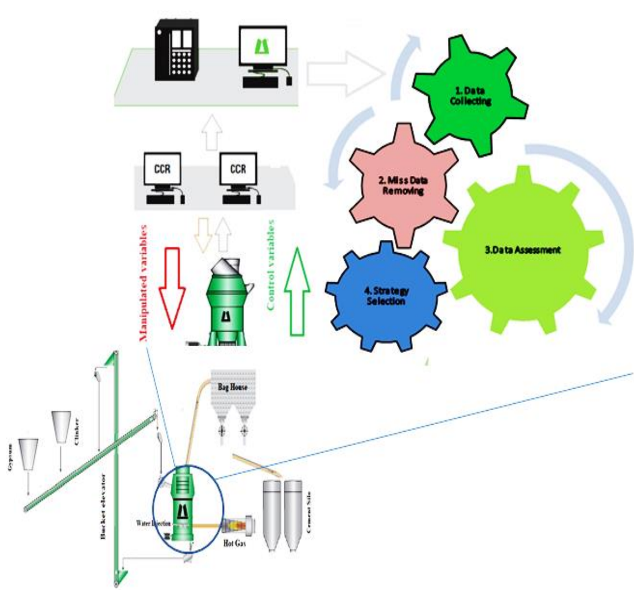

Fig. 1 The schematic of dataset collection stages from the cement VRM grinding circuit.

2.2. Cement VRM grinding process

The cement VRM operates through a sophisticated grinding mechanism powered by a main drive connected via a vertical gearbox. Before the operation begins, a hydraulic system lifts the master and support rollers from the grinding table. The grinding process initiates when feed material, consisting primarily of clinker (with d_{80} approximately 32 mm) and gypsum in a 97:3 ratio, is introduced to the center of the rotating table. Centrifugal forces drive these materials toward the edges where they encounter significant pressure from the master rollers, resulting in grinding action between the rollers and the table surface. The VRM features a unique four-roller mechanism: two large master rollers responsible for grinding operations and two smaller support rollers that stabilize material layering on the grinding table. Bed breakage stability is maintained through both support roller action and water injection. After grinding, the processed material passes through a dam ring that regulates the height of the material layer before being collected by hot gas entering through a nozzle ring. This hot gas serves dual purposes-drying the materials and transporting finer particles to a dynamic separator above the mill. The cement powder exits with the gas stream and is collected in a bag house, while coarser particles return to the table for additional grinding. Many modern VRMs incorporate external recirculation systems where coarse materials falling into the mill's gas ducts through the louver ring are reintroduced alongside fresh feed via conveyors or bucket elevators, achieving significant energy savings (Authenrieth et al., 2012; Fedoryshyn et al., 2012; Xu & Sun, 2020; Pareek & Sankhla, 2021;; Fatahi, Pournazari, et al., 2022). The process control parameters of the cement VRM are shown in Table 1.

2.3. Shapley Additive exPlanations (SHAP)

Shapley Additive Explanations (SHAP) are an innovative approach introduced by Lundberg and Lee to enhance the interpretability of machine learning models (Lundberg & Lee, 2017). SHAP delivers local and global explanations by assigning feature importance at the instance level and across the dataset. It breaks down model outputs into feature-specific contributions, enabling tasks like debugging, feature engineering, and decision optimization (Mangalathu et al., 2021; Mao et al., 2021). Visualizing feature importance and prediction explanations enhances model interpretability and validation. Mathematically, outputs are expressed as the weighted sum of SHAP values for input features:

$$\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{\varphi_0} + \sum_{i=1}^{N} \boldsymbol{\varphi_i X'_i} \tag{1}$$

Here, $\boldsymbol{f}$ is the model's mapping function, $\boldsymbol{N}$ is the number of input features, $\boldsymbol{\varphi_0}$ is the average prediction and $\boldsymbol{\varphi_i}$ is the SHAP value for the $\boldsymbol{i}$-th feature. The coalition vector $\boldsymbol{X'_i}$ is computed from the original input $\boldsymbol{X_i}$ using a mapping function $\boldsymbol{X_i} = \boldsymbol{h_x}(\boldsymbol{X'_i})$ (Bussmann et al., 2021; Mangalathu et al., 2021).

