EFFICIENT PRODUCTION MONITORING AND PREDICTIVE OPTIMIZATION FOR CLINKER MANUFACTURING

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ABSTRACT*: Integrating machine learning into the monitoring of automated production systems is key to optimizing energy use and reducing economic and environmental impacts. Cement production, particularly the kiln workshop, represents a complex and vital cement manufacturing process in a cement plant (SCIMAT-Algeria). Over recent years, various machine learning methods have been proposed to tackle these issues by predicting gas amounts. This study evaluates the effectiveness of several supervised machine learning techniques, including Decision Tree (MSE: 83.1676, R^2: 0.9999), Linear Regression (MSE: 0.2174, R^2: 0.9999), Support Vector Machines (MSE: 0.2212, R^2: 0.9999), and Random Forests (MSE: 30.0465, R^2: 0.9999). These results demonstrate a significant impact by preventing unit shutdowns, reducing raw material costs, and optimizing energy consumption.*

KEYWORDS*: Machine Learning; Energy Optimization; Production Efficiency; Manufacturing Supervision; Control Systems*

1 INTRODUCTION

Automation has not eliminated malfunctions that can cause unnecessary stops during process execution. These problems have forced industries to seek effective solutions, such as new technologies and Artificial Intelligence (AI), including Machine Learning (ML). These are used in several fields such as manufacturing systems (Karrupusamy, 2020), economy (Nosratabadi et al., 2020), industry 4.0 (Çınar, 2020), healthcare and medical informatics (Kavitha et al., 2024), photovoltaics (Buratti, 2024), Physics (Jain, 2024), oil and gas industry (Kanoun, 2024), and many other domains.

ML is an application ability system that learns and improves automatically from experience without being explicitly programmed. It focuses on developing computer programs that access and use data to learn independently (Asongo, 2021). Data-driven ML techniques can discover highly complex, nonlinear patterns in various data types and sources. They transform the raw data into feature spaces or models, which can then be used for prediction, regression, detection, forecasting, or classification (Ayaz, 2021; Taffese & Espinosa-Leal, 2022).

One industry that requires the integration of intelligent techniques is cement production, where cement quality depends strongly on the effectiveness of all phases, from raw material extraction to obtaining the product. The crucial phase is the kiln workshop due to the complexity of physical processes and chemical reactions that occur inside the kiln, which makes it difficult to automate its operation. Also, it's the most energy-intensive workshop, representing approximately the highest percentage of the total energy use (Fatahi et al., 2023).

Our field of study is the energy-intensive process, the kiln workshop in a cement plant (SCIMAT-Algeria). The main objective is a predictive development model of the gas quantity required for clinker production. The supervised ML algorithms including Support Vector Regression (SVR), Random Forests (RF), Decision Trees (DT), and Linear Regression (LR) are applied to the data collected from the real-time automatic industrial system of the kiln workshop. Through a comparative analysis of these methods, we aim to provide information on their efficiency and applicability in industrial environments.

The paper begins with a literature review, articles, and previous studies on the evolution of ML methodologies in the field of defect prediction of industrial processes. We then illustrate the materials, data, and the kiln workshop process used in our approach. Then, a section on the evolution of supervised ML methods. The next section focuses on the results and performance measurement. The paper ends with final suggestions, limitations, and future work of this study.

2 MOTIVATION AND CONTRIBUTION

This study contributes to the kiln workshop in the cement production process. This zone determines the chemical composition and properties of the final cement and also consumes a significant amount of energy, whether through the gas burner entering the kiln or by utilizing the heat exiting the kiln to enter the cyclones, where it heats the raw material and prepares it for the preheating stage. This also helps avoid under-burning, which leads to losses, or over-burning, which causes briquettes to fall into the kiln, resulting in kiln shutdown.

Therefore, supervised ML techniques integrated into the kiln workshop are necessary to avoid several challenges. The first and most important is the need to optimize energy consumption, in which the high temperatures required for clinker formation contribute to substantial energy expenditures, making energy efficiency a major concern. In addition, inefficient clinker processes can lead to lower product quality, increased production costs, and high environmental impact due to higher emissions per rotary kiln.

Finally, we aim to develop an intelligent model that can optimize the process and predict the amount of gas in the kiln process, simplify the monitoring process, reduce maintenance costs, and predict equipment failures.

3 LITERATURE REVIEW

Artificial Intelligence (AI) refers to the development of machines that can perform tasks traditionally requiring human intelligence, such as learning, problem-solving, and decision-making. The work conducts a literature survey on AI, offering an overview of its applications, challenges, and advancements. ML, a subset of AI, involves creating algorithms that learn from data or past experiences to perform tasks without explicit programming.

