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A Novel Multi-Domain Adaptation-Based Method for Blast Furnace Anomaly Detection

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ABSTRACT

In the steelmaking process, ensuring stable and reliable furnace plays a vital role for guaranteeing production quality of steel products. Traditional methods for detecting furnace anomalies in blast furnaces rely on operator judgment models built upon expert knowledge that can be limited by human experience. Moreover, data generated in blast furnace ironmaking process can be multidimensional, non-Gaussian distributed, and periodical, which can be easily affected by environmental and human factors and thus resulting in low accuracy of anomaly detection. Therefore, an online intelligent framework for detecting furnace anomalies is in high need. In this paper, the authors propose a novel anomaly detection method based on a furnace condition parameter-characterization model, a mining model of periodic patterns in the ironmaking process, and a multi-domain adaptive anomaly detection algorithm. They conduct extensive numerical analysis based on real-world production datasets as well to evaluate the effectiveness and accuracy of the method.

KEYWORDS

Anomaly Detection, Data Driven, Dimensional Adaptation, Frequency Domain, Furnace Condition Anomalies, PCA, Periodicity, Probability Transformation, Time Domain

INTRODUCTION

The blast furnace, as the cornerstone of the steel manufacturing process, stands as the world's largest chemical reactor, boasting a staggering capacity of up to $6000m^3$. Inside the furnace, a complex interplay of up to 108 chemical reactions takes place (Li et al., 2017). The stable and seamless operation of blast furnaces not only guarantees safe production but also serves as a prerequisite for

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cost reduction, efficiency improvement, and quality enhancement. In the era of cutting-edge technologies, such as big data and artificial intelligence, harnessing blast furnace production data for comprehensive digitization and intelligence has emerged as an effective means of optimizing manufacturing processes for steel enterprises (Han et al., 2018; Kawahata et al., 1988; Zagoskina et al., 2019). Notably, the detection of furnace anomalies with the aid of data analysis has emerged as a focal point of research in the realm of blast furnace intelligence application.

The blast furnace is a vertical reactor that produces liquid pig iron from coke, iron ore (natural rich ore and sintered ore and pellets), and flux (limestone and dolomite) in a continuous process. The blast furnace has five sections: the throat, the furnace body, the furnace waist, the belly, and the hearth from top to bottom. The reliability of the furnace is decided by various factors such as raw materials, operation, environment, and equipment. Typical anomalies are hanging burden, slipping burden, channeling, chilled hearth, low stockline, scaffolding, and hearth accumulation.

Furnace anomalies can be detected and diagnosed by two main categories of methods: expert system-based methods and data-driven methods. Expert systems use process knowledge and historical experience to construct rules and knowledge bases for furnace anomalies. These methods can achieve high accuracy and meet process requirements. However, these methods are unscalable and show low tolerability to status changes in the furnaces. Moreover, they require high maintenance costs. Some examples of blast furnace expert systems are AGS system by Kawasaki Steel Corporation in Japan, SIMETAL BF VAiron by Primetals Technologies, AI-based expert systems by Baosteel (Dou et al., 2015), etc.

Data-driven anomaly detection algorithms have been a popular research direction in recent years (Abdel-Sayed et al., 2016; Shi et al., 2020; Zeberli et al., 2021). They can be categorized into four types: (1) reconstruction algorithms, (2) clustering-based methods, (3) multivariate statistical methods, and (4) improved PCA algorithms.

Reconstruction algorithms, such as Auto Encoder (AE) (Chen et al., 2018), Variational Auto Encoder (VAE) (An & Cho, 2015), Auto-Regressive Integrated Moving Average (ARIMA) (Yaacob et al., 2010), and Prophet (Thiyagarajan et al., 2020), use deep learning or machine learning techniques to detect anomalies based on the reconstruction errors between the original and the generated data. Clustering-based methods, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), detect anomalies by identifying the samples that are isolated from the main clusters (Çelik et al., 2011). Multivariate statistical methods, such as Principal Component Analysis (PCA), reduce the dimensionality of multidimensional parameters and detect anomalies based on the deviation from the normal distribution (Ringberg et al., 2007). Improved PCA algorithms, such as Convex Hull PCA (B. Zhou et al., 2016) and PCA-Independent Component Analysis (PCA-ICA) (P. Zhou et al., 2020), enhance the performance of PCA by incorporating additional features or constraints. Data-driven methods usually have advantages in generalization and maintenance. However, the key to their successful application lies in how to utilize data effectively while aligning with the process requirements.

