Volume 12 Issue 4, 2026
DOI: 10.6919/ICJE.202604_12(4).0014

A Dynamic Monitoring System for Three-dimensional Operation of Blast Furnace Shape and Slag Skin Morphology based on PINNs -MPF

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Abstract

With the deepening implementation of the "dual carbon" strategy, the steel industry is facing enormous pressure for green transformation.As the core equipment of ironmaking, the high temperature and high pressure "black box" characteristics inside the blast furnace seriously restrict refined operation and energy conservation and consumption reduction.The slag hanging state of the blast furnace cooling wall and the operating furnace type directly determine the service life and safety of the blast furnace.This paper proposes an intelligent dynamic monitoring system for blast furnace three-dimensional operation furnace shape and slag skin morphology, which integrates physical information neural networks (PINNs) and multiphase field (MPF) methods, to address the difficulties of traditional monitoring methods in real-time quantifying furnace wall thickness, slag skin detachment frequency, and effectively responding to the coupling effects of multiple physical fields.This study first uses a shared encoder and modality specific adapter to generate an adversarial network (SE-MSA-GAN) to solve the spatiotemporal alignment and denoising problems of multi-source heterogeneous data;Secondly, a three-dimensional heat transfer forward problem model based on PINNs MFF was constructed, and millisecond level high-precision reconstruction of the cooling wall temperature field was achieved through extended domain decomposition and pyramid training strategy;At the same time, a mathematical model based on water temperature difference was established to invert the thickness of slag skin and heat flux intensity in real time.The system integrates a high-precision sensor array and a digital twin visualization platform, which can dynamically display the three-dimensional status of the entire furnace and provide graded safety warnings.The experimental results show that the system can significantly improve the accuracy of fault diagnosis, providing strong technical support for the longevity maintenance and low-carbon smelting of blast furnaces.

Keywords

PINNs-MPF; Blast Furnace Cooling Wall; Digital Twin; Inverse Problem Inversion; SE-MSA-GAN.

1. Introduction

The steel industry is the pillar of the national economy and a key area of carbon emissions.

Driven by policies such as the 14th Five Year Plan for Industrial Green Development and the Implementation Plan for Carbon Peak in the Steel Industry, improving blast furnace energy efficiency and reducing carbon emission intensity have become industry consensus.

The process of blast furnace ironmaking is extremely complex, with temperatures inside the furnace reaching over 1500 ℃, accompanied by intense interactions between gas, liquid, and solid phases.

As a key component for protecting the furnace shell and maintaining furnace stability, the working state of the cooling wall is directly related to the safe and smooth operation of the blast furnace.[2]

However, statistical data shows that abnormal furnace conditions caused by improper operation of furnace types can result in economic losses of several million yuan per year for a single blast furnace, and the cost of shutdown and replacement caused by cooling wall burnout can be as high as tens of millions of yuan.

The traditional management model overly relies on manual experience, making it difficult to respond promptly to micro changes such as furnace wall thickening and slag peeling.

The main technical bottlenecks currently faced by blast furnace monitoring include:

The "black box" state is difficult to break through: existing detection methods are mostly point like distributions, making it difficult to reproduce continuous field changes in three-dimensional space.[8]

The accuracy of the model is limited: traditional integer order heat conduction models often ignore the coupling effects of multiple physical fields such as dynamic growth of slag skin and gas flow erosion, resulting in significant prediction errors.[6]

Data quality issues: Industrial field data has high noise and multimodal features (structured data and image data) that are difficult to integrate.

In response to the above issues, this article proposes an intelligent monitoring scheme based on PINNs MFF algorithm, aiming to achieve transparency and intelligent perception of the cooling wall status of blast furnaces through deep integration of mechanism models and data-driven approaches.

2. Multimodal Data Acquisition and Preprocessing

(1) Multi source heterogeneous data system

The data collection of this system covers the key physical quantities of blast furnace smelting, mainly divided into two categories:

Structured data: By using high-precision digital water temperature sensors and electromagnetic flow meters, the cooling water temperature, flow rate, gas temperature, gas flow rate, and slag skin thickness (including historical calibration data for three states: furnace lining only, slag skin only, and coexistence) are collected at a frequency of 10Hz.[5][9]

Unstructured data: Obtain temperature field radiation images of the cooling wall surface using an infrared thermal imager.