According to (Sarker, 2021), several ML approaches, tools, and techniques exist, each with advantages and limitations. Many of these, explore applying ML techniques in manufacturing systems, for quality monitoring and prediction (Ismail et al., 2021), focusing on supervised and unsupervised learning methods and their significance in maintaining product quality and operational efficiency. Other authors (Yang et al., 2021) discuss various algorithms and techniques that improve reliability and efficiency in power systems, shedding light on contemporary control strategies. (Lei, 2020) presented the milestones in intelligent fault diagnosis using ML methods. Research (Carvalho, 2019; Dev, 2021) provide a systematic ML techniques study for predictive maintenance and efficiency enhancements in manufacturing. Current works (Alzubi, 2018; Muhammad, 2015) synthesize existing methodologies and applications, delivering valuable insights into the strengths and weaknesses of various supervised learning techniques.

Many ML techniques have been successful in manufacturing and are already being implemented in industrial applications (Çınar, 2020; Zermane, 2022b). (Alghobiri, 2018) performed a comparative analysis of three ML algorithms, DT, Naïve Bayes (NB), and SVM, where SVM is the best classifier. (Ayaz, 2021) evaluates various ML algorithms, DT, Artificial Neural Networks (ANN), Bagging, and GB, for predicting concrete's compressive strength at high temperatures where Bagging proved most effective, excelling in anomaly detection. RF method demonstrated that it’s the best algorithm in approaches (Mokhtari et al., 2021; Ruiz de Miras et al., 2024). According to (Jain, 2024), SVM is the best classifier, after comparing various ML algorithms, to predict the chloride resistance of concrete. The authors (Kanoun, 2024) demonstrate that Gradient Boosting (GB) is also the best classifier for predicting potential failures in refinery piping systems.

The cement plant is a prime example of a complex manufacturing system, especially the rotary kiln workshop. Several papers review the industrial applications of rotary kilns across sectors, emphasizing key energy consumption factors (Vijayan & S, 2014; Voldsund, 2019). The role of refractory bricks in energy reduction is also discussed, with a study (Atmaca, 2014) offering optimization solutions for kiln operations. Research (Kabul, 2015; Sati, 2022; Tua, 2022) presented the importance of coal usage, feed amount, kiln temperature, and heat loss in determining energy consumption in the calcining zone. Additionally, (Crego, 2024) examines transient mathematical modeling of gas rotary kilns for energy recovery to enhance thermal efficiency.

According to previous literature, cement manufacturing systems must be optimized by integrating AI techniques. (Oguntola, 2024) review research on energy efficiency in cement production from 1993 to 2023, focusing on the impact of AI in fostering advancements. The clinker quality is explained by (Ateş, 2021), who developed a prediction model with two techniques, ANN and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). The study (Fatahi et al., 2023) develops a GB model to predict rotary kiln factors like feed rate and induced draft fan current, whereas (Usman, 2024) develops a hybrid model combining Genetic

Algorithms and Neural Networks, to optimize kiln operation, ensuring the desired quality.

This review examines the need for advanced solutions to optimize cement manufacturing and prevent disruptions and focuses on ML techniques used in real-time monitoring. (Zermane, 2022b) develop an intelligent system capable of fault diagnosis, real-time data classification, and forecasting the operational status of the cement plant. This study implemented various ML algorithms, where RF achieved the highest classification accuracy at 97%, proving to be the most effective model for fault diagnosis, SVM at 94.18%, K-NN at 93.83%, DT at 83.73%, and LR at 80.25%. The proposed approach (Zermane, 2022a) involves integrating SVM into the industrial supervision system, innovating the complex supervision system to learn and maintain the usual operator's language, and enabling appropriate responses and critical situations prevention. The objective of (Zermane, 2024) is to capitalize on advancements in ML and DL techniques to build robust predictive models, using historical data, for accurate real-time predictions in the materials quantity estimation in a cement plant. The ML regressors were evaluated based on several metrics SVR, RF, Multi-Layer Perceptron (MLP), and GB, where RF (R-squared 0.9990, MAE 0.0026) and SVM (R-squared 0.9739, MAE 0.0403) are the best metrics.

4 MATERIALS

Our approach is applied to the kiln workshop in the SCIMAT plant located in the East of Algeria, which contains the following three zones: preheating tower, rotary kiln, and balloon cooler when the role is cooking raw meals to obtain clinker. Figure 1 shows the clinker production process.