Expert system-based methods for anomaly detection have several drawbacks (Li et al., 2012; Stein et al., 2003), such as relying on limited experience, lacking generalization ability, and requiring high maintenance costs. Data-driven methods also face some challenges, such as having low compatibility with the process characteristics, and encountering difficulty in handling data variations, non-Gaussian distributions, periodicities, etc. To effectively detect, identify, and warn of multiple types of anomalies in blast furnace operation, it is essential to select appropriate parameters and models that reflect the process knowledge. Therefore, the algorithm system should be able to adapt to different data dimensions, distributions, periodicities, etc. In this paper, the authors propose a novel blast furnace anomaly detection algorithm that integrates periodicity detection, multi-domain feature extraction, and adaptive anomaly detection. They first extracted the parameters that were decisive for an anomaly detection model from the production data. Then the parameters were combined with the process knowledge to analyze their non-Gaussian and periodic features. Finally, the algorithm was applied to detect anomalies based on the extracted features. The algorithm was validated on real-world blast furnace production data and its effectiveness and robustness was then demonstrated.

MATERIALS AND METHODS

Characteristics and Effect of Blast Furnace Anomaly Characterization Data

Data Dimensions

Blast furnace ironmaking is a complex and continuous production process that requires various parameters for monitoring its working status, such as top gas temperature and top gas pressure. These parameters can be collected and recorded at a minute-level temporal resolution with the help of digital technologies in data collection, processing, transmission, and storage. This paper uses minute-level data for all research. The parameters that characterize the blast furnace anomalies are multidimensional, correlated, and type-specific. Hence, the proposed algorithm can adapt to the data dimension changes according to the process requirements.

Data Distribution

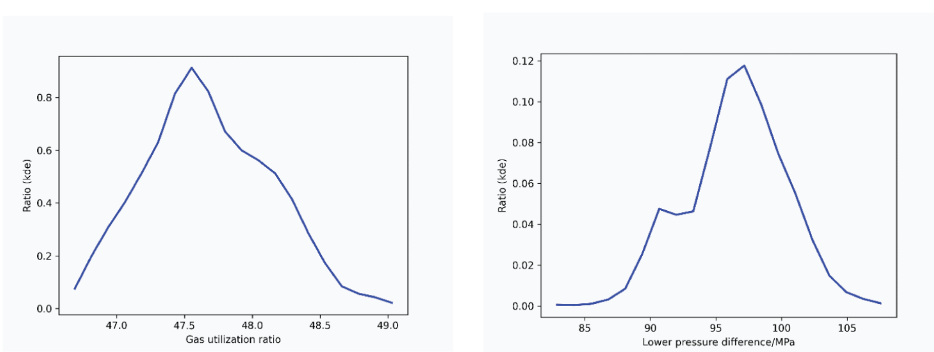
The data distribution of blast furnace characterization parameters exhibits significant non-Gaussian characteristics. Taking the gas utilization ratio and the lower pressure difference as examples, Figure 1 shows their kernel density plots, (a) shows the distribution of gas utilization ratio and, (b) shows the distribution of lower pressure difference. Therefore, the anomaly detection algorithm needs to consider how to better handle the data with non-Gaussian distribution (Madar et al., 2011).

Data Periodicities

The blast furnace characterization parameters have different periodicities. The data can be divided into two categories: one has longer periodicity and shows as instantaneous spikes, and the other has shorter periodicity and shows as oscillations. In addition, the periodicity of the data also has some dynamics with the changes of blast furnace smelting production.

For the data with longer periodicity and instantaneous spikes, anomaly detection is easily affected if these disturbance segments are not removed. For the data with shorter periodicity and oscillations, if the peaks and valleys are not handled well, they can easily cause false alarms of the anomaly detection system (Wen et al., 2021; Y. Zhu et al., 2015; Zhu, 2006).

Figure 1. Kernel density plot of blast furnace characterization parameters



(a) (b)

Multi Domain Adaptive Anomaly Detection

Overall Algorithm Structure

The Multi Domain Adaptive Anomaly Detection (MDAAD) algorithm, whose overall structure is shown in Figure 2, mainly consists of three parts:

- **Period Detection:** Identify the significant periodicity in the data by using Fast Fourier Transform (FFT) and power spectrum calculation.
- **Multi Domain Feature Extraction:** Remove the interference in the data and extract features for periodic and non-periodic parameters, respectively, based on peak-valley detection algorithm.
- **Adaptive Anomaly Detection:** Support one-dimensional, two-dimensional, and high-dimensional anomaly detection, and support distribution adaptation by calculating deviation distance and performing anomaly distribution and probability transformation.

