Deep MLP-Based Prediction of Process Parameters for Roller Kilns

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Abstract: Under high-load aviation conditions, internal non-uniform sintering within battery cathode materials readily induces thermal runaway, presenting a critical bottleneck constraining the safe development of low-altitude aviation. Addressing this, this paper proposes a temperature prediction model based on Deep Multi-Layer Perceptron (Deep MLP) to tackle the non-linear and strongly coupled characteristics of temperature field distribution during roller kiln sintering. The model incorporates critical process parameters such as heating rod setpoint temperature and airflow rate as inputs. It employs a layer-wise contraction network architecture, utilising ReLU activation functions and Dropout mechanisms to enhance nonlinear expressive capability and generalisation performance. Standardised processing via StandardScaler, MSE loss function, and Adam optimisation algorithm ensure efficient and stable training. Experimental results demonstrate the model's capability to accurately capture complex mapping relationships between input parameters and temperatures at multiple measurement points, exhibiting outstanding performance in metrics such as RMSE and MAPE. This research offers a data-driven approach for thermal field modelling and energy efficiency optimisation in cathode material sintering processes. It establishes a technical foundation for achieving closed-loop "perception-prediction-regulation" control in roller kilns, holding significant implications for advancing intelligent manufacturing in the lithium battery industry and ensuring the safe, high-quality development of the low-altitude economy.

Keywords: Roller Kiln; Process Indicators; Temperature Prediction; Deep Learning; Multi-layer Perceptron; Low-altitude Economy

1. Introduction

With the deepening reform of low-altitude airspace management and the rapid development of the general aviation industry, the demand for high-energy-density, high-safety power batteries for aviation equipment such as drones and electric vertical take-off and landing aircraft is becoming increasingly urgent [1]. As the ‘heart’ of lithium-ion batteries, the uniformity of the microstructure and the integrity of the crystal morphology of cathode materials directly determine the battery's endurance and thermal safety boundaries. Roller kiln sintering represents the most critical process step in cathode material preparation[2]. It involves complex gas-solid heat transfer, chemical reactions, and mass migration, constituting a typical multi-physics coupled system. This process encompasses multiple physicochemical transformations including gas combustion, convective heat transfer, radiative heat transfer, and material phase transitions. Its dynamic characteristics exhibit strong nonlinearity, significant hysteresis, and high coupling between variables. The dynamic interactions among multiple temperature zones within the kiln, coupled with complex nonlinear relationships between hundreds of process parameters (such as set temperatures for each zone and gas inlet flow rates), render traditional experience-based control methods inadequate for precisely balancing the multiple objectives of ‘product quality – production energy consumption – equipment capacity’. There is an urgent need to introduce data-driven intelligent modelling methods to achieve precise perception and collaborative optimisation of the sintering process[3] .

2 Relevant Work

In recent years, the application of deep learning techniques[4] to address modelling and prediction challenges in complex industrial processes has emerged as a research hotspot. Within the field of kiln temperature forecasting, researchers have explored the integration of various advanced neural network architectures. For instance, Zhu Junwen et al. [4] proposed a hybrid model based on KPCA-CNN-GRU for temperature prediction in ceramic roller kilns. This work employed Kernel Principal Component Analysis (KPCA) for feature dimensionality reduction, combined with Convolutional Neural Networks (CNN) to extract spatial features and Gated Recurrent Units (GRU) to capture temporal dependencies, demonstrating the hybrid model's potential in handling industrial time-series data.

However, such approaches typically rely on complex model structures, entailing high training costs and sensitivity to data quality. In contrast, Deep Multi-Layer Perceptron (Deep MLP) models demonstrate unique application value across numerous industrial scenarios due to their clear structure, stable training, and ease of deployment. Addressing the intricate static nonlinear mapping between roller kiln process parameters and temperature fields, Deep MLP effectively uncovers deep correlations between process parameters and multiple performance indicators through its robust layer-by-layer nonlinear feature transformation capability.

Inspired by the aforementioned research, this paper aims to explore a solution that balances predictive accuracy with engineering practicality. Unlike the complex spatio-temporal feature extraction approach employed in[5] , this study directly addresses the steady-state conditions of the roller kiln sintering process. It focuses on the static nonlinear mapping problem between process setting parameters and output indicators, constructing a Deep MLP-based intelligent multi-process indicator prediction model. By constructing a deep fully-connected network architecture and employing regularisation techniques such as Dropout to ensure its generalisation capability, this model provides core support for achieving closed-loop control of roller kilns through 'sensing-prediction-regulation'. It holds significant value for advancing the safe and high-quality development of the low-altitude economy industrial chain [6].