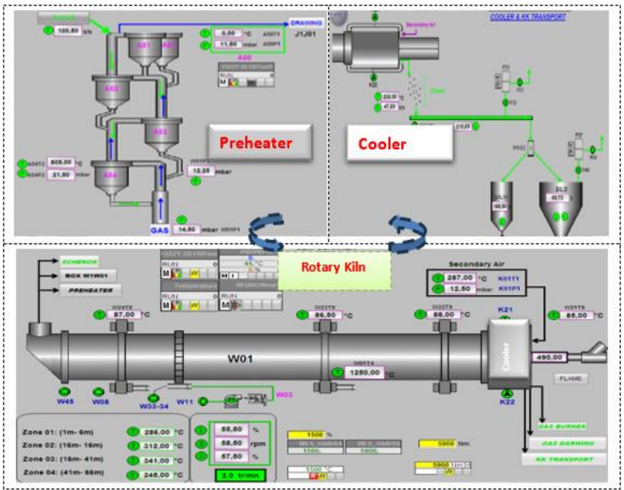

Fig. 1 The clinker production process

First, the raw meal is heated to about 800 °C in a cyclone preheater, where the powder poured from the top descends to the entrance of the rotary kiln. After the flame reaches 2000 °C and raises the material to 1450 °C, calcium oxide reacts, at high temperatures with silica, alumina, and ferrous oxide to form calcium silico-aluminates, which make up the clinker. At the end of the kiln workshop process, the material is rapidly cooled in air, which allows it to reach clinker temperatures of 150 °C, and it is then transported to storage silos.

Simultaneously with the clinker production process, a gas distribution process to various machines, equipment, and devices is triggered. The gas flow is adjusted to maintain a temperature flame between 2000-2200 °C. The airflow rate (primary and secondary) is adjusted following that of the gas to ensure complete combustion. A gas analyzer is placed at the kiln outlet to measure the percentage of CO in the flue gas, which helps control whether the combustion is complete. The obtained clinker, with a temperature between 1200 and 1400 °C, must undergo thermal treatment in the form of air quenching, which will then circulate in the cooler's balloons, counterflowing to the clinker, promoting heat exchange between the two streams. Next, the clinker cools down and exits the cooler at temperatures around 200 °C, while the air entering the kiln as secondary air heats up and supplies this heat to the kiln. Also, the gaseous emissions are reused as heated returns inside the oven and the preheater to prepare the raw flour.

The draft fan ensures airflow at the preheating tower outlet, which allows air from the balloons to the cyclones. Figure 2 illustrates the flow input/ output for the kiln workshop.

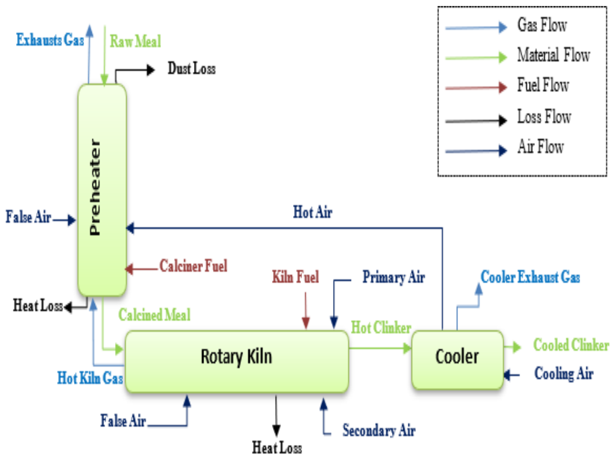

Fig. 2 Flowchart of input/output kiln workshop

Several parameters are monitored during the cement manufacturing process, with 42 specific parameters taken for the kiln workshop, which is illustrated in Table 1.

Table 1. Description of parameters kiln workshop

Parameter Designation	Parameter	Measure (Unit)
Flowmeter, Flow	W1A04_F1	t/h
Flowmeter, flow	W1B04_F1	t/h
Fan, pressure	J1J01_P1	mbar
Aft_Cyclones, Temp	W1A50_T1	°C
Aft_Cyclones, Pres	W1A50_P1	mbar
Aft_Cyclones, Temp	W1A52_T1	°C
Aft_Cyclones, Temp	W1A53_T1	°C
After_Cyclones, Pres	W1A53_P2	mbar
Aft_Cyclones, Temp	W1A54_T1	°C
Aft_Cyclones, Pres	W1A54_P2	mbar
Fan, Speed	J1FN1_S1	%
Kiln, Pressure	W1W01_P1	mbar
Second_Air,Pres	W1K01_P1	mbar
Fan, Speed	J1J01_S1	%
Fan, Current	J1J01_I1	%
Kiln, NOx	W1W01_A4	ppm
Gas Burner, Flow	W1V01_F1	Nm³/h
Gas Burner, Flow	W1V31_F1	Nm³/h
Total Gas	Total Gaz	Nm³/h
Fan, pressure	W1V07_P1	mbar
Prim_ Air Fan, Flow	W1V07_F1	m³/min
Kiln-Gas_Pres	431BU520A01P01	bar
Kiln, Torque	W1W01_X1	%
Kiln, Speed	W1W01_S1	rpm
Kiln Motor, Current	W1W03_I1	%
Kiln-1, Feed Ratio	W1FEED_RATIO	
Total Kiln Feed	W1FEED_TOT	t/h
Clinker_Production	W1A01_B01_Y1	t/h
Gas_Consumption	W1FUEL_CCS	Kcal/Kg
Elevator, Current	H1U07M1I01	%
Elevator, Current	H1U17M1I01	%
Buff_Hopper, Weight	W1A01_W1	t
Buck_Convey,Current	W1U21M1I01	%
Buck_Convey,Current	W1U22M1I01	%
Buck_Convey,Current	W1U27M1I01	%
Drag_Chain_Convey, Current	W1U31M1I01	%
Clinker_Outlet, Temp	W1U01_T1	°C
OP-PL	QCX_W1_PL	g/l
OP-CAOL	QCX_W1_CAOL	%
OP-LSF	QCX_FOUR_LSF	%
OP-MS	QCX_FOUR_MS	%
OP-ALM	QCX_FOUR_ALM	%

Approximately 480,063 samples were collected during the production running line operation in 2022.