Periodicity Detection Module

The periodicity detection module identifies whether the blast furnace parameters have significant periodicity, mainly including: FFT, power calculation, and periodicity identification.

Any time-domain signal can be represented in the frequency domain as the superposition of sinusoidal waves with different amplitudes and phases. The Discrete Fourier Transform (DFT) of a finite-length discrete signal $x\left(n\right),\ n = 0,1,\ldots,N-1$ is defined as:

$$X\left(k\right) = DFT\left[x\left(n\right)\right] = \sum_{n=0}^{N-1} x\left(n\right) e^{-j\frac{2\pi}{N}nk}, \qquad k = 0,1,\ldots,N-1 \tag{1}$$

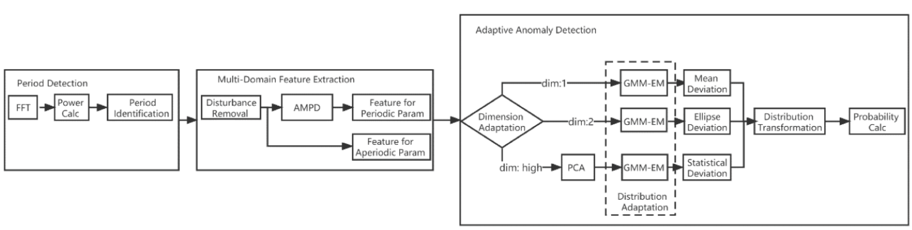
The Inverse Discrete Fourier Transform (IDFT) of $X\left(k\right)$ is defined as:

$$x\left(n\right) = IDFT\left[X\left(k\right)\right] = \frac{1}{N} \sum_{k=0}^{N-1} X\left(k\right) e^{j\frac{2\pi}{N}nk}, \qquad n = 0,1,\ldots,N-1 \tag{2}$$

which means $x\left(n\right)$ is represented as the sum of the different frequency components of the coefficient $X\left(k\right)$.

Fast Fourier Transform (FFT) is the general name of the efficient and fast calculation methods for computing the Discrete Fourier Transform (DFT) using a computer (Yang et al., 2004). Frequency domain measurement can obtain the energy of the signal at a specific frequency. The frequency with significant energy corresponds to the significant periodicity.

Figure 2. Schematic of multi-domain adaptive anomaly detection algorithm



Multi Domain Feature Extraction Module

Based on the periodicity detection results, extract time domain, frequency domain, and other features of multi-dimensional characterization parameters. As shown in Table 1, the extracted features include current value, trend index, peak-valley, etc.

To extract frequency domain related features, the Automatic Multiscale-Based Peak Detection (AMPD) algorithm is introduced, which is an automatic multiscale peak finding algorithm. For a periodic signal X, the AMPD algorithm calculates the local maximum scalar (LMS) by using a sliding window method. The LMS of signal X can be expressed as:

$$M = \begin{bmatrix} m_{1,1} & m_{1,1} & \cdots & m_{1,\mathrm{N}} \\ m_{2,1} & m_{2,1} & \cdots & m_{2,\mathrm{N}} \\ \cdots & \cdots & \cdots & \cdots \\ m_{L,1} & m_{L,2} & \cdots & m_{L,N} \end{bmatrix} = \left(m_{k,i}\right) \tag{3}$$

$$m_{k,i} = \begin{cases} 0, & x_{i-1} > x_{i-k-1} \wedge x_{i-1} > x_{i+k-1} \\ r+\alpha, & otherwise \end{cases} \tag{4}$$

where r denotes a uniformly distributed random number in the range $\left[0,\ 1\right]$ and α denotes a constant number $\left(\alpha = 1\right)$.

By row reducing M and finding the minimum r, and then calculating the standard deviation of the column extremes, peak detection can be achieved (Scholkmann et al., 2012).

Adaptive Anomaly Detection Module

For detecting anomalies in blast furnaces, each type of anomaly typically needs a separate model. The data may vary in dimension and exhibit non-Gaussian features, hence, requiring adaptation accordingly. The proposed anomaly detection algorithm can adapt to both the dimension and distribution changes.

