Key Indicators of Predicting the Aluminium Reduction Cells Based on a Transformer Model Driven by Multi-Source Time Series Data

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https://doi.org/10.71659/icsoba2025-al034

Abstract

Aluminium electrolysis is regarded as a complex industrial process, and accurate prediction of its key indicators is crucial to optimize energy consumption and stabilize production. A key indicator prediction method based on a Transformer model is put forward in this research due to the fact that it is difficult to process the heterogeneous data and the dependency relationship of long-term time series data is mined insufficiently through traditional models. Through the integration of multi-source time series data of the aluminium reduction cell, the valid features of sequence data are captured based on the self-attention layer and multi-head attention mechanism of the Transformer architecture, and the synergistic effect of aluminium electrolysis process is mined, to ultimately build a key indicator prediction model for industrial scenarios. In the experiment, the Partial Least Square (PLS) and Convolutional Neural Network (CNN) models are compared based on the electrolytic cell data collected over three consecutive months of a smelter. The results indicate that the Transformer model has the optimal prediction accuracy, and that the average relative error is less than 3 % for the predicted molecular ratio and aluminium output of the test set. According to the results, the Transformer-based key indicator prediction model for electrolytic cells can be effectively implemented in production, supporting the process optimization and energy consumption management, and offering valuable insights into the intelligent upgrading of the aluminium electrolysis industry.

Keywords: Multi-source time series data, Attention mechanism, Indicator prediction, Transformer, Aluminium electrolysis process.

1. Introduction

As the digital economy becomes deeply integrated with the real economy, the traditional manufacturing industry is undergoing a paradigm shift from mechanized production to intelligent production. Integrated application of such new-generation information technologies as big data, artificial intelligence and the Industrial Internet has grown into a key engine for enhancing industrial production quality and driving efficiency improvements. Although a complete industrial system has been developed for the electrolytic aluminium, the industry still faces several key challenges in actual production and operation, including lagging dynamic assessment of key electrolytic cell parameters and reliance on experiential decision making for raw material feeding, which are restricting the precise regulation and energy efficiency enhancement during production.

Regarding process properties, the aluminium electrolysis process shows a strong multi-physics field coupling feature that, with the electrolytic cell as the core, complex electrochemical reactions occur among materials such as carbon anodes, alumina, electrolytes and catalysts under the coupling of the strong electric field, magnetic field, flow field and temperature field [1]. Harsh working conditions result in significant spatial-temporal heterogeneity of key process parameters, such as aluminium level, electrolysis temperature and material composition. It is hard to accurately collect all the parameters in real time by traditional sensor technologies, which further affects the dynamic assessment accuracy of key process indicators, including molecular ratio, current efficiency and aluminium output [2]. Regarding prediction modelling, most of the existing methods, which are mainly based on the linear mechanism assumption or the shallow machine learning framework, fail to capture the high-dimensional nonlinear association and spatio-temporal evolution law of the process parameters effectively, resulting in prominent lagging and systematic deviations in the predicted results [3, 4].

Accurate prediction of key indicators during aluminium electrolysis is crucial to optimize energy consumption and stabilize production [4, 5]. In researches on the prediction of aluminium electrolysis indicators and parameters, Yong Chen, et al. [3] have successfully predicted the feeding amount of aluminium fluoride through the deep belief network, Ziling Zhao, et al. [6] have predicted the molecular ratios by the least squares support vector machine and the autoregressive neural networks, and Xiaofeng Ni, et al. [7] have predicted the aluminium output based on the multilayer perceptron neural networks. These researches explored the complex relevance of aluminium electrolysis parameters, analysed the main factors affecting the aluminium electrolysis, and predicted the trends of related indicators. However, there are still opportunities for the enhancement of prediction accuracy. Moreover, the above researchers rely more on mass historical data and have not yet realized the rolling prediction of the indicators. They still need abundant historical references.

Due to the fact that it is difficult to process the heterogeneous data and the dependency of long-term time series data is mined insufficiently through traditional models, a Transformer-based [8] key indicator prediction method is put forward in this research, enabling accurate and prompt predictions of aluminium output and molecular ratio. Besides, a rolling prediction solution has been designed, which reduces the subjective human intervention and keeps the indicators and parameters at a reasonably optimal level. They support the process optimization and energy consumption improvement of electrolytic cells with data available, raise the energy consumption efficiency, and offer valuable insights into the intelligent upgrading of the aluminium electrolysis industry.