5 SUPERVISED MACHINE LEARNING TECHNIQUES

Artificial intelligence (AI) is a subset of Information Technology that enables systems to gather information, understand, learn, and make decisions based on their objectives (Batu, 2023). ML, a subset of AI, uses algorithms that learn from data and past experiences to perform tasks without explicit programming. This learning process involves recognizing patterns and fitting models to data for accurate analysis and results (Geetha, 2022). The evolution of ML, including its techniques and methodologies, has expanded significantly (Shalev-Shwartz, 2013), and detailed in (Alzubi, 2018). So, ML is widely used for prediction and classification to support decision-making, where his models fall into three categories: supervised, semi-supervised, and unsupervised (Sarker, 2021).

This research utilizes a range of ML algorithms to accurately forecast the amount of gas required for clinker production, including Support Vector Machine (SVM), Decision tree (DT), Random Forest (RF), and Linear Regression (LR).

SVMs are supervised learning algorithms that use hyperplanes to classify data or perform regression, effective in high-dimensional spaces and resistant to overfitting, though they require careful parameter tuning (Asongo, 2021). Developed by Vladimir Vapnik in 1998, SVMs improve upon neural networks by optimizing learning through hyperplanes (Lalik, 2022).

DTs are non-parametric models for classification and regression, known for their ability to split data based on features and their interpretability (Asongo, 2021). They use recursive partitioning to create homogeneous subgroups and have been utilized since their introduction by Morgan and Sonquist in 1963.

RFs are an ensemble learning method comprising multiple decision trees, enhancing classification accuracy through collective voting and trained on bootstrap samples with random feature selection (Asongo, 2021). Proposed by Tin Kam Ho and later refined by Leo Breiman, RFs require tuning of key parameters like the number of trees (Awad, 2015).

LR is a classical statistical method for modeling the relationship between variables, developed by Gauss in the 19th century (Shalev-Shwartz, 2013). This model remains relevant in data analysis due to its simplicity and effectiveness in handling complex data (Kecheng, 2024).

Each of these ML models has its strengths and weaknesses, and their performance depends on the nature of the data and the problem they are applied to.

6 METHODOLOGY

The study methodology, model development, and extensive discussions on the implications of our findings are based on the rich dataset that allows the application of various machine-learning models to predict the gas quantity.

We structured our work according to the flowchart illustrated in Figure 3. This flowchart outlines the step-by-step process for developing and implementing an ML model to predict gas quantities and ensure a systematic and efficient methodology.

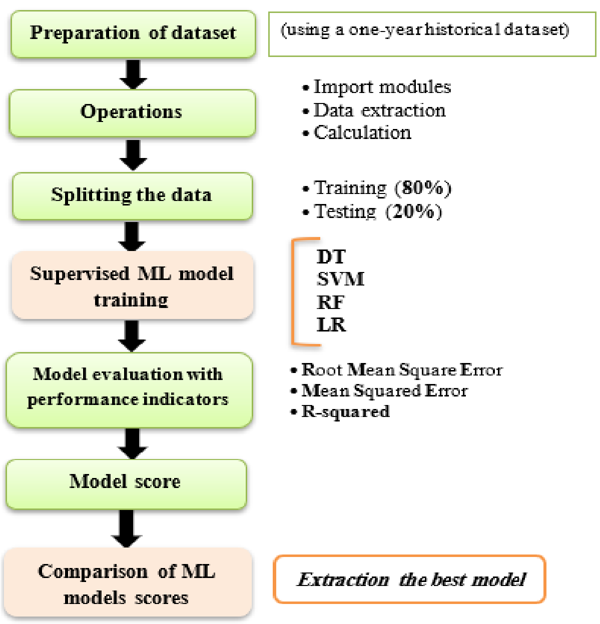

Fig. 3 The workflow used for the ML

The process begins with dataset preparation, identifying input and output parameters using a one-year historical dataset, followed by data extraction, computation, and splitting into training (80%) and testing (20%) subsets. Various supervised ML models, including DT, SVM, RF, and LR, are then trained. Model performance is assessed using metrics like root mean square error (RMSE), mean square error (MSE), and correlation coefficient. Which helps score and compare models to identify the best-performing one for gas quantity accuracy.