3. Data Sources

3.1 Data Overview

This study utilises the industrial dataset provided by iFlytek's 1024 Developer Competition "Challenge on Predictive Modelling and Multi-Objective Co-Optimisation for Cathode Material Sintering Quality and Energy Efficiency", with approved usage rights. The dataset comprises two primary files:

train1.csv: 86-dimensional features, 26,641 samples

train2.csv: 122-dimensional features, 13 samples

	TIME	V1	V11	...	T3-16	T1-10	T4-4
0	2022/11/6 9:08	35.668999	16.298000	...	844.647428	827	490.205165
1	2022/11/6 9:09	35.995998	16.381001	...	821.427610	827	491.171201
2	2022/11/6 9:11	35.340000	16.319000	...	821.228985	827	502.578337
3	2022/11/6 9:12	35.585999	16.257000	...	828.664707	827	500.899392
4	2022/11/6 9:13	35.946999	16.288000	...	816.663360	827	501.276662

Figure 1. Data Pattern Diagram for Train1

	V1	V2	V12	T3-6	T3-17	T1-11	T4-5
0	33.369999	34.382000	15.900	647.370432	746.465979	829	571.493127
1	28.222000	33.589001	15.990	720.173473	748.104516	768	656.280096
2	35.125000	38.756001	15.672	668.086869	686.545330	835	588.922570
3	14.983000	13.962000	15.250	869.468985	844.206691	940	765.088959
4	26.125000	25.424999	16.892	623.269262	743.983342	832	535.304793

Figure 2. Data Sample from Train2

As evident from Figures 1 and 2, the industrial process time-series dataset incorporates timestamps and continuous numerical variables (such as process input parameters, equipment temperature measurements, and performance metrics), documenting the comprehensive "process input – operational status – output indicator" information of the roller kiln at different time points.

3.2 Feature Composition

Based on the task requirements and expert domain understanding, 51 input features were selected, categorised into three groups:

1) Upper heating rod setpoint temperatures: T1-1 to T1-17

2) Lower heating rod setpoint temperatures: T2-1 to T2-17

3) Set flow rate at air inlet for each temperature zone: V1 ~ V17

1) A total of 71 output features were selected, categorised into three groups:

2) Temperature field distribution metrics: T3-1 to T3-17, T4-1 to T4-17

3) Crucible temperature indicators: T5-1 to T5-17, T6-1 to T6-17

Process performance indicators: Energy consumption (E), Temperature uniformity (H), Length of high-temperature zone (L)

4. Data Preprocessing

4.1 Feature Selection

Defined input features and output targets for model training. Input features comprise inlet air flow rate and set temperatures at the upper and lower heating rod sections, totalling 51 variables. Output targets vary according to requirements: one set comprises only the actual temperatures at upper and lower measurement points (34 variables); another expands to include upper/lower measurement points, crucible temperature, high-temperature zone length, temperature uniformity, and energy consumption (71 indicators). By explicitly defining input and output columns, the model accurately extracts required features and targets from the data, enabling precise multi-objective prediction.

4.2 Standardisation

The input features and output targets underwent standardisation, transforming the data into a form with a mean of zero and a standard deviation of one to eliminate the influence of differing feature dimensions. This standardisation not only accelerated model convergence during training but also ensured features with differing scales—such as temperature setpoints and gas flow values—carried equal weight in the training process. This prevented the model from favouring certain features due to disparate numerical ranges, thereby enhancing predictive accuracy and stability at the data preprocessing stage.

5 Model Training

The competition task comprises two parts:

Test Set 1: Inputs comprise the upper heating rod setpoint temperature, lower heating rod setpoint temperature, and inlet airflow setpoint. Participants predict the actual temperatures at the upper and lower temperature measurement points respectively.

Test Set 2: Using the upper heating rod set temperature, lower heating rod set temperature, and inlet airflow set value as inputs, participants predict the actual temperature at the upper measurement point, actual temperature at the lower measurement point, actual temperature at the top of the crucible, actual temperature at the bottom of the crucible, kiln energy consumption, crucible temperature uniformity, and length of the high-temperature zone.

5.1 Training the Prediction Model Based on Test Set 1

Using the upper heating rod setpoint temperature, lower heating rod setpoint temperature, and inlet airflow setpoint as inputs, predict the actual temperature at the upper measurement point and the actual temperature at the lower measurement point respectively.

1) Defining the SinteringDataset class

Standardised input features X and target outputs y are encapsulated into PyTorch-recognisable dataset objects. DataLoader is utilised to load data in batches (batch size = 64). During model training, the DataLoader efficiently supplies training samples in small batches. Setting shuffle=True randomises the data order, enhancing the model's generalisation capability and training stability. This process provides an efficient, controllable data input mechanism for subsequent model iteration and optimisation.

