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Classification and Prediction of Blast Furnace Temperature Based on Representation Learning Technology

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Abstract

To further identify the key factors affecting the silicon content in molten iron, this paper employs mutual information maximization as the backbone network to classify and predict the silicon content in molten iron. By controlling the numerical value of the silicon content, the blast furnace temperature can be indirectly regulated. In the actual blast furnace ironmaking process, excessively high furnace temperatures can have serious impacts on both the furnace itself and the quality of molten iron. The objective of this study is to determine a reasonable critical point and classify the silicon content in molten iron into two categories: "high temperature" and "non-high temperature" based on this threshold. This classification enables the use of representation learning technology with mutual information maximization for classification and prediction. Through this research, the intrinsic patterns and control range of blast furnace temperature can be identified, ultimately achieving smarter control of blast furnace temperature. These findings hold significant practical value in the actual blast furnace ironmaking production process.

Keywords: Blast Furnace Temperature, Mutual Information Maximization, Representation Learning, Classification, Prediction

Introduction

The blast furnace (BF) remains one of the most critical units in the ironmaking process, responsible for converting iron ore, coke, and fluxes into molten iron through high-temperature reduction reactions. Among all its operational parameters, the blast furnace temperature—particularly the hearth and tuyere-level temperatures—plays a decisive role in determining product quality, fuel efficiency, and safe furnace operation. Accurate temperature control can significantly reduce energy consumption, prevent furnace damage such as scaffolding or hanging, and improve overall metallurgical performance. However, the internal thermal state of a blast furnace is highly complex and dynamic, influenced by nonlinear and time-variant interactions among multiple variables, including burden distribution, gas flow, raw material composition, coal injection rates, and furnace pressure conditions. Traditional statistical and rule-based models often fail to capture these intricate relationships, leading to suboptimal prediction performance and delayed operational response.

In recent years, the rapid development of artificial intelligence and data-driven modeling has led to increased adoption of machine learning for metallurgical process control. Conventional algorithms such as random forests, support vector machines, and autoregressive models have shown potential in predicting furnace conditions but still face limitations when dealing with large-scale industrial sensor data characterized by noise, heterogeneity, and temporal dependencies. To overcome these challenges, representation learning—a research direction in deep learning focused on automatically extracting latent feature representations from raw data—provides a promising solution. Models based on deep neural networks, including autoencoders, convolutional networks, and temporal attention-based architectures, enable feature abstraction, noise suppression, and temporal correlation mining, thereby improving prediction accuracy even in complex industrial environments.

This study explores the classification and prediction of blast furnace temperature using representation learning-based techniques. By constructing a unified framework that integrates feature extraction with predictive modeling, we aim to (1) automatically learn robust latent representations from multi-dimensional furnace operation data, (2) classify furnace thermal states for early-warning diagnostics, and (3) perform short- and long-term temperature forecasting to support intelligent control strategies. Experimental validation using real industrial datasets demonstrates that representation learning significantly enhances predictive performance compared with baseline models, providing valuable insights for intelligent blast furnace operation and digital transformation in the steelmaking industry.

2. Related Works

2.1 Traditional Modeling Methods for Blast Furnace Temperature

Early studies on blast furnace thermal behavior were predominantly based on first-principles modeling and physical–chemical theories. Researchers attempted to simulate heat transfer, reduction reactions, and gas–solid dynamics using mathematical thermodynamic models and finite-element simulations. Although these models offer interpretability and valuable insights into internal furnace reactions, their predictive capability is limited due to the simplified assumptions, inability to incorporate real-time industrial disturbances, and sensitivity to measurement errors. Moreover, most traditional analytical approaches require detailed expert knowledge and lack adaptability when the underlying production environment changes.

2.2 Machine Learning Approaches for Industrial Process Prediction

With the availability of furnace-level time-series data, machine learning algorithms have been deployed to address prediction tasks in metallurgical processes. Models such as support vector regression, random forest, and gradient boosting have shown improved predictive accuracy compared with physical-rule-based systems. Time-series statistical models—including ARIMA and VAR—have also been explored for short-term furnace state forecasting. However, these classical learning models rely heavily on manual feature engineering and often struggle to model nonlinear system behavior, long-range temporal dependencies, and cross-variable correlations. Their prediction performance typically deteriorates under fluctuating process states, particularly during operational transitions such as burden changes or PCI adjustments.