Dimensional Adaptation

The proposed framework can detect anomalies in data with different dimensions. The authors measured the degree of anomaly by the deviation distance from the mean for one-dimensional data, by the deviation distance from the confidence ellipse for two-dimensional data, and by the deviation distance

Table 1. Multi domain features

Parameter	Domain	Feature
Periodic	Time domain	Current value
	Time domain	Trend index
	Frequency domain	Difference between current value and peak mean value
	Frequency domain	Difference between current value and valley mean value
	…	…
Aperiodic	Time domain	Current value
	Time domain	Trend index

from the dimensionality reduction statistic for high-dimensional data. In addition, a distribution adaptation submodule was incorporated into each dimensional anomaly detection method. The adaptive dimensional detection algorithms output deviation distances, which are converted to anomaly probabilities by the distribution and probability transformation module.

Distribution Adaptation

The authors assumed that a random variable X follows a Gaussian mixture distribution with density function given by:

$$p(X) = \sum_{k=1}^{K} \pi_k \mathrm{N}\left(\mathrm{X} \mid \mu_{\mathrm{k}}, \Sigma_k\right) \tag{5}$$

where each component is a Gaussian distribution with mean μ_{k} and variance Σ_k^2, and π_k is the coefficient of the k_{th} Gaussian distribution. The expectation maximization (EM) algorithm estimates the parameters (Zhu et al., 2021):

$$\left(\pi_k, \mu_{\mathrm{k}}, \Sigma_k\right) \tag{6}$$

The EM algorithm consists of the following steps:

Step 1: Initialize the parameters with some initial values.
Step 2: Perform the E-step and the M-step to update the parameters using the current data.
Step 3: Repeat Step 2 until convergence or a stopping criterion is met.

One-Dimensional Anomaly Detection

The authors considered a one-dimensional data x that follows a Gaussian mixture distribution with K components. The GMM-EM algorithm can estimate the parameters of each component and assign x to the most likely component k. The probability density function of the k_{th} component is:

$$\mathrm{N}\left(x \mid \mu_k, \Sigma_k\right) \tag{7}$$

The deviation distance of the mean of the normal distribution was used as a criterion for anomaly detection:

$$d = deviation\left(x, \mu_k\right) \tag{8}$$

where the deviation function calculates the Euclidean distance.

Two-Dimensional Anomaly Detection

The authors considered two-dimensional data that followed a Gaussian mixture distribution with K components. The GMM-EM algorithm can estimate the parameters of each component and assign each data point to the most likely component k. The confidence ellipse detection algorithm was used for anomaly detection. The confidence ellipse is an elliptical region that contains a certain proportion of the data points from the same component at a given confidence level p. The deviation distance of a data point from the center of the confidence ellipse was calculated and output by the algorithm. The probability density function of a bivariate normal distribution is given by:

$$f\left(\boldsymbol{x}\right)=\frac{1}{\left(2\pi\right)^{n/2}\left|\Sigma\right|^{1/2}}\exp\left(-\frac{1}{2}\left(\boldsymbol{x}-\mu\right)^{'}\Sigma^{-1}\left(\boldsymbol{x}-\mu\right)\right) \tag{9}$$

where Σ denotes the covariance matrix of x, and μ denotes the mean of x.

The confidence region of the bivariate normal distribution is also an elliptical area enclosed by an ellipse curve. The deviation distance of a data point from the center of the confidence ellipse is computed and returned by the two-dimensional anomaly detection module:

$$d=deviation\left(\boldsymbol{x},ellipse_{k}\right) \tag{10}$$

where the $ellipse_k$ denotes the k_{th} confidence ellipse.

High-Dimensional Anomaly Detection

The authors used principal component analysis (PCA) to compress high-dimensional data into two orthogonal subspaces: the principal and the non-principal. The principal subspace contains the main information, and the non-principal subspace contains the residual information. Applying PCA to the standardized data X, one gets the following decomposition:

$$X=SP^{T}=s_{1}p_{1}^{T}+s_{2}p_{2}^{T}+\ldots+s_{m}p_{m}^{T}+\ldots+s_{l}p_{l}^{T}=\sum_{i=1}^{m}s_{i}p_{i}^{T}+E \tag{11}$$

where m is the number of principal components, S is the score matrix, and P is a load matrix consisting of eigenvectors. Using the following formulas, the statistics SPE and T^2 was calculated:

$$SPE=\left\|\left(I-P_{m}P_{m}^{T}\right)x\right\|^{2} \tag{12}$$

$$T^{2}=X^{T}P_{\mathrm{m}}\Lambda_{\mathrm{m}}^{-1}\mathrm{P}_{\mathrm{m}}^{\mathrm{T}}X \tag{13}$$

where P_m denotes the top m columns of the load matrix and Λ_m denotes a diagonal matrix of the top m singular values.