2.4. LightGBM

Gradient Boosting Decision Tree (GBDT) is highly efficient and reliable but faces challenges with big data as its scalability decreases due to the need to scan all instances (Friedman, 2001). LightGBM, introduced by Microsoft in 2017, addresses these issues (Ke et al., 2017). Unlike other algorithms, LightGBM builds trees by focusing on leaves with the most loss, enhancing accuracy. Its speed benefits from Gradient-based One-Side Sampling (GOSS), and Exclusive Feature Bundling (EFB) (Ke et al., 2017). It minimizes the loss function while adding weak learners, with the final prediction being the weighted sum of their forecasts (Liu et al., 2022).

$$\textbf{loss function} = (\boldsymbol{y_i} . \boldsymbol{\hat{y}_i}) \tag{2}$$

For each iteration(t), the negative gradient of the loss function relative to the predictions made by the previous model is calculated as:

$$\boldsymbol{g_i^{(t)}} = -\frac{\boldsymbol{\partial L(y_i . \hat{y}_i{}^{(t-1)})}}{\boldsymbol{\partial \hat{y}_i{}^{t-1}}} \tag{3}$$

Table 1. The process control parameters of the cement VRM grinding circuit.

Variables	Description of variables	Max	Min	Mean	STD
Mill output pressure	The outlet pressure of the mill	-27.95	-33.04	-29.33	0.61
Mill body vibrating (mm/s)	The vibration of the mill body due to operational parameters	8.84	2.31	4.12	0.89
Main Drive (Kw)	The power drawing of the main motor	1887.80	1005.10	1552.713	224.24
Mill fan power (Kw)	The power drawing of the motor mill fan	677.44	513.38	555.77	19.79
Water injection (m^3/hr)	The rate of water spray for stabilization of bed breakage.	1.51	1.25	1.43	0.07
Differential pressure (mbar)	The differential pressure between the inlet and outlet of the mill	36.61	30.62	33.23	0.92
Mill body vibrating (mm/s)	The vibration of the mill body due to operational parameters	8.84	2.31	4.12	0.89
Counter pressure (bar)	The applied pressure for adjustment of the distance of the master roller from the table	16.90	14.35	15.29	0.61
Feed rate (t/h)	A load of mill feed	29.27	86.41	114.08	9.51
Silo Elevator (A)	The amper drawing of the main elevator motor	64.71	44.49	55.38	4.70
Bed Height(cm)	The thickness of the material bed	30	0.0	4.94	9.17
Mill fan speed (rpm)	The speed of the mill fan impeller	813.27	747.99	767.32	9.04

In LightGBM, the tree is constructed in a leaf-wise approach. For each node (m), the optimal split is determined in a way that minimizes the loss function. In this context, if (S) represents the set of samples that reach leaf node 'm', the optimal split point is found by:

$$\mathbf{split_m = arg\ min_{split}} \sum_{i \in S} \mathbf{L}(\,y_i.\,\hat{y}_i^{(t-1)} + \mathbf{split}) \tag{4}$$

Once the tree construction is completed, the output value for each leaf node 'm' is estimated by calculating a weighted sum of the negative gradient of the samples in that leaf:

$$\mathbf{leaf\_output_m} = -\frac{\sum_{i \in S} \mathbf{g}_i^{(t)}}{\sum_{i \in S} \mathbf{h}_i^{(t)} + \lambda} \tag{5}$$

LightGBM uses histogram-based feature splitting and gradient-based one-side sampling, making it practical, especially for skewed datasets under similar parameters (Li et al., 2022).

2.5. Random forest

Random Forest (RF), a tree-based predictive model renowned for handling high-dimensional data and for not relying on parametric assumptions, was introduced by Breiman and utilizes ensemble learning techniques for tasks such as classification and regression (Matin et al., 2016). The RF method builds upon bootstrap aggregating (bagging) by incorporating random variable selection at each node (Breiman, 1996). Essentially, it extends bagging by randomly selecting a subset of features within each data sample. RF modelling offers several advantages, including reduced overfitting, minimal tunable parameters, robustness to outliers, low bias, and decreased variance compared to traditional decision trees (DT) (Gong et al., 2018; Ouallouche et al., 2018) .Typically, RF generates an ensemble of N decision tree estimators, with the final prediction calculated as follows:

$$\hat{\boldsymbol{T}}(\mathbf{X}) = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{n}=\mathbf{1}}^{\boldsymbol{N}} \hat{\boldsymbol{T}}_{\mathbf{n}}\,(\boldsymbol{X}) \tag{6}$$

where x represents the input feature vector, and $\hat{\boldsymbol{T}}_{\mathbf{n}}(\boldsymbol{X})$ denotes the nth decision tree's prediction (Wager & Athey, 2018).