The top model, selected through cross-validation and evaluation metrics (MSE, RMSE, R^2), was implemented for predictions and process optimization at the SCIMAT plant. Its predictions were validated against real results and domain knowledge, providing valuable insights to refine strategies, optimize processes, and improve kiln performance.

Our methodology is implemented in Python (version 3.9.12) using the Anaconda environment, which offers a user-friendly interface and includes libraries for incorporating ML techniques.

7 RESULTS AND DISCUSSION

Exploratory data analysis examines the dataset and reveals patterns and relationships influencing the clinker firing efficiency. The correlation heatmap in Figure 4, helps to understand dependencies and interactions between variables, supporting decisions on feature selection, model building, and process optimization, by the factors that may impact process outcomes such as clinker production rates and gas quantity.

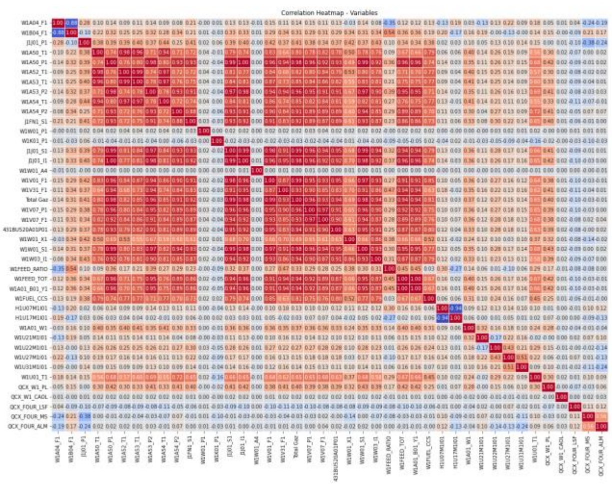

Fig. 4 Correlation matrix

The heatmap analysis identifies strong positive correlations (deep red cells), with variables like "W1A50_T1" and "W1A52_T1" (0.99 correlation) moving together, indicating they measure similar processes. High correlations among variables such as "W1W01_P1," "W1K01_P1" and "W1W01_A4" suggest these belong to the same system. Negative correlations (blue cells), such as between “W1A04_F1” and “W1B04_F1” (-0.88), represented the inverse relationships. Clusters of correlated variables in the heatmap indicate interconnected variable groups, while near-zero correlations, like “Total Gaz” and “W1W01_A4” show independence. Redundant variables, such as “H1U07M1/01” and “H1U17M1/01” suggest potential multicollinearity in models.

In such cases, feature selection or dimensionality reduction techniques can help eliminate redundant variables to improve model performance. Feature engineering can also benefit from these insights by combining highly correlated variables or creating new features that capture the relationships, improving the ML model's predictive power.

The ML models trained on the dataset are rigorously evaluated using standard metrics to assess their predictive performance. The MSE and RMSE quantify the accuracy of predictions for continuous variables, whereas the R^2 measures the proportion of variance explained by the models illustrated in Table 2.

Table 2. Model results

Method	**MSE**	**RMSE**	**R-squared**
Linear Regression	00.2174	0.4663	0.9999
Decision Tree	82.5384	9.0850	0.9999
Random Forest	30.8318	5.5526	0.9999
Support Vector Machines	00.2213	0.4704	0.9999

Table 2 evaluates the performance of four machine learning models, LR, DT, RF, and SVM in predicting "Total Gaz" LR and SVM achieve nearly perfect accuracy (R^2 of 0.9999) with low errors (MSE around 0.22, RMSE around 0.47), making them the best models. RF also shows a high R^2 but has higher errors, while DT, despite a high R^2, overfits the data, resulting in significantly larger errors. LR is identified as the optimal model due to its strong linear relationship and minimal error. The study illustrates the effectiveness of these ML techniques for accurate predictions.

This research compares the performance of various ML models in predicting “Total Gaz”, with the results being evaluated against experimental data. The study examines the different performance techniques and their effectiveness in making accurate predictions, which is illustrated in Figure 5.