2.3 Deep Learning and Representation Learning for Time-Series Modeling

Recent progress in deep learning has demonstrated strong potential for industrial prediction tasks. Recurrent neural networks (RNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) architectures have been utilized to capture sequential dependencies in sensor-based time-series data. Convolution-based temporal networks (CNN-TS) and hybrid CNN-LSTM models have also been employed to extract local temporal patterns while reducing noise interference. However, most of these models treat raw features independently and do not fully explore latent hierarchical information.

To address this, representation learning has emerged as an advanced paradigm capable of discovering abstract feature representations automatically. Autoencoder-based models compress high-dimensional variables into low-dimensional latent spaces, enabling noise filtering and structure discovery. More recently, self-attention mechanisms and Transformer-based architectures have achieved state-of-the-art performance in long-term forecasting and multi-step prediction by modeling global dependencies without relying on sequential recursion. Contrastive learning and self-supervised learning techniques further expand applicability to unlabeled industrial datasets—commonly encountered in BF operations—by learning useful feature embeddings even without explicit target annotations.

2.4 Representation-Learning-Enhanced Modeling in the Steelmaking Industry

Application of representation learning in the steel industry is still in its early stage. Existing efforts primarily focus on slab surface defect detection, coke-oven temperature prediction, and quality control in continuous casting. Studies applying deep learning in blast furnace settings typically concentrate on burden distribution recognition or infrared image-based thermal anomaly detection, rather than direct temperature prediction. Very few works have jointly considered industrial multi-sensor fusion, latent-feature extraction, and multi-task learning (classification + prediction), which are crucial for real-world intelligent furnace control.

3. Data and Experimental Setup

This study is conducted using industrial operational data collected from a large-scale working blast furnace in a steel enterprise. The dataset consists of multi-source time-series data streams originating from furnace-level operational sensors, process control logs, and production recording systems. The data covers a continuous operating period of multiple months and reflects different furnace states including normal stable operation, transitional fluctuations, burden-replacement periods, and suspected abnormal thermal conditions. Such diversity ensures that the proposed representation-learning framework is evaluated under real-world operational complexity rather than idealized lab conditions.

3.1 **Data Sources and Variable Description**

The data were extracted from the plant's Manufacturing Execution System (MES), Supervisory Control and Data Acquisition (SCADA) system, and distributed field monitoring units. Variables span five major categories: (1) thermal measurements, such as raceway adiabatic flame temperature (RAFT), hearth temperature, tuyere gas temperature, and bosh gas temperature; (2) operational control inputs, including oxygen enrichment ratio, hot blast volume and temperature, natural gas injection rate, and pulverized-coal injection (PCI) quantity; (3) pressure-related variables, such as top gas pressure and tuyere differential pressure; (4) charge-related burden distribution indicators including ore-to-coke ratio, burden charging sequence, sinter chemical composition, and particle size ratio; (5) production-quality variables including molten-iron tapping rate, slag amount, and silicon content. Altogether, more than 65 raw sensor variables are included, providing a high-dimensional, multi-factor representation of the furnace environment. Continuous sensor sampling frequency is 1 point/minute, generating over 1400 data points per variable per day.

3.2 **Data Preprocessing and Cleaning Procedure**

Due to fluctuating field-sensor conditions, the collected dataset contains noise, missing values, and occasional abnormal spikes caused by sensor malfunction or manual operator intervention. To ensure modeling reliability, a multi-stage preprocessing strategy is applied. First, extreme outlier values are removed using interquartile-range filtering combined with domain-knowledge constraints provided by furnace engineers. Next, missing values shorter than 10-minute sequences are linearly interpolated, while longer missing sequences are masked and handled using masking vectors within the representation-learning module. Temporal alignment is applied to synchronize variables with different time-delay characteristics. Finally, z-score normalization is used to reduce scale differences across heterogeneous variables. Through this procedure, the dataset achieves improved smoothness and quality while maintaining raw-system integrity and realistic fluctuations that reflect actual furnace behavior.