2. Data and Methods

2.1 Data Acquisition

This research collected data from 34 sets of 200 kA cell control systems and process reports over three consecutive months (from February 15, 2025 to May 15, 2025). Thirty-four electrolytic cells were in the same electrolysis shop. Data including the voltage, anode stroke, blanking amount, electrolysis temperature, molecular ratio and aluminium output were collected for each cell. Detailed data is shown in Table 1, and the data collected from the first three cells on February 15 is taken as an example.

2.2 Prediction Model

The partial least squares regression (PLSR) [9] is a multivariate statistical method integrating principal component analysis and regression analysis. The covariance of two groups of variables is maximized with this method by iteratively optimizing the latent variables of independent variable and dependent variable spaces, making the dimension reduction and multicollinear processing of data available. This algorithm balances the variable interpretability and the model simplicity through the latent variable projection mechanism, and completes the prediction

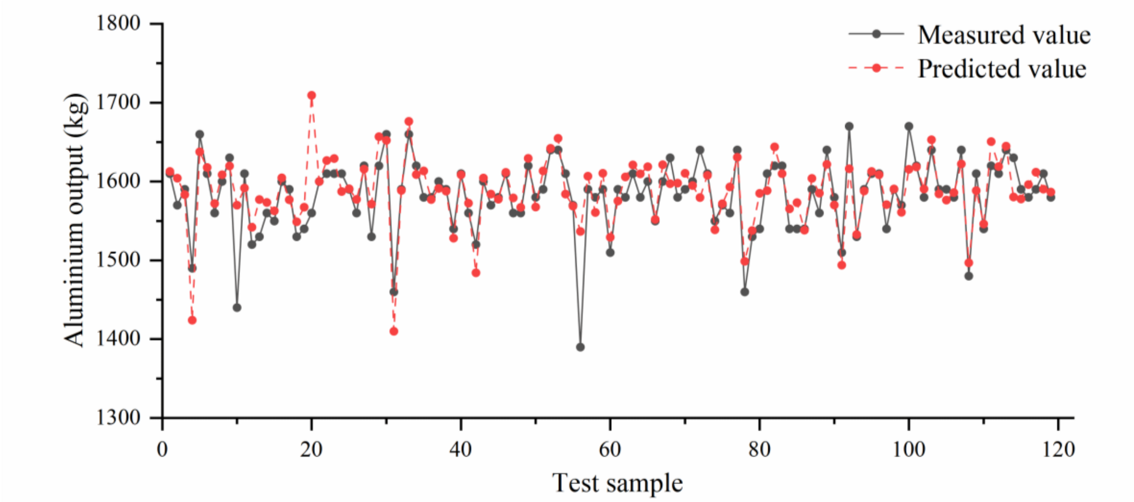

Figure 7. Aluminium output prediction results.

5. Conclusions

In this research, the multi-source time series data is collected from 34 electrolytic cells in a smelter over three consecutive months. After data pre-processing, a time series data set is designed and established. Prediction models were built with three machine learning frameworks, namely PLSR, CNN and Transformer, for two key indicators of aluminium electrolysis, i.e., molecular ratio and aluminium output. Effective features of sequence data are captured and the synergistic effect of aluminium electrolysis is explored by taking full advantage of the Transformer architecture's strengths in self-attention layer and multi-head attention mechanism, and fully exploring the dependency between multi-source data information and long-term time series data, to build the key indicator prediction model for industrial scenarios. The Transformer model has the best predictions of the two key indicators: for the molecular ratio prediction model, the relative error is 2.50 %, which is optimal, and the absolute error is 0.062; for the aluminium output prediction model, the relative error is 1.40 %, which is optimal, and the absolute error is 22.130 kg. According to the results, the Transformer-based key electrolytic cell indicator prediction model is effective in production and able to predict the aluminium output and molecular ratio accurately and promptly. What's more, it reduces subjective human intervention through the rolling prediction solution, keeping the indicators and parameters in a reasonably optimal level. It supports the process optimization and energy consumption improvement of electrolytic cells with data available, raises the energy consumption efficiency, and offers valuable insights into the intelligent upgrading of the aluminium electrolysis industry.

In the subsequent experimental research, there will be two extended topics:

1) More key indicators are added for timely and accurate prediction, and more fine-grained data is collected for more refined indicator predictions.
2) Visualization analysis is conducted on the prediction model so that effective features are selected and optimized regulation model is built to guide and regulate production "reversely".

6. References

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