3. Results and discussion

3.1. Relationship of parameters assessments

The linear assessment results indicated the likelihood of multiple multivariate relationships among the operational variables in the cement VRM. Numerous studies have highlighted the potential for complex interactions between operational variables in the cement industry (Fatahi et al., 2021; Fatahi, Nasiri, et al., 2022; Fatahi et al., 2023). Based on Fig. 2, when the target variable for modelling is the feed rate, it shows the highest correlation with the following parameters in descending order: working pressure (0.94), water injection (0.83), main drive (0.81), and dp (0.80). Similarly, the parameters with the strongest linear correlation to dp are working pressure (0.83), mill fan speed (0.82), and feed rate (0.80). In contrast, mill output (-0.592), counter pressure (-0.332), and bed height (-0.255) display negative correlations with dp, highlighting both positive and negative relationships among the operational variables.

3.2. SHAP analyses of operational variables

SHAP is a highly effective technique for interpreting machine learning models, offering precise insights into the contribution of each variable to the model's predictions (Chelgani et al., 2021). Fig. 3 which ranks variables based on importance, clearly illustrates their individual effects. The SHAP analysis revealed a ranking pattern similar to the Pearson correlation evaluation regarding parameter importance. For modelling with feed rate as the target variable, SHAP indicated that working pressure and dp have the most significant influence on the model, both showing a positive correlation on average. As the feed rate increases, operators raise the working pressure to enhance comminution efficiency, resulting in higher dp values (Yan-yan et al., 2011).

Fig. 4 derived from SHAP analysis, identifies three key variables that significantly influencing dp prediction in cement vertical roller mills. Their average impact on the model's output highlights that Dp is primarily affected by the material feed rate, the mill fan flow rate (or fan speed), and the working pressure (Pareek & Sankhla, 2021).

SHAP can identify and analyze multi-correlations and complex patterns among variables (Chelgani et al., 2023). Fig. 5 presents the SHAP analysis which highlights the multi-correlation between key parameters impacting feed rate modelling. The working pressure increases as operators raise the feed or product rate, as noted by Altun et al., (2017). At lower feed rates, the working pressure remains minimal (blue points) whereas at higher feed rates, the pressure rises significantly (red points). DP which reflects the difference between the inlet and outlet pressures of the mill, indicates the mill's internal load and feed rate (Yan-yan et al., 2011). The inter-correlation between feed rate and dp shows that up to 115 t/h, increasing the feed rate leads to a sharp rise in dp, while beyond this threshold, the increase becomes more gradual. Feed rate variations during VRM operation influence the mill's load and, consequently, the dp. Adjusting the feed rate during operation requires increasing the working pressure which allows the rollers to apply greater force on the grinding bed for effective comminution. Counter pressure plays a role in this process by bringing the rollers closer to the table to optimize the application of working pressure.

Fig. 6 shows that the SHAP analysis reveals that mill fan speed significantly impacts on dp, with SHAP values transitioning from negative to positive as fan speed increases from 750 to 810 rpm. The highest dp values (around 36) are observed at 810–815 rpm fan speeds where the inlet-outlet pressure differential is maximized. Similarly, working pressure shows a positive, though non-linear, correlation with dp. At lower pressures (80–90), SHAP values are negative, improving as pressure rises to 110, with peak dp performance in the 105–110 range. Operators align higher working pressures with feed rate increases to maintain stable operation. Feed rate exhibits a more complex relationship. At lower feed rates (85–95), SHAP values are negative, becoming positive around 100–105. Data scatter in the middle range (100–115) suggests the influence of additional factors. At higher rates