2) MLP[7] Model Construction

A Multi-Layer Perceptron (MLP) model[8]was defined and instantiated for the multi-objective regression task. The model comprises three hidden layers with 512, 256, and 128 neurons respectively. Each layer is followed by a ReLU activation function to enhance non-linear modelling capability. Dropout (dropout rate 0.3) is introduced in the first two layers to mitigate overfitting risks. The final layer is a linear output layer with dimensions matching the number of target variables.

3) Loss Function and Optimiser

Defined the model's loss function and optimiser. criterion = nn.MSELoss() indicates the use of Mean Squared Error (MSE) as the loss function, measuring the overall deviation between model predictions and true values, suitable for regression tasks. optimizer = torch.optim.Adam(model.parameters(), lr=0.001) employs the Adam optimiser for iterative parameter updates. This method features adaptive learning rate adjustment, enabling faster and more stable convergence during training.

5.2 Training the Prediction Model Based on Test Set 2

Using the upper heating rod set temperature, lower heating rod set temperature, and inlet airflow set value as inputs, participants predict the actual temperatures at the upper and lower measurement points, the actual temperatures at the top and bottom of the crucible, the roller kiln energy consumption, the temperature uniformity of the crucible, and the length of the high-temperature zone.

1) Defining the SinteringDataset Class

By defining the SinteringDataset class, the standardised input features X_scaled and multi-objective outputs y_scaled are encapsulated into a PyTorch-recognisable dataset object, ensuring sample pairs (X[i], y[i]) can be accessed via indexing. Combined with DataLoader, this enables batch loading of training data (batch size = 64) with shuffle=True activated to randomise sample order before each epoch. This enhances model generalisation and training stability, providing an efficient data input mechanism for modelling large-scale industrial datasets.

2) MLP Model Construction

A Multi-Layer Perceptron (MLP) model[9]was constructed for multi-objective continuous variable prediction tasks. This model comprises three hidden layers with 512, 256, and 128 neurons respectively. Each layer employs the ReLU activation function to enhance nonlinear fitting capability, with Dropout (dropout rate 0.3) introduced between the first two layers to mitigate overfitting risks. The output layer employs a linear mapping with dimensions matching the number of multi-output variables (totalling 71, comprising 17 measurement points each for T3–T6, plus the three key performance indicators L, H, and E), demonstrating robust feature representation capability and task adaptability.

3) Loss Function and Optimiser

This model employs Mean Squared Error (MSE) as the loss function to measure the overall deviation between model predictions and actual multi-objective outputs, making it suitable for continuous regression tasks. The Adam optimiser is selected for adaptive parameter updates with a learning rate of 0.001, demonstrating excellent convergence and stability. This approach is well-suited for complex industrial data modelling tasks involving high-dimensional inputs and multiple output targets.

6. Visualisation Analysis

To conduct an in-depth analysis of model performance, this study systematically examined prediction outcomes and error distributions using visualisation libraries such as Matplotlib and Seaborn within the Python ecosystem [10]. In industrial data modelling, visualisation serves not only as a means of presenting results but also as a critical component of model diagnosis and validation. By transforming high-dimensional data into intuitive graphics, we achieved a multidimensional assessment of model performance: error distribution histograms validated the statistical properties of prediction errors, confirming compliance with the idealised assumption of a zero-mean normal distribution; furthermore, visualising model performance under diverse operating conditions effectively assessed its robustness and generalisation capability. This closed-loop analysis methodology—encompassing data, models, and visualisation—significantly enhances the interpretability and engineering guidance value of research outcomes, providing crucial foundations for practical model implementation.

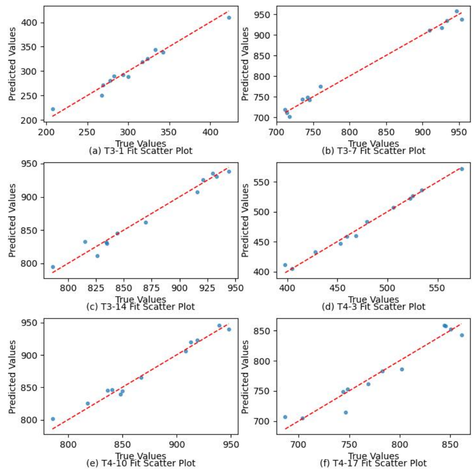

Figure 3. Randomly Sampled Comparison of Training Set 2

Figure 3 indicates that the model exhibits overall favourable fitting performance, with low prediction errors and a concentrated distribution. It demonstrates stable and accurate results across multiple temperature measurement points, showcasing strong generalisation capabilities.