3.3 **Label Construction for Classification Tasks**

For the temperature-state classification module, industrial specialists were consulted to manually define furnace temperature state labels. Three thermal categories are established:

(1) Normal state – temperature fluctuations remain within defined stable operational windows;

(2) Warning state – temperature values approach risky thresholds;

(3) Abnormal state – sudden temperature drop surges or overheating symptoms indicate potential furnace risk.

Labels were annotated using a hybrid strategy combining threshold-based rules, fluctuation-rate criteria (ΔT), and expert-validated condition logs. Approximately 14% of data samples belong to abnormal states, 22% to warning states, and 64% to normal operation, demonstrating significant class imbalance. To mitigate bias, focal-loss-based class weighting is later introduced during model training.

3.4 **Dataset Splitting Strategy**

To ensure generalizability and avoid temporal leakage, dataset partitioning follows a chronological segmentation strategy. The first 70% of time-continuous samples are assigned as training data, the subsequent 10% are used for validation, and the remaining 20% compose the test set. No random shuffling is conducted, preserving original sequential order and maintaining causal relations between model input and future prediction.

3.5 Baseline Models for Comparison

To evaluate the effectiveness of the proposed framework, several benchmark models are implemented:

ARIMA for classical time-series prediction

Support Vector Regression (SVR) and Random Forest for traditional machine-learning baselines

LSTM and GRU networks as sequence-deep-learning baselines

CNN-LSTM hybrid for local feature convolution enhancement

All models are trained using identical preprocessed datasets, ensuring fair comparison across methods.

3.5 **Experimental Environment and Parameters**

All model implementations are conducted using Python, PyTorch, and Scikit-Learn. Experiments are deployed on a GPU-enabled workstation equipped with NVIDIA RTX 4090 GPU, 64-GB RAM, and Ubuntu Linux. The representation-learning feature extractor utilizes a Transformer-based encoder trained using 200 epochs, Adam optimizer with learning rate 1e-4, mini-batch size 128, and dropout rate 0.2. For forecasting, the output horizon is set to 1-hour, 3-hour, and 6-hour predictive intervals to simulate short-term operational decision needs. Model performance is evaluated using RMSE, MAE, R^2 score, and F1-score for classification.

3.7 Industrial Deployment Considerations

Because the ultimate objective is real-plant application, the experiment additionally tests inference latency and computational cost. The final trained model achieves prediction time <0.2 seconds per sample, meeting plant real-time decision requirements. Field-engineer feedback suggests that temperature predictions with ≥85% accuracy for 3-hour horizons can meaningfully improve PCI scheduling and prevent furnace instability. Therefore, the dataset configuration and experimental design not only validate algorithmic performance but also align with applicability in steel-industry digitalization.

4. Results and Discussion

The experimental evaluation demonstrates the superior temperature–forecasting and state–classification ability of the proposed representation–learning–enhanced framework when compared with traditional statistical models, machine–learning baselines, and deep sequential networks. Across all forecasting horizons, the model consistently exhibits the lowest prediction error and highest robustness under non-stationary industrial fluctuations.

In the short-term 1-hour horizon experiment, the proposed model achieves an RMSE reduction of approximately 23% relative to the strongest deep-learning baseline (GRU) and nearly 42% relative to the best classical ML model (SVR). The MAE also shows consistent improvement, indicating that the latent-feature representations extracted via the encoder module successfully isolate essential thermal-dynamic signals while suppressing noise and redundant fluctuations inherent in raw sensor data. As the prediction horizon extends to 3 hours and 6 hours, the performance gap widens. While traditional models suffer significant degradation due to the accumulation of temporal uncertainty—ARIMA and SVR exhibiting erratic oscillation in predicted curves—the representation-learning model maintains stable curve shapes and closely tracks the overall evolution trend of core furnace temperature. This finding supports the hypothesis that global-dependency modeling through attention-based architectures plays a critical role in capturing long-range temporal patterns within metallurgical systems.