(2) Data preprocessing based on SE-MSA-GAN

Faced with the problems of diverse industrial data sources, asynchronous timestamps, and severe noise interference, this study introduces a shared encoder and modality specific adapter generative adversarial network (SE-MSA-GAN) for deep preprocessing.

Data cleaning and normalization: cubic spline interpolation is used to complete missing values;

Using non local mean filtering to remove noise from temperature field images;

Normalize all physical quantities to eliminate the impact of dimensional differences on model training.

Shared encoder mechanism: Design modality specific adapters to extract features from both temporal and image data, and then map them to a common latent space through a shared encoder.

This mechanism effectively solves the feature alignment problem of cross modal data and preserves the inherent physical correlations between data.

Data augmentation and anomaly correction: By utilizing the generative adversarial ability of GAN, virtual samples under boundary conditions are generated in the latent space, expanding the training dataset under extreme working conditions (such as large-scale shedding of slag skin), effectively solving the problem of industrial sample imbalance.

3. PINNs MFF Coupled Modeling Method

The core of this study is to construct a high-precision heat transfer model that can handle strong nonlinearity and multi physics field coupling.

To study the factors and aspects of slag hanging ability and slag hanging environment that affect the operation furnace type and self-protection ability of the cooling wall, a three-dimensional heat transfer calculation model is established for the specific design structure and refractory parameters of the cooling wall in different areas of the blast furnace.[2]

Adopting a three-dimensional physical model.

From the outside to the inside, they are the furnace shell, filling material, copper cooling wall, and tiling. The model also includes brick lining and slag skin.

Three dimensional temperature field calculation mathematical model.

Based on the above physical model, establish a three-dimensional furnace wall heat transfer control differential equation in a Cartesian coordinate system, as shown in the following formula, where k (t) is the thermal conductivity and a function of temperature t.

x.y.z are the coordinate axes.

$$\frac{\partial}{\partial x}\left(k(t)\frac{\partial T}{\partial x}\right)+\frac{\partial}{\partial y}\left(k(t)\frac{\partial T}{\partial y}\right)+\frac{\partial}{\partial z}\left(k(t)\frac{\partial T}{\partial z}\right)=0 \tag{1}$$

Boundary conditions: The model has two types of boundary conditions, one is convective boundary conditions, which occur at the interface between the furnace wall and air, water and water pipe walls, and the interface between the inner surface and gas;

The other type is adiabatic boundary conditions, which occur at all interfaces in the model except for convective boundaries.[1]

Discrete processing: The model is composed of multiple materials, and the thermal conductivity k of each material varies greatly, so the internal node method is used to partition the grid.

The thermal conductivity of the node at the junction of two materials is calculated using the harmonic mean method.

For the development of grid division standards, a three coordinate measuring instrument (accuracy ± 0.01mm) is used to obtain the key dimensions of the cooling wall fins. According to the ASME V&V 20-2023 standard, local encryption triggering conditions are defined. Then, the actual cooling wall is scanned using X-ray industrial CT (accuracy 5 μ m) to establish an error evaluation function.[3]

Construction of a slag skin abnormal shedding warning system: Based on 5-year historical data from a certain ironmaking plant (sampling frequency 10Hz), the critical value is determined using kernel density estimation method, and the temperature gradient threshold is quantified. The upper limits of the 99% and 90% confidence intervals of the probability density function are taken as level I and level II thresholds, respectively.

Calibrate the acoustic emission energy, simulate slag shedding on a 1:1 hot state test bench, synchronously collect acoustic emission signals, and classify them into levels.

Fusion of multi-source data: Install a triple composite sensor array at key locations on the cooling wall and develop a D-S evidence theory fusion model.

The conduction and accumulation of abnormal fluctuations in the cooling wall temperature during the blast furnace ironmaking process pose significant risks to the longevity and safety production of the blast furnace.