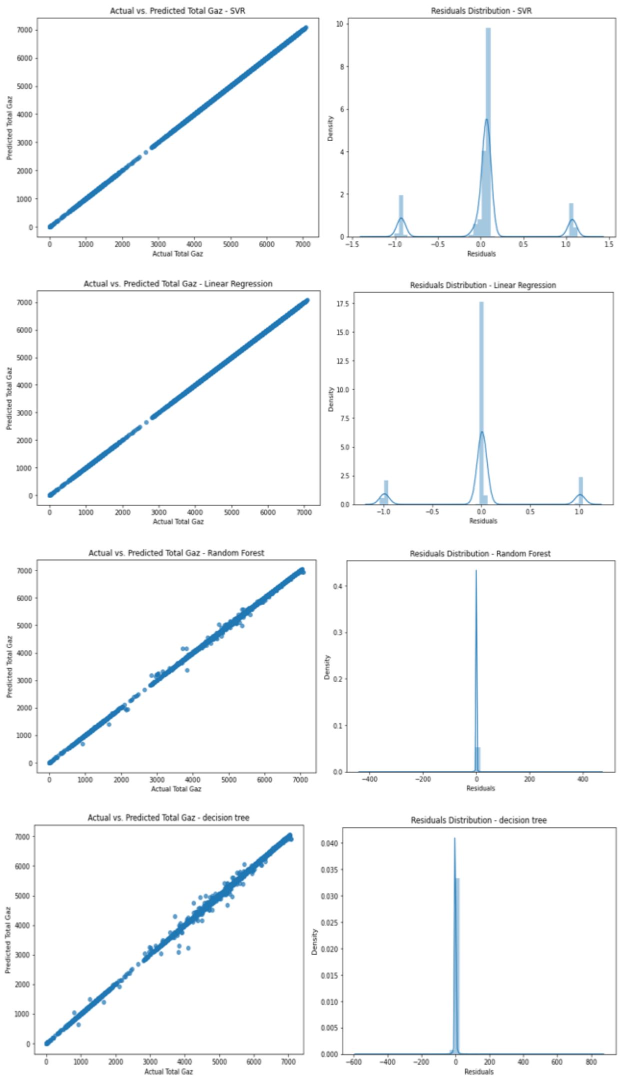

Fig. 5 (a) **Fig. 5 (b)**

Fig. 5 Predicted Value using ML Techniques

Each ML model includes two plots: a scatter plot (Figure 5. a) comparing actual and predicted "Total Gaz" values, where close alignment along the diagonal shows a strong fit with low error, and a residual density plot (Figure 5. b) to illustrate the distribution of prediction errors.

The SVM model accurately predicts "Total Gaz," with actual and predicted values closely aligned and residuals centered around zero, indicating high accuracy. Minor peaks at the distribution's ends suggest rare, larger prediction errors.

The LR model shows strong predictive performance for "Total Gaz," with predicted values closely matching actual values along the diagonal, indicating minimal error. Residuals are centered around zero, reflecting high accuracy and low bias, as evidenced by the sharp, symmetrical peak. Minor bumps in the residuals, however, may suggest potential outliers in the data.

The RF scatter plot reveals an almost perfect diagonal line, indicating a strong correlation between actual and predicted "Total Gaz" values, demonstrating that the RF model accurately captures the relationship between the input features and the target variable with minimal deviation. The residuals suggest low error rates and highly accurate predictions, with near-zero residual values indicating minimal bias in the model's output.

The DT model shows a strong correlation between actual and predicted "Total Gaz" values, with residuals centered around zero, but it has slightly higher error dispersion compared to the RF model, likely due to DT's tendency to overfit. This results in good accuracy overall but with minor prediction deviations for some data points.

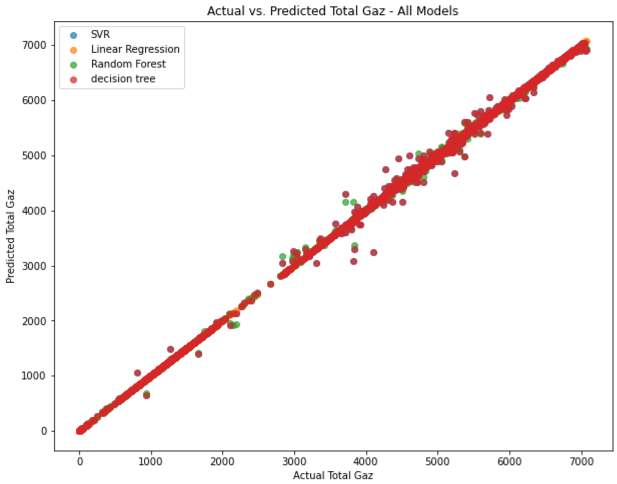

Fig. 9 Example figure

This plot (Figure 9) presents a comparative analysis of multiple models (SVM, LR, RF, DT) for predicting "Total Gaz" values (gas quantity). The models show strong alignment with actual values, though slight variations across regions are noted, particularly with RF and DT exhibiting more spread than SVM and LR. The residuals, centered around zero, indicate minimal errors, with LR showing slightly tighter clustering. RF's ensemble nature leads to more robust predictions compared to the DT. Both SVM and LR demonstrate high prediction accuracy.

Evaluation metrics such as MAE, RMSE, and R-squared are crucial for assessing model accuracy in predicting inlet gas levels for the kiln workshop and selecting the best model for application in a cement plant. This study emphasizes predictive accuracy, computational efficiency, and interpretability to optimize the clinker production process and confirms the reliability of ML models with real data. The results underscore the complexity of industrial prediction systems, emphasizing the need for a multi-method approach, and demonstrate the potential of machine learning to enhance gas prediction accuracy, reduce costs, and improve clinker quality.