The authors assigned each data point to its k_{th} Gaussian component using the mixed Gaussian model and obtained the statistic for that component:

$$GMM\_T_{k}^{2}=\left(t_{k}-\mu_{k}\right)^{T}\Sigma_{k}^{-1}\left(t_{k}-\mu_{k}\right) \tag{14}$$

where T_k, μ_k and Σ_k denote the principal component, mean, and covariance of the k_{th} Gaussian component, respectively, trained offline (Zhu et al., 2021). The control line for the statistical quantity that corresponds to the k_{th} Gaussian distribution is defined by:

$$GMM\_T^2\_UCL_k = quantile\left(GMM\_T_k^2, q\right) \tag{15}$$

$$SPE\_UCL = quantile\left(SPE, q\right) \tag{16}$$

where q is a quantile, such as 0.99. The final deviation distance based on the statistical quantity is defined by:

$$d = deviation\left(\left(GMM\_T_k^2 \middle/ GMM\_T^2\_UCL_k, SPE \middle/ SPE\_UCL\right), \left(0,0\right)\right) \tag{17}$$

Probability Transformation

The deviation distance output by each dimension anomaly-detection algorithm is transformed to anomaly probability. First, the normality transform is performed, and then the probability is calculated. The normality transform uses Box-Cox transform (Cheddad, 2020). The formula is:

$$y^{(\lambda)} = \begin{cases} \left(d^\lambda - 1\right) / \lambda, & \lambda \neq 0 \\ \log d, & \lambda = 0 \end{cases} \tag{18}$$

where y has a normal distribution with mean μ and variance σ, d denotes the transformation of input data (i.e. deviation distance), and λ is a transformation parameter. The probability transform maps the transformed values to probability intervals. The values of a and b are set according to the business needs (the default values are $a = 0.6$, $b = \mu + 3\sigma$):

$$p\left(y\right) = \begin{cases} \left(y - b\right) \cdot \left(1 - a\right) / \left(1 - b\right) + a, & y >= b \\ y \cdot a / b, & y < b \end{cases} \tag{19}$$

RESULTS

Experimental Data

A blast furnace data set was selected for simulation. The time span of the data set covered from 2021-04-01 to 2022-03-31. The channeling anomalies that occurred during this period were validated. Channeling anomaly refers to: when the permeability of a local area on the blast furnace cross-section is exceptionally high, resulting in uneven distribution of gas flow, and a region with exceptionally high gas flow, which forms a channeling. The relevant parameters of the blast furnace are shown in Table 2.

Table 2. Blast furnace anomaly characterization parameters

ID	Parameter
1	Top gas temperature
2	Top gas pressure
3	Pressure difference
4	Upper pressure difference
5	Lower pressure difference
6	Cross temperature
7	Permeability index
8	Throat steel brick temperature
9	Center cross temperature
10	Z value
11	W value
12	Blast furnace burden depth
13	Gas utilization ratio
14	Theoretical flame temperature
15	Shaft static pressure
16	Cooling wall temperature of each layer
17	Air volume
18	Hot blast pressure
19	Oxygen enrichment ratio
20	Blast kinetic energy
21	Hot blast temperature
22	ROD descent speed