To solve this problem in the system, it is necessary to focus on the core control capability of simulating heat transfer in the cooling wall: firstly, optimizing the boundary condition setting, and accurately simulating the heat exchange process between the high-temperature furnace environment and the cooling wall through dynamic correction of key parameters such as furnace gas radiation heat transfer coefficient and slag skin thermal conductivity;

The second is to improve the heat transfer model by adjusting parameters such as cooling water flow rate and velocity distribution, optimizing the convective heat transfer effect inside the cooling wall, and enhancing the accuracy and reliability of temperature field simulation;

The third is to improve the ability to predict extreme working conditions, by establishing a multi parameter hierarchical warning model and integrating XFEM crack propagation simulation, optimizing slag skin detachment warning and crack dynamic tracking, and enhancing the reliability of blast furnace safety monitoring and maintenance response timeliness.[4]

This study combines PINN with MPF algorithm to overcome the complex problem of strong nonlinearity and multi factor coupling in simulating heat transfer in blast furnace cooling walls.

This method first integrates the adaptive embedding strategy of heat conduction equation and the dynamic correction mechanism of boundary conditions into PINN, enhancing its accurate simulation ability of heat transfer process in high-temperature and strong convective heat transfer environment of blast furnace;

Then, using the joint extraction technique of spatiotemporal features, the time series and spatial distribution characteristics of data such as cooling wall temperature and cooling water flow rate are collected, and a multidimensional feature matrix containing transient changes and spatial differences is constructed;

Then, the fused features are input into the PINN-MPF hybrid model, leveraging the multi physics coupling advantage of the MPF algorithm to achieve collaborative simulation of multiple processes such as furnace radiation, slag skin heat conduction, and cooling water convection.

PINN is an artificial intelligence computing method that integrates prior knowledge of physics. Its core architecture constructs physically interpretable deep learning models by embedding physical constraint mechanisms such as control equations and boundary conditions.

The basic idea of PINN was first proposed by Lagaris et al. (1998) in the 1990s, and later by Raissi et al. (2019).

PINN is located at the intersection of data-driven supervised neural networks and physical equations, using data-driven methods to learn models while ensuring consistency with the known physics of the system.

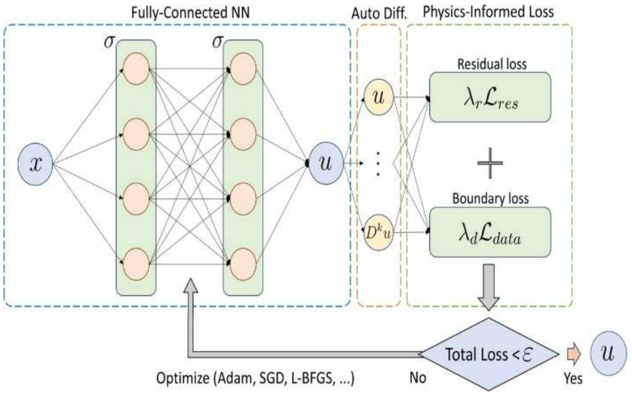

Figure 1. PINN model diagram

MPF is an important extension of the phase field method, which describes the interface evolution and dynamic behavior of multiphase, multi-component, or complex physical field coupled systems by introducing multiple order parameters such as phase fraction, concentration, temperature, etc.

Its core idea originates from the classic Cahn Hilliard equation and Allen Cahn equation, originally used to simulate phase separation and grain growth in materials.

With the development of theory, multiphase field models have gradually integrated multiple physical field coupling mechanisms such as mechanics, thermodynamics, and electrochemistry.[1] Steinbach and other scholars proposed a multiphase field framework to deal with polycrystalline material problems in the 1990s, and the Boettinger team applied it to cross scale simulations of alloy solidification processes.

The PINNs MPF framework introduces key novelty through its optimization strategy:

(1) Extended Domain Decomposition

When using the extended domain decomposition method, the central coordination network (main network) allocates computing tasks reasonably to each sub network (working network) based on different working conditions such as cooling water velocity and temperature in task allocation.

In simulating high gas flow rate conditions, the main network coordinates the sub networks to parallelly process the heat transfer differences caused by changes in gas flow rate in different regions, while ensuring data exchange and collaboration among the sub networks regarding factors such as thermal shock and slag thickness.

(2) Fine modeling of phase field interface region

For the interface area between slag skin and refractory materials in the cooling wall, an extreme mesh refinement strategy is adopted for local mesh refinement and adaptive optimization.