8 CONCLUDING REMARKS

The study explores the use of supervised ML techniques to optimize the kiln workshop process at SCIMAT-Algeria. Algorithms like SVM, LR, RF, and DT were used to predict gas levels and improve efficiency. The models were evaluated using metrics such as MSE, RMSE, and R-squared, where LR emerged as the best model, validated by real process data. Leveraging insights from ML, the SCIMAT-Algeria plant could improve energy efficiency and optimize production, strengthening its competitiveness in the cement industry.

Future research should expand the number of Machine or Deep Learning algorithms to identify the best approach for manufacturing processes. The ultimate goal is to develop intelligent supervision systems to optimize complex processes, reduce production costs, and maximize productivity.

9 REFERENCES

Alghobiri, M. (2018). A Comparative Analysis of Classification Algorithms on Diverse Datasets. Engineering, Technology & Applied Science Research, 8(2), 2790–2795. https://doi.org/10.48084/etasr.1952

Alzubi, J. (2018). Machine Learning from Theory to Algorithms: An Overview. IOP Conf. Series: Journal of Physics, 1142(1). https://doi.org/10.1088/1742-6596/1142/1/012012

Asongo, I. . (2021). Machine Learning Techniques, methods and Algorithms: Conceptual and Practical Insights. International Journal of Engineering Research and Applications, 11(8), 55–64. https://doi.org/10.9790/9622-1108025564

Ateş, K. . (2021). Sustainable production in cement via artificial intelligence based decision support system: Case study. Case Studies in Construction Materials, 15. https://doi.org/10.1016/j.cscm.2021.e00628

Atmaca, A. (2014). Analysis of the parameters affecting energy consumption of a rotary kiln in cement industry. Applied Thermal Engineering, 66(1–2), 435–444. https://doi.org/10.1016/j.applthermaleng.2014.02.038

Awad, M. (2015). Efficient learning machines: Theories, concepts, and applications for engineers and system designers. https://doi.org/10.1007/978-1-4302-5990-9

Ayaz, A. (2021). Comparative study of supervised machine learning algorithms for predicting the compressive strength of concrete at high temperature. Materials, 14. https://doi.org/10.3390/ma14154222

Batu, T. (2023). Application of Artificial Intelligence for Surface Roughness Prediction of Additively Manufactured Components. Materials, 16(18). https://doi.org/10.3390/ma16186266

Buratti, Y. (2024). Machine learning for advanced characterisation of silicon photovoltaics: A comprehensive review of techniques and applications. Renewable and Sustainable Energy Reviews, 202. https://doi.org/10.1016/j.rser.2024.114617

Carvalho, T. . (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers and Industrial Engineering, 137. https://doi.org/10.1016/j.cie.2019.106024

Çınar, Z. . (2020). Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0. Sustainability, 12. https://doi.org/doi:10.3390/su12198211

Crego, O. (2024). Transient mathematical modelling of a gas rotary furnace for melting slag. Applied Thermal Engineering, 246. https://doi.org/10.1016/j.applthermaleng.2024.122928

Dev, P. (2021). Machine learning and its impact on control systems: A review. Materials, 47, 3744–3749. https://doi.org/10.1016/j.matpr.2021.02.281

Fatahi, R., Nasiri, H., Homafar, A., Khosravi, R., Siavoshi, H., & Chelgani, S. C. (2023). Modeling operational cement rotary kiln variables with explainable artificial intelligence methods–a “conscious lab” development. Particulate Science and Technology, 41(5), 715–724. https://doi.org/10.1080/02726351.2022.2135470

Geetha, T. . (2022). Machine Learning: Concepts, Techniques and Applications. https://doi.org/10.1201/9781003290100

Ismail, M., Mostafa, N. A., & El-Assal, A. (2021). Utilization of Machine Learning Techniques for Quality Monitoring and Prediction. 11th Annual International Conference on Industrial Engineering and Operations Management, 4830–4839. https://doi.org/10.46254/an11.20210838

Jain, P. (2024). Comparative analysis of machine learning techniques for predicting wear and friction properties of MWCNT reinforced PMMA nanocomposites. Ain Shams Engineering Journal, 15(9). https://doi.org/10.1016/j.asej.2024.102895

Kabul, A. (2015). Exergetic assessment of a rotary kiln for clinker production in cement industry. International Journal of Exergy, 16(3), 263–277. https://doi.org/10.1504/IJEX.2015.068226

Kanoun, Y. (2024). Failure prediction in the refinery piping system using machine learning algorithms: classification and comparison. Procedia Computer Science, 232, 1663–1672. https://doi.org/10.1016/j.procs.2024.01.164

Karrupusamy, P. (2020). Machine Learning Approach to Predictive Maintenance in Manufacturing Industry - A Comparative Study. Journal of Soft Computing Paradigm, 2(4), 246–255. https://doi.org/10.36548/jscp.2020.4.006