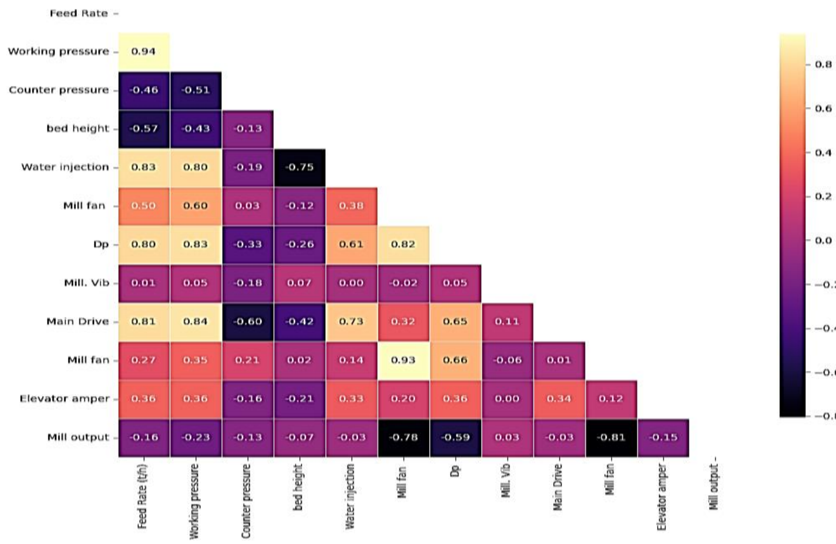

Fig. 2. The Pearson correlation between process variables of the cement VRM grinding circuit.

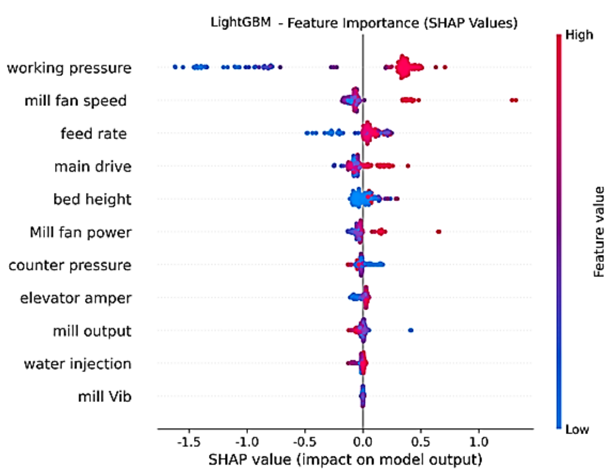

Fig. 3. Ranking variables based on their mean SHAP value for feed rate prediction.

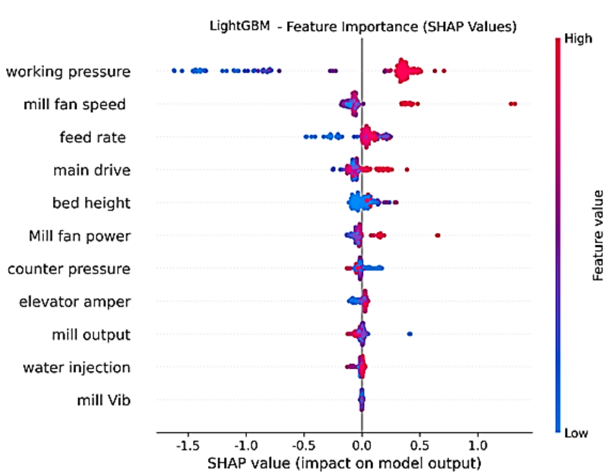

Fig. 4. Ranking variables based on their mean SHAP value for dp prediction.

(115–125), SHAP values remain positive, with peak dp observed at feed rates of 110–115. Like fan speed, higher feed rates amplify the pressure differential. Maximum dp performance is achieved through high mill fan speed, elevated working pressure, and moderate to high feed rates.

Working pressure shows the most linear and predictable relationship with dp, while fan speed and working pressure have more significant impacts than feed rate. Stabilizing dp and maintaining a consistent material bed under the rollers is essential, as a thick bed increases energy consumption, while a thin bed risks internal wear in the mill (Sahasrabudhe et al., 2006).