On the basis of establishing a mathematical model of the three-dimensional heat transfer equation, the mesh of the phase field interface area is refined to enhance the spatial resolution of this area.

(3) Hyperparameter optimization and model simplification

When training the PINNs MFF based cooling wall temperature field simulation model, the hyperparameter reduction algorithm is used to optimize the model performance.

Through theoretical analysis of the physical laws and neural network training mechanism in the heat transfer process of the cooling wall, combined with experimental verification, core control parameters such as embedded weights of the heat conduction equation and multi physics field coupling coefficients of the MPF algorithm are selected, and a low dimensional parameter space is constructed.

(4) Synchronization mechanism of phase field interaction

Establish a real-time information exchange and gradient synchronization mechanism across subnetworks.

During the model training process, when a sub network calculates the convective heat transfer of cooling water, relevant information is synchronously transmitted to the sub network that handles slag skin heat conduction, ensuring that the two phase fields maintain physical consistency during parallel evolution.

(5) Adaptive Application of Pyramid Training Method

Introducing pyramid training strategy as a robust alternative to adaptive weighting method.

When training at low resolution and low complexity levels, first let the model learn the basic influence laws of factors such as cooling water velocity and temperature on the temperature field of the cooling wall;

As the training progresses to the high-resolution level, further study the temperature field changes and slag hanging ability response under the coupling effect of complex factors such as thermal shock and gas flow rate with other factors.

This algorithm includes data collection, data preprocessing, feature extraction and selection, parameter optimization, training, and prediction.

The overall structure and key components of PINNs MPF algorithm are shown in the figure:

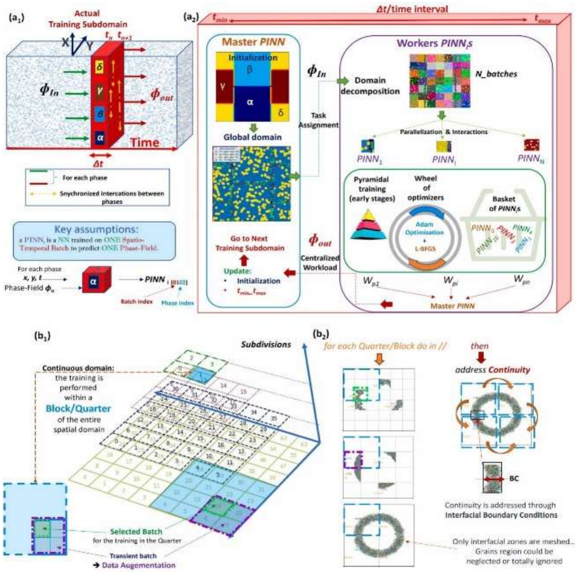

Figure 2. PINNs MPF model diagram

In the PINNs MPF algorithm, the first step is to collect multi-source heterogeneous data during the operation of the cooling wall, including temperature sensor timing values, cooling water flow rate, wall material parameters, and environmental thermal boundary conditions, and eliminate dimensional differences through data standardization.

In response to the complex thermodynamic behavior of blast furnaces, PINN-MPF deeply integrates physical prior knowledge, embeds the heat conduction equation, multiphase flow equation, and latent heat effect of phase change into the neural network loss function, and constructs a multi field coupled solution framework under physical constraints.

At the same time, by using an adaptive weight allocation strategy to balance the data-driven term and the physical residual term, the network's generalization ability to key field quantities such as temperature gradient and heat flux density is optimized.

During the training process, an improved implicit spatial discretization technique is utilized to enhance the resolution of the local high-temperature zone of the cooling wall, and a transfer learning strategy is combined to improve the simulation efficiency under different operating conditions.

Ultimately, the algorithm is capable of accurately reconstructing the three-dimensional transient temperature field of the cooling wall, predicting thermal stress distribution and burn risk, and providing key theoretical support for intelligent operation and maintenance of blast furnace longevity.

4. The Inverse Problem Mathematical Model for Calculating the Thickness of Brick Inlaying and Slag Skin in Cooling Fireplace Walls

Based on real-time water temperature difference data, the thickness of slag skin is calculated in real time to obtain prior laws between cooling parameters, furnace airflow, slag skin thickness, brick spraying changes, and cooling wall water temperature difference, heat flux, and wall temperature.