Periodic Detection and Analysis

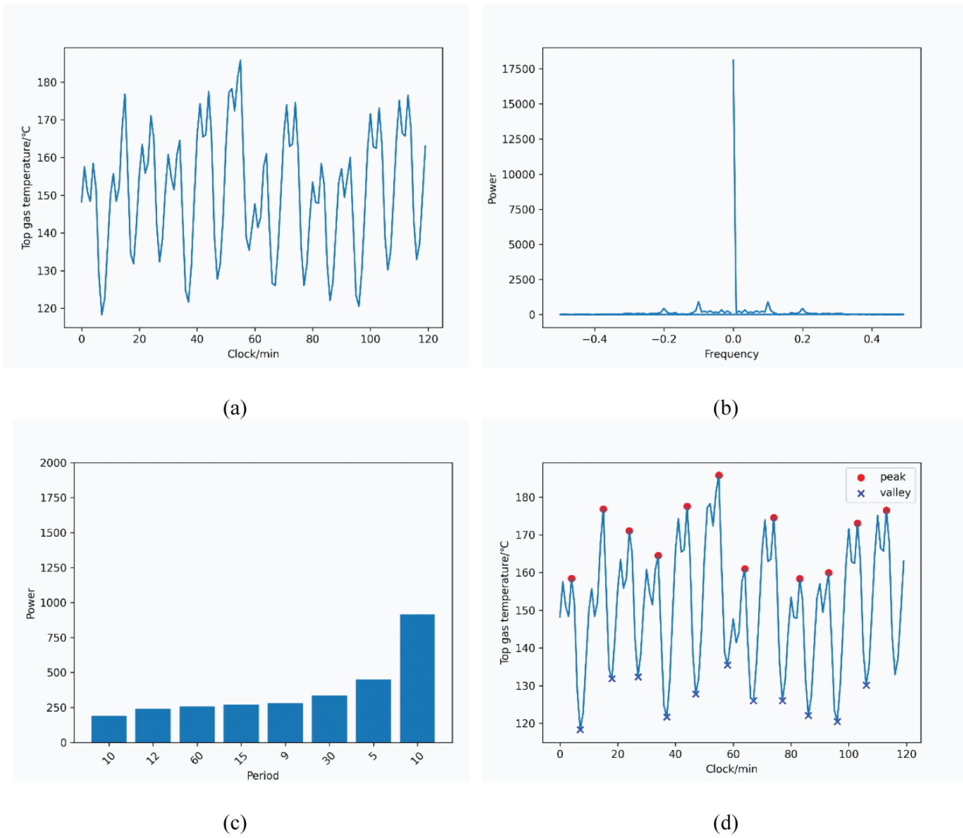
Periodic Detection Results

By using the periodic detection module, two types of periodicity were mainly observed in the blast furnace characterization parameters.

The first type was short-term fluctuations with a period length of 10 minutes. Related parameters: top gas temperature, top gas pressure, Z value, and W value. The peak and valley detection of this type of periodic data can be used for multi-domain feature extraction. As shown in Figure 3, (a) shows the time series data, (b) shows the spectrogram, (c) shows the dominant period, and (d) shows the peak and valley detection.

The second type was long-term transient spikes with a period length of 60 minutes. Related parameters: blast kinetic energy, air volume, and hot blast pressure. This type of periodic data uses a disturbance elimination method to remove the time segments corresponding to the transient spikes, as shown in Figure 4.

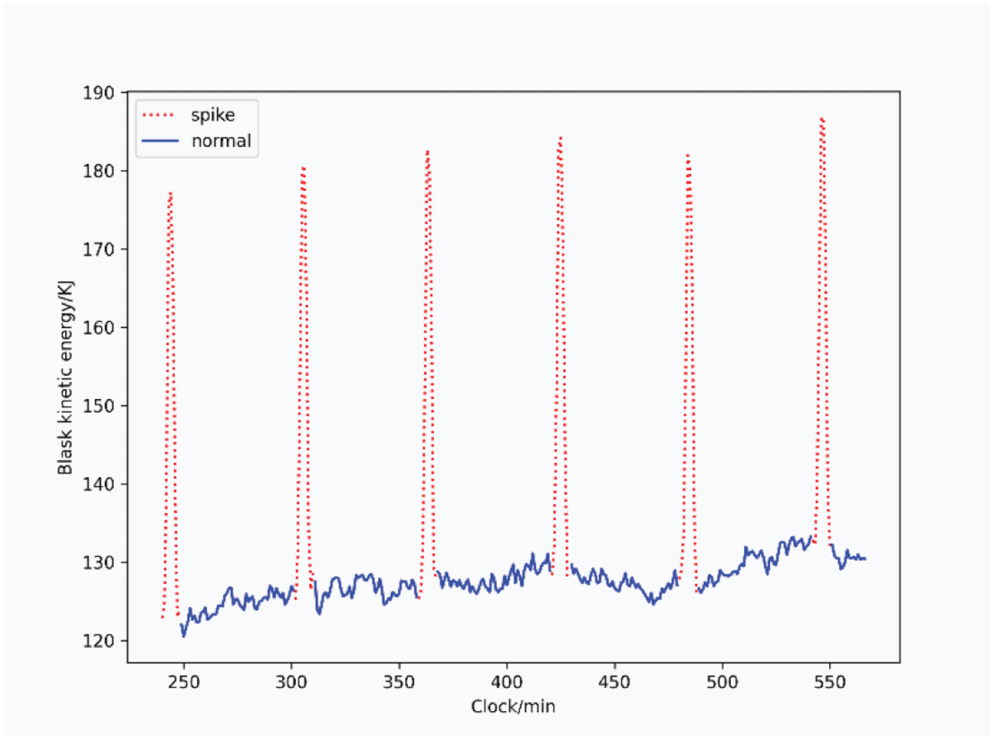
Figure 3. Top gas temperature: Periodic detection results