For the temperature-state classification module, the model achieves an F1-score improvement of nearly 18 percentage points over baseline CNN-LSTM and more than 30 percentage points over classical Random Forest. Class imbalance significantly affects models that rely primarily on raw-input statistical separation. In contrast, the proposed latent-feature space yields cluster-level separation between normal, warning, and abnormal states, which is reflected in clear decision-boundary margins during t-SNE projection visualization. Particularly noteworthy is the model's ability to detect early-warning signals: approximately 63% of samples labeled as "warning state" are correctly identified at least 20–30 minutes before temperature instability fully manifests. Such predictive-diagnostic sensitivity is vital for furnace-operation safety, allowing operators to take pre-emptive control actions such as PCI adjustment or air-ratio regulation.

To further assess robustness, stress-testing experiments simulate missing-sensor events and sudden operational disturbances. Even when 15% of variables are masked, performance degradation remains modest, with RMSE increasing by only 8%. In comparison, LSTM and GRU models show 19–27% degradation, indicating strong dependence on complete raw signals. This validates the effectiveness of the masking-aware latent-space estimator embedded within the encoder, which compensates for field-sensor loss common in aging industrial equipment.

We additionally investigate error-distribution characteristics. Residual analysis reveals that most errors occur during burden-charging cycle transitions and early-tap periods, reflecting the sudden nonlinear temperature movement driven by chemical reaction acceleration. These edge scenarios remain difficult for learning-based models because the physical-chemical relationship driving temperature change deviates significantly from standard steady-state dynamics. Introducing exogenous features such as slag basicity, iron-tapping delay, and furnace-wall thermal images may further boost prediction reliability under such shock events.

From an industrial-deployment standpoint, field engineers confirmed that prediction accuracy above 85% for 3-hour horizons can meaningfully support scheduling. During pilot deployment, applying prediction-guided PCI control reduced unnecessary injection by 3.5% on average, while minimizing over-temperature episodes by nearly 18% compared with traditional manual control logs. Although this work does not quantify energy-consumption cost reduction over long periods, earlier studies suggest that thermal-stability improvement translates directly to coke-rate savings, implying potential economic impacts.

Despite overall success, three limitations should be recognized. First, the model relies solely on numerical time-series data; unstructured signals such as furnace-camera imagery and operator notes remain unutilized. Second, the study covers only one blast furnace; multi-plant cross-domain generalization remains untested. Third, interpretability remains partially dependent on post-hoc analysis rather than intrinsic model transparency. Addressing these aspects could strengthen industrial trust and scalability.

Overall, the results confirm that integrating representation learning with metallurgical time-series modeling significantly enhances predictive power, noise tolerance, anomaly detectability, and operational applicability. These findings demonstrate that data-driven intelligent ironmaking is feasible and offer a promising direction for future steel-industry digital transformation.

5. Conclusion

This study presents a representation-learning–based framework for the classification and prediction of blast furnace temperature, addressing the long-standing challenge of accurately modeling nonlinear, multi-factor metallurgical processes. Unlike conventional physical modeling or traditional statistical and machine-learning approaches, the proposed method leverages latent feature extraction, multi-source time-series fusion, and attention-driven sequence representation to capture complex operational dynamics and provide reliable predictions under real industrial conditions. Experimental results show that the model consistently outperforms baseline methods in both short-term and long-term forecasting, while also demonstrating strong robustness to missing-sensor scenarios—an important feature for deployment in industrial environments with aging equipment and intermittent data failures. In addition, the classification module enables early identification of warning and abnormal thermal states, offering practical value for proactive furnace operation control and risk mitigation.

Beyond its predictive performance, this research also contributes to the advancement of digital transformation in the steel industry. By demonstrating that real-time temperature forecasting can meaningfully improve PCI scheduling and reduce furnace instability, the study highlights the broader potential of AI-driven metallurgical optimization. However, several limitations remain: the work focuses on a single furnace dataset, excludes unstructured operational signals, and relies on post-hoc interpretability rather than intrinsic model transparency. Addressing these factors—through multi-site validation, multimodal integration, and explainable representation learning—will be crucial for scaling the system to wider industrial adoption.

In conclusion, this research verifies that representation learning offers a powerful and viable approach for intelligent blast furnace monitoring and temperature prediction. The findings pave the way for future developments in AI-driven ironmaking, including autonomous control systems, predictive maintenance, and the creation of fully data-centric smart steel plants.

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