MLA for Electric Arc Furnace in Steel Industry

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The steel industry has been forced to switch from the traditional blast furnace to the electric arc furnace (EAF) process to reduce carbon emissions. However, EAF still relies entirely on the operators' proficiency to determine the electrical power input.

machine learning | steel manufacturing industry | carbon neutral | electric arc furnace | stainless steel | temperature prediction

1. Machine Learning Application in the Steel Industry

Previous studies that applied machine learning (ML) technology in the steel industry were reviewed. There were a number of studies on the prediction of iron ore prices using the ML technique. Lee et al. [1] developed a prediction model for Chinese iron ore prices by applying the long short-term memory (LSTM) algorithm. Their model used the volumes of steel exported from Korea, China, and Japan; the demand and supply volumes of Chinese steel; and scrap raw material prices as the variables. Their model's mean absolute percent error (MAPE) was 5.96%. Most of the studies that applied ML were related to the steel manufacturing process. Liu et al. [2] studied a support vector machine (SVM)-based model that determines whether the operation is abnormal through the interpretation of 14 factors and 1600 training data that were obtained via measurements taken during the operation of the blast furnace. They also verified its feasibility and effectiveness with 800 test data. Liu et al. [3] developed a model for calculating the optimal raw material mixing ratio in the sintering process and applied it to actual operation to verify the effect of reducing raw material costs by 4.63 USD/ton (3.8%).

Predicting a precise endpoint of the converter process to remove impurities from pig iron is vital for productivity and quality. Jo et al. [4] predicted the oxygen-blowing amount, which is a factor that determines the endpoint, using existing operation data. Schlueter et al. [5] produced the data by attaching a sensor to measure off-gas composition and used these data for training. Bae et al. [6] sought to predict the final temperature and composition ratio of carbon and phosphorus under current operating conditions. Tian et al. [7] developed a hybrid model that predicted the optimal parameters of the thermal model previously used in the ladle furnace (LF) process. They improved the prediction performance within ±5 °C of the temperature deviation of molten steel. Laha et al. [8] developed a crude steel yield prediction model using random forest (RF), artificial neural network (ANN), and support vector regression (SVR) algorithms. They verified that SVR performed better than RF and ANN algorithms. Santos et al. [9] calculated the distance between the operation data of 645 regular products and 244 defective products to determine whether or not the ultra-tensile strength products were from the iron casting process. They achieved a detection success rate of 78%. Previous studies seeking to predict the clogging of a submerged entry nozzle (SEN), a chronic problem in the continuous casting process, were also reviewed. Wang et al. [10] developed an LSTM model that detects the time series change of the clogging index data for three minutes using the calculation method presented in previous studies. The clogging index after 36 s was predicted, and the coefficient of determination performance was 0.971.

Several studies were found on the application of ML to the prediction of strip quality in the rolling process. Ghorai et al. [11] developed an image recognition model capable of detecting 24 defects in real time by training 1432 strip surface images taken in hot rolling processes. However, their model worked only at 5 m/second or less and under an ideal environment without vibration and noise. Ding et al. [12] predicted the camber of the product caused by the asymmetry of the roll pressing control in the plate process based on SVM. They also conducted a study wherein they were able to control camber generation within ±6% in conjunction with roll tilt controls.

Studies on the application of AI and ML technologies for digitalization and carbon emission reduction in the steel industry were also reviewed. Colla et al. [13] proposed various ML models and theories for digitalization that can improve carbon neutrality in steel manufacturing processes by using AI and ML technologies. However, their study was limited due to the absence of an attempt to apply their results to an actual industrial site. Stavropoulos et al. [14] developed a framework utilizing big data techniques to reduce carbon dioxide emissions in the steel manufacturing industry. Their study proposed different metrics from the perspectives of carbon emissions and cost. Zhou et al. [15] suggested optimizing manufacturing processes using simulation, visualization, and ML for digitalization in the manufacturing industry.

2. Machine Learning Model for Electric Arc Furnace

Previous studies that applied ML to the electric arc furnace (EAF) process were reviewed. The literature research results regarding the prediction of the amount of power input are discussed in this section. Reimann et al. [16] developed a model applying three ML algorithms, including an artificial neural network (ANN), using over 21,000 operational data extracted from five EAF locations. As a result of the performance evaluation, the gaussian process regression (GPR) model performed best among the three ML algorithms. Their newly developed model was superior to the empirical (Köhle) model. However, their study had a limitation as it was only a theoretical study and it was thus difficult to use in actual operation through the application of a tapping amount factor that could not be obtained. In addition, several studies have used factors that cannot be obtained during operation. Kovačič et al. [17] developed a model by training 25 factors, such as input raw material information and operation waiting time. However, there was a limitation in that, due to the subjective intervention of the operator, unoptimized power input performance data were involved. Carlsson et al. [18] conducted a theoretical study on whether an operation can be statistically modeled using the tap-to-tap time (T-T) and discharging time of molten steel. However, it was similarly limited in its application to the actual operation site.

The prior studies on EAF tap temperature prediction are as follows. Li et al. [19] developed a model that predicts tapping temperature with 95% accuracy within ±20 °C by applying LSTM. However, it was unclear what factors were used and whether predictions could be made in real time by applying them to actual operations. Blažič et al. [20] sought to predict the molten metal temperature in real time during the melting operation. However, electricity supply must be stopped, and the roof must be opened to measure the molten metal temperature during operation. This means that the study suffered from a limitation wherein production time delays of longer than 1 min occur. As a result, their approach cannot be applied to an actual EAF process because productivity and power efficiency would be seriously degraded.

As a result of reviewing the previous studies above, it was found that various studies that applied ML technology to the steel industry were implemented under the rapid development of ML applications and computing power. The authors focused on the studies that applied ML or deep learning (DL) techniques to accumulate operation data regarding the prediction of electrical power input or the tap temperature of EAF, which are closely related to this research. Firstly, the electric power input is a factor that includes the operator’s subjective judgment. Therefore, it is possible to imitate the inefficient operator’s manual operation when an ML model is trained with the existing data. Accordingly, this research aimed to predict the tapping temperature, which is an objective indicator. Previous studies that did not produce satisfactory performance were benchmarked, though less than ten factors were used, and the maximum achievable factors were secured and applied to model development. Because this research aimed to develop a sustainable