Periodic Process Interpretation

- **10-minute short-term fluctuations:** Based on process analysis, it was found that this type of periodicity was related to the alternation of charging pattern in blast furnace ironmaking. The blast furnace charges the burden materials into the blast furnace throat in batches through the charging hopper. The newly charged burden materials absorb heat due to thermal conduction, and the top gas temperature gradually decreases. Alternating charging pattern causes periodic variations in top gas temperature.
- **10-minute short-term dynamic changes:** The blast furnace monitors the changes in the level of burden surface through the main scale data, and performs charging when the preset conditions are met. The above process leads to dynamic changes in the charging time, that is, the descent rate of burden surface in blast furnace ironmaking is not a constant speed, and the time interval when the charging condition is met varies dynamically.
- **60-minute long-term transient spikes:** Based on process analysis, it was found that this type of periodicity was related to the blast furnace stove change. The blast furnace supplies air alternately through multiple hot stoves, usually switching hot stoves every 60 minutes or so. This process flow results in transient spikes in blast furnace characterization parameters at 60-minute intervals.

Figure 4. Blast kinetic energy: Transient spike elimination



Periodic Application Performance

By conducting periodic detection on the parameters and detecting the transient spikes of long periods, about 13% of the disturbance effects in the data can be removed. By conducting periodic detection on the data, about 52% of the peak and valley data that do not match the periodicity can be filtered out, thereby enhancing the application performance of the peak and valley-related features.

Blast Furnace Anomaly Detection

The main goal of blast furnace anomaly detection is to identify anomalies as early as possible so that more time is available for operational intervention. This can minimize damage and improve production stability, fuel efficiency, product quality, and other benefits. In this paper, the authors compared the performance of the proposed MDAAD algorithm, AAD algorithm (MDAAD without the multi-domain feature module), ConvexHull-PCA algorithm (PCA based on convex hull), and the MD-ConvexHull-PCA algorithm (ConvexHull-PCA algorithm with multi-domain features). As shown in Table 3, they used the following metrics: false alarm rate, early warning rate, lead-time of early warning, and duration of early warning.

The experiment showed that the MDAAD algorithm achieved the best results in terms of early warning rate and duration of early warning, and also obtained significant improvement in terms of false alarm rate and lead time of early warning.

CONCLUSION

In this paper, the authors presented a multi-domain adaptive anomaly detection (MDAAD) method for blast furnace anomaly detection. The proposed method takes into account the features of data

Table 3. Comparison of anomaly detection algorithms

Methods	False Alarm Rate	Early Warning Rate	Time Advance of Early Warning	Duration of Early Warning
MDAAD	0.500	**0.833**	11.500 min	**20.833 min**
AAD	0.600	**0.833**	**11.667 min**	20.167 min
MD-ConvexHull-PCA	**0.400**	0.500	7.333 min	21.000 min
ConvexHull-PCA	0.647	0.500	7.333 min	20.167 min

dimensionality change, as well as non-Gaussianity and periodicity in data distribution. The method is built upon a furnace condition parameter-characterization model, a mining model of periodic patterns in the ironmaking process, and a multi-domain adaptive anomaly detection algorithm. Extensive numerical analyses based on multiple datasets obtained from real-world steel manufacturing processes were performed as well. Numerical results clearly suggest that the proposed method out performs its peers in terms of detection effectiveness and accuracy.

Future research directions include evaluating the impact of multiple periodicities on anomaly detection, performing periodic lag analysis (for example, the actual blast furnace charging pattern, the charging-related pattern of top gas temperature, the charging-related pattern of top gas pressure, the time lag among them), and optimizing the multi-dimensional metric weights of anomaly detection algorithm.

AUTHOR NOTE

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