Kavitha, M. ., Roobini, S., & Karthik, S. (2024). A systematic review on Machine learning and Neural Network based models for disease prediction. Journal of Integrated Science and Technology, 12(4). https://doi.org/10.62110/sciencein.jist.2024.v12.787

Kecheng, Q. (2024). Research on linear regression algorithm. MATEC Web of Conferences, 395. https://doi.org/10.1051/matecconf/202439501046

Lalik, K. (2022). SVM Algorithm for Industrial Defect Detection and Classification. MATEC Web of Conferences, 357. https://doi.org/10.1051/matecconf/202235704004

Lei, Y. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. Mechanical Systems and Signal Processing, 138. https://doi.org/10.1016/j.ymssp.2019.106587

Mokhtari, S., Yen, K. K., Abbaspour, A., & 3, A. S. (2021). A machine learning approach for anomaly detection in industrial control systems based on measurement data. Electronics, 10(407). https://doi.org/10.3390/electronics10040407

Muhammad, I. (2015). Supervised Machine Learning Approaches: a Survey. ICTACT Journal on Soft Computing, 05(03), 946–952. https://doi.org/10.21917/ijsc.2015.0133

Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S. S., Reuter, U., Gama, J., & Gandomi, A. H. (2020). Data science in economics: Comprehensive review of advanced machine learning and deep learning methods. Mathematics, 8(10). https://doi.org/10.3390/math8101799

Oguntola, O. (2024). Towards Leveraging Artificial Intelligence for Sustainable Cement Manufacturing: A Systematic Review of AI Applications in Electrical Energy Consumption Optimization. Sustainability, 16(11). https://doi.org/10.3390/su16114798

Ruiz de Miras, J., A, M. J. G., Blanc, M. R., Arroyo, G., L´opez, L., Torres, J. C., & Martín, D. (2024). Machine learning regression algorithms for generating chemical element maps from X-ray fluorescence data of paintings. Chemometrics and Intelligent Laboratory Systems, 248. https://doi.org/10.1016/j.chemolab.2024.105116

Sarker, I. . (2021). Machine Learning: Algorithms, Real-World Applications and Research. SN Computer Science, 2. https://doi.org/https://doi.org/10.1007/s42979-021-00592-x

Sati, A. . (2022). Analisis Energi Dan Eksergi Pada Sistem Rotary Kiln Rkc-2 Pt. Semen Baturaja. Jurnal Multidisipliner Bharasumba, 1(04), 523–537. https://doi.org/10.62668/bharasumba.v1i04.300

Shalev-Shwartz, S. (2013). Understanding machine learning: From theory to algorithms. CAMBRIDGE. https://doi.org/10.1017/CBO9781107298019

Taffese, W. ., & Espinosa-Leal, L. (2022). Prediction of chloride resistance level of concrete using machine learning for durability and service life assessment of building structures. Journal of Building Engineering, 60. https://doi.org/10.1016/j.jobe.2022.105146

Tua, R. (2022). Calculating the specifics of energy consumption calculating zone rotary kiln PT. SEMEN BATURAJA (PERSERO) Tbk. Jurnal Multidisipliner Bharasumba, 1(4), 560–571. https://doi.org/https://doi.org/10.62668/phenomenon.v1i02.773

Usman, M. (2024). Prediction and optimization of emissions in cement manufacturing plant under uncertainty by using artificial intelligence-based surrogate modeling. Environment, Development and Sustainability. https://doi.org/10.1007/s10668-024-05068-5

Vijayan, S. ., & S, S. (2014). Industrial Applications of Rotary Kiln in Various Sectors - A Review. International Journal of Engineering Innovation & Research, 3(3), 342–345. https://ijeir.org/administrator/components/com_jresearch/files/publications/IJEIR_972_Final.pdf

Voldsund, M. (2019). Comparison of technologies for CO 2 capture from cement production—Part 1: Technical evaluation. Energies, 12(3). https://doi.org/10.3390/en12030559

Yang, H., Liu, X., Zhang, D., Chen, T., Li, C., & Huang, W. (2021). Machine learning for power system protection and control. Electricity Journal, 34. https://doi.org/10.1016/j.tej.2020.106881

Zermane, H. (2022a). Development of an efficient cement production monitoring system based on the improved random forest algorithm. International Journal of Advanced Manufacturing Technology, 120(3–4), 1853–1866. https://doi.org/10.1007/s00170-022-08884-z

Zermane, H. (2022b). Intelligent Control System of a Real Industrial Process. Eurasia Proceedings of Science, Technology, Engineering and Mathematics, 19, 61–67. https://doi.org/10.55549/epstem.1219167

Zermane, H. (2024). Forecasting material quantity using machine learning and times series techniques. Journal of Electrical Engineering, 75(3), 237–248. https://doi.org/10.2478/jee-2024-0029