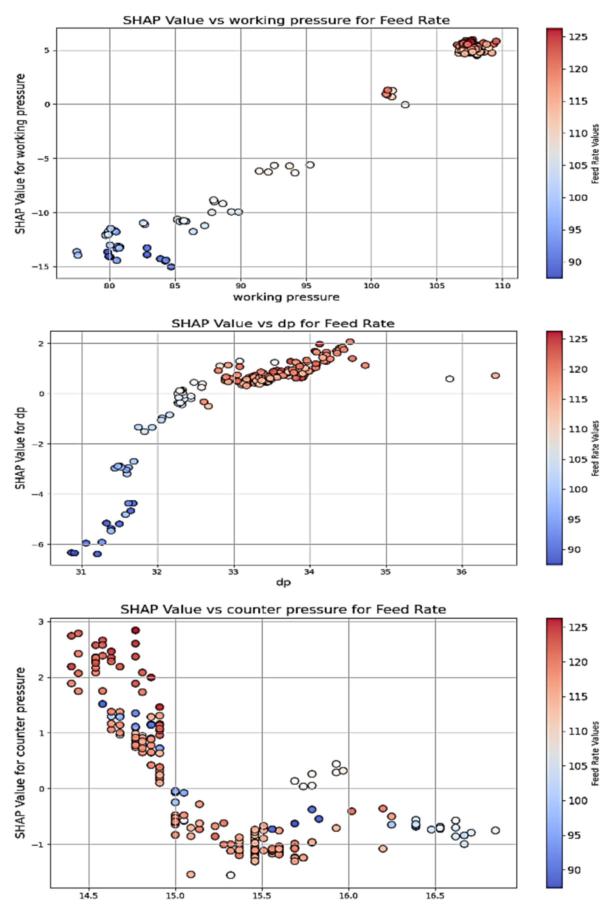

Fig. 5. SHAP values for multi-interactions dependent operational variables on feed rate prediction.

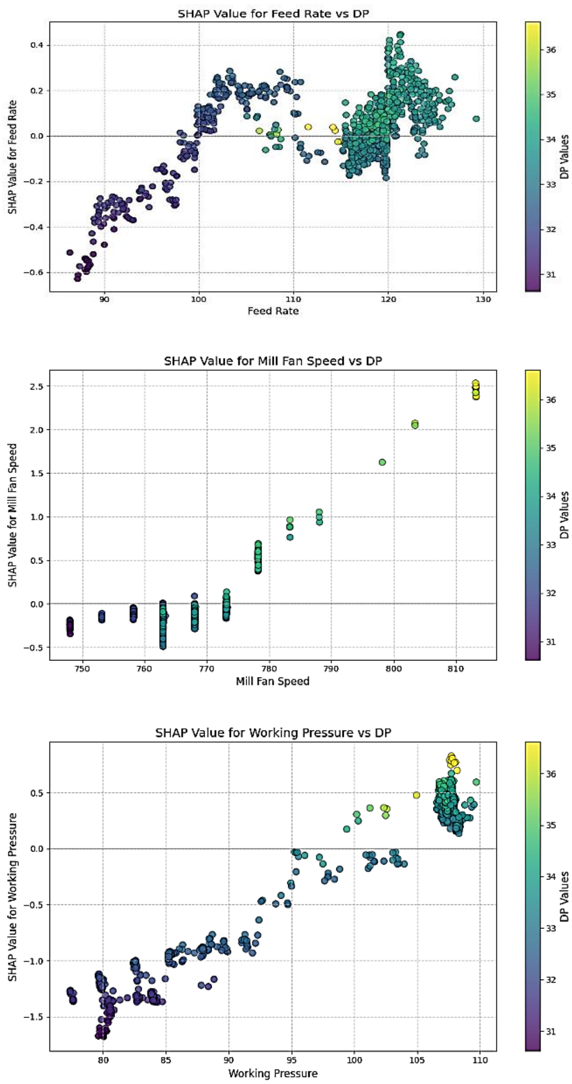

Fig. 6. SHAP values for multi-interactions dependent operational variables on dp prediction.