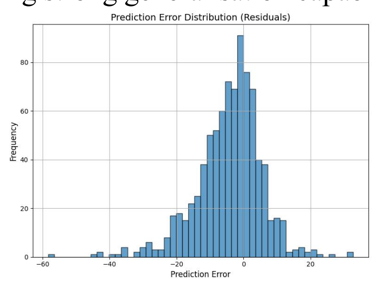

Figure 4. Prediction Error Distribution Plot for Training Set 2

As shown in Figure 4, the errors exhibit a standard normal distribution centred around zero, with the majority falling within the ±10 range. This indicates that the model displays no significant systematic bias. The distribution features short tails on both sides, with very few samples exhibiting extreme deviations (e.g., greater than ±20). This demonstrates that the model maintains consistent and stable performance across the majority of samples.

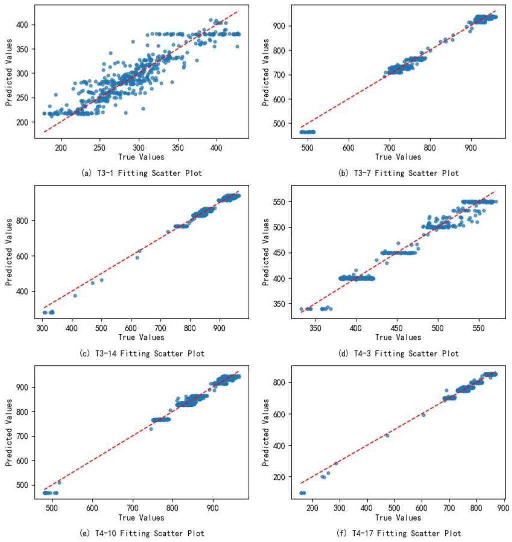

Figure 5. Prediction Error Distribution Plot for Training set 1

As shown in Figure 5, the model demonstrates overall favourable fitting performance, exhibiting small prediction errors with a concentrated distribution. It displays stable and accurate results across multiple temperature measurement points, indicating strong generalisation capabilities.

As shown in Figure 6, the errors exhibit a standard normal distribution overall, centred around zero, with the majority falling within the ±25 range. This indicates that the model displays no significant systematic bias. The distribution features short tails on both sides, with very few samples exhibiting extreme deviations (e.g., greater than ±25). This demonstrates that the model maintains consistent and stable performance across the majority of samples.

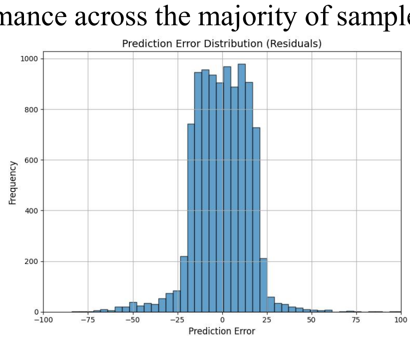

Figure 6. Prediction Error Distribution for Training Set 1

7. Conclusions

This study successfully constructed a multi-process indicator prediction model for roller kilns based on deep multi-layer perceptrons, achieving precise forecasting of temperatures across multiple temperature zones and key process parameters. By employing a network architecture combining multiple hidden layers with Dropout regularisation, the model maintained strong non-linear fitting capabilities while effectively mitigating overfitting risks, demonstrating excellent generalisation performance. Experimental results demonstrate that the model accurately captures the complex mapping relationship between process parameters and temperature fields, with prediction errors exhibiting a standard normal distribution and no discernible systematic bias.

The primary contribution of this research lies in establishing an end-to-end multi-objective prediction framework capable of simultaneously forecasting multiple critical indicators, including temperature field distribution, crucible temperature, and energy consumption. Employing a three-layer hidden architecture with ReLU activation functions and Dropout mechanisms, the model significantly enhances expressive capability and generalisation performance. Input-output data standardisation further ensures training stability and convergence.

Future research will pursue three directions: firstly, exploring deeper or hybrid network architectures incorporating advanced structures like attention mechanisms to improve prediction accuracy; Secondly, developing real-time monitoring systems for the training process to enable refined control over model training; thirdly, investigating online learning and adaptive optimisation strategies to enable the model to adapt to dynamic changes in production conditions. Concurrently, further exploration will focus on combining data-driven approaches with micro-coupling mechanism models, embedding physical prior knowledge into the network structure to achieve more precise synergistic optimisation of sintering regimes.

This research delivers a reliable technical solution for intelligent control of roller kilns. The established predictive model serves as a core module for advanced control systems, laying the foundation for achieving closed-loop 'perception-prediction-regulation' control. With ongoing research, this technology holds promise for greater value in lithium battery cathode material sintering processes, providing robust technical support for enhancing product quality and reducing production energy consumption.

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