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Condition Identification of Calcining Kiln Based on Fusion Machine Learning and Semantic Web

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ABSTRACT

The static control limits restrict self-healing capabilities and decision-making processes, impeding adaptability to the dynamic shifts in intricate industrial operations, frequently leading to suboptimal or anomalous conditions that undermine production efficiency. This paper presents a methodology for the identification of suboptimal operating conditions with respect to yield and quality. A GSR model for the identification of suboptimal operating conditions of yield and quality based on random forest classification was established. The experimental results demonstrate that the method is capable of rapidly and accurately identifying the production and quality of the calcining kiln. The identification accuracy of the yield and quality of the suboptimal operating conditions is 99.82% and 99.18% respectively. In the production process, real-time identification of operating parameters enables rapid detection of suboptimal operating conditions in yield and quality, providing the basis for optimal regulation and control, which in turn can improve production efficiency.

KEYWORDS

Suboptimal Operating Conditions, Machine Learning, Prodiction and Identification, Calcining Kiln

INTRODUCTION

The fault diagnosis and condition identification are of paramount importance in the context of ensuring the safety of production processes. In industrial production processes such as calcining kiln, the comprehensive and complex nature of the production system presents a significant challenges with respect to all aspects of detection, diagnosis, feedback, decision-making, and control. It is not uncommon for production runs to be suboptimal. The advancement of computer and information technology has facilitated the development of more efficient and environmentally conscious intelligent control systems. These systems not only enhance operational safety but also offer superior control efficacy and higher return on investment. As modern industry progresses towards greater integration, the diagnosis, recognition, prediction, and control of faults or abnormal conditions on a large scale, on an uninterrupted basis, and based on data and machine learning have demonstrated promising performance, attracting significant attention and study (Qin, 2012; Wu et al., 2014; Liu et al., 2018; Wu et al.,2018.).

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The application of machine learning in the domain of calcining kiln diagnostics and prediction represents a vibrant area of research. The objective is to enhance the precision and efficacy of fault detection and abnormal working condition identification through the integration of automated and intelligent methodologies. The field of machine learning encompasses a range of techniques, including unsupervised learning, supervised learning, and deep learning.

The application of unsupervised learning methods, including cluster analysis and anomaly detection, facilitates the identification of hitherto unknown failure patterns and the automatic detection of data points that deviate from normal behavior, respectively. Yang et al. (2016) employed a combination of the fuzzy C-means clustering algorithm and the subtraction clustering algorithm to diagnose abnormal states, and subsequently applied the system in a pelletizing plant. The results demonstrate that the control system is effective in maintaining the thermal equilibrium of the equipment under examination. To solve the problem of lack of label information in image models, an improved semantic representation learning method based on clustering is proposed to generate more reliable pseudo-labels for target 3D models and improve the recognition accuracy of 3D models (Chu et al., 2022). Jiang and Luo (2023) put forth a proposal for an attention-based pruning graph convolutional network unsupervised multi-sensor self-diagnosis model. The feasibility and effectiveness of the method were demonstrated by means of a nickel flash furnace temperature measurement system.

Unsupervised learning is capable of finding patterns and structures in unlabelled data and is suitable for data exploration and anomaly detection in calciners, especially in cases where failure modes are unknown or labels are difficult to obtain. The ability to reduce data dimensions and extract key features helps to simplify models and improve diagnostic efficiency.However, poor interpretation of the results can affect the accuracy of the decision. Sensitivity to outliers and noise often requires pre-processing steps to improve the robustness of the algorithm.

The supervised learning method employs classification algorithms, including support vector machines (SVMs), decision trees, and random forests et. al, to discern various fault types. Additionally, it utilizes regression analysis to anticipate the trajectory of specific parameters, thereby identifying potential issues proactively. For example, Kadri et al. (2012) proposed a hybrid algorithm for rotary kiln fault diagnosis in Algeria based on binary ant colony (BACO) and SVM algorithms. The efficacy of the algorithm was assessed using two authentic cement rotary kiln datasets. Liu et al. (2015) proposed an enhanced Bayesian network structure learning algorithm to construct a fault diagnosis model for cement rotary kilns, which enables precise and expedient fault diagnosis. Catal et al. (2011) developed an Eclipse-based software tool for failure prediction using the naive Bayes classifier. da Silva et al. (2023) employed ultrasonic signals to identify carburizing damage in furnace tubes and analyzed these signals using three machine learning models: Gaussian Naive Bayes (GNB), Kernel Naive Bayes (KNB), and Subspace Discrimination (SD). The findings indicate that the GNB model exhibits the highest accuracy (99.2%) and high sensitivity on a dataset comprising 26 features, thereby substantiating the efficacy of the integration of ultrasonic detection and machine learning for the identification of HP steel furnace tube carburizing.

The supervised learning method can learn from the labelled data and has good generalisation ability, and can extract more meaningful features combined with domain knowledge to improve the accuracy of diagnosis.However, data needs to be labelled, parameters need to be adjusted and more computational resources are required, which can be expensive and time-consuming in real industrial applications.

The application of deep learning methodologies can address more intricate non-linear correlations and is more appropriate for scenarios where multi-dimensional data must be interpreted. Rippon et al. (2021) put forth a comprehensive representation learning and prediction classification framework to predict plasma arc loss events in arc furnaces in large-scale metallurgical processes. Moosavi et al. (2024) put forth a deep neural network framework for induction furnaces to diagnose electrical faults by measuring electrical parameters on the power supply side in real time. The results demonstrate that this model can accurately diagnose electrical faults. Galeazzi et al. (2024)