3.3. Feed rate and dp prediction

During the modelling process for predicting feed rate and dp, the dataset was randomly split into three parts: 70% was allocated for training. In contrast, two equal portions of 15% were designated for testing and validation. Several hyperparameters were explored to optimize the model's performance using a randomized search strategy. This optimization process utilized the validation set to determine the best combination of parameters. The outcomes of this process are summarized in Table 2, which details the optimal values for the model's hyperparameters.

Based on the cross-validation results shown in Table 2 and Fig. 7, both the LightGBM and RF algorithms successfully predicted the controlled variable "dp" and the adjustable variable "feed rate" with satisfactory accuracy. Among the tested algorithms, LightGBM outperformed RF in terms of predictive precision. Regarding performance metrics, LightGBM achieved the highest accuracy, with an R^2 of 0.98, an RMSE of 1.34 and 0.96, and an RMSE of 0.16 for feed rate and dp prediction, respectively, while RF performed slightly less effectively with an R^2 of 0.93 and an RMSE of 1.95 and 0.92 and an RMSE of 0.18 for feed rate and dp prediction, respectively. These findings underscore LightGBM's ability to predict mill feed rate set points and differential pressure efficiently.

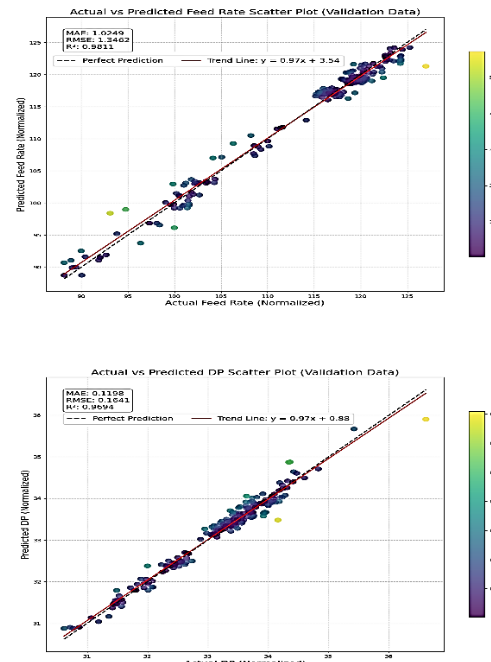

Fig. 7. Comparison between predicted and actual values by LightGBM in the validation step.

The results indicated that the SHAP-lightGBM model, as an advanced AI system, has successfully designed and implemented a CL system for Vertical Roller Mills (VRM). This model is capable of accurately modelling feed rates and main drive power. Furthermore, the SHAP analyses comprehensively reveal nonlinear relationships among various parameters. Studies show that this system can be utilized for modelling, controlling, and maintaining cement VRM circuits on an industrial scale. This capability enables operators to identify key parameters during operations, assess the effects of critical factors on feed rate increases (an essential operational parameter), optimize energy consumption by identifying factors influencing the main drive power, and take measures to enhance operational efficiency. The SHAP-lightGBM model is an effective tool for optimizing energy consumption and identifying key parameters in industrial processes.

4. Conclusions

This study investigated the variables influencing feed rate and dp in VRM, using machine learning algorithms such as RF and LightGBM. The developed models accurately reflected the feed rate setpoint performance and the mill's subsequent dp while identifying linear and complex nonlinear relationships among operational variables. SHAP analyses highlighted the impact of variables such as working pressure, dp, and counter pressure on operators' determination of the feed rate setpoint. Furthermore, for dp, three key variables, working pressure, mill fan speed, and feed rate, were identified in order of significance, aligning with the operational principles under a CL approach. SHAP data also revealed that working pressure, a shared variable for predicting both feed rate and dp, had the most significant impact, establishing it as one of the critical operational parameters in VRM. This parameter is crucial in regulating mill feed rate and affects the mill's dp. Model evaluation via validation tests demonstrated the algorithms' stable performance and high generalization capacity. Among the models, LightGBM exhibited the highest R^2 value, equal to 0.98 and 0.97 for feed rate and dp prediction, respectively, and the lowest RMSE, equal to 1.34 and 0.16, positioning it as the best choice for predicting feed rate and dp. Overall, using the CL approach combined with machine learning algorithms demonstrated high-quality modelling in identifying complex relationships among operational variables, paving new paths for sustainable control and optimizing VRM performance in the cement industry.

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