By deeply integrating a three-dimensional heat transfer model with big data machine learning algorithms, an online intelligent model is constructed to predict the operation furnace type, slag thickness, slag skin detachment frequency, and cooling wall leakage probability.[4]

The following conclusions were obtained from the calculation of the direct problem, which are the basis for online monitoring of the inverse problem.

The influence of temperature and cooling water flow rate on the "bare standard" (the lowest temperature of the copper cooling wall hot surface with completely detached slag skin) has been calculated from the "positive problem".

Table 1. Algorithm for residual furnace lining and slag skin thickness

Hot surface temperature/°C	$T_{hot}=f(\mathrm{Q},R_c,R_r)$
When only the furnace lining is present	$h_b=A\lambda_b f(\mathrm{Q},R_c,R_r,T_g,\frac{1}{A\alpha})$
When there is only slag skin	$h_s=A\lambda_s f(\mathrm{Q},R_c,R_r,T_g,\frac{1}{A\alpha})$
When furnace lining slag and skin coexist	$h_s=A\lambda_s f(\mathrm{Q},R_c,R_r,R_b,T_g,\frac{1}{A\alpha})$

(2) The effects of temperature, cooling water flow rate, gas temperature, and gas flow rate on heat loss are minimal, and their impact is even smaller when slag skin is present.[7]

If there is lining and slag skin in the furnace wall, the concept of heat transfer can be used to obtain:

$$Q=f\left(T_g,R_c,R_r,R_h,R_s,\frac{1}{A\alpha}\right) \tag{2}$$

Build a three-dimensional operation furnace shape, slag skin morphology, and cooling wall safety intelligent dynamic monitoring and warning system for blast furnaces. The system can display three-dimensional different horizontal and vertical profiles as well as panoramic views of the blast furnace from top to bottom.[2]

The system integrates intelligent modules such as blast furnace life cycle big data, machine learning algorithms, and airflow recognition, achieving linkage with airflow distribution diagnosis.

Through this system, it is possible to achieve comprehensive dynamic online intelligent monitoring, warning, diagnosis, and prompt of the internal operation furnace type, slag skin status, and their changes in the blast furnace.

The implementation of this study enables blast furnace operators to have real-time and intuitive understanding of the operating furnace type and slag skin status inside the furnace, further providing scientific basis for evaluating the uniformity of the circumferential airflow distribution of the blast furnace, identifying local small pipeline problems, analyzing the distribution of the upper, middle, and lower three airflows, and controlling the rationality of edge loads.

The system conducts online monitoring and statistics on the operating furnace type, slag thickness, and slag skin shedding frequency of the belly, waist, and lower parts of the furnace body based on the water temperature difference, heat load, and their changing trends of the cooling wall. The big data probability prediction machine learning model is used to predict the probability of cooling wall leakage. The implementation process is briefly described as follows.

(1) First stage feature parameter extraction

Based on the numerical model of the operating furnace type, the distribution of the temperature field on the hot surface of the cooling wall and the dynamic growth data of the slag skin are output. The system records key characteristic parameters such as the cumulative duration and frequency of the hot surface temperature exceeding the standard for each cooling wall, as well as the occurrence of slag skin detachment.

(2) Second stage probability calculation modeling

Using a feature weighted fusion algorithm, the average temperature of the hot surface and the duration of abnormal operating conditions are taken as feature inputs, and a pre trained probability prediction machine learning model is used to calculate the risk value of water leakage.

Among them, the higher the frequency and longer the duration of abnormal working conditions of the cooling wall, the significantly positively correlated the corresponding water leakage risk prediction value.

5. Conclusion

This article addresses the urgent need for digital transformation in the steel industry and develops an intelligent monitoring system for blast furnaces based on PINNs MPF.

The system has successfully overcome the challenge of "black box" monitoring in blast furnaces through advanced data preprocessing techniques and physical fusion algorithms, achieving a breakthrough in the entire chain of technology from data acquisition, model calculation to 3D visualization.

The application of the system will provide a "perspective eye" for blast furnace operators, providing a solid scientific basis for achieving long-term stable operation and green low-carbon production of blast furnaces.

Acknowledgments

This study was supported by the Innovation and Entrepreneurship Training Program for College Students at North China University of Science and Technology, project number: 202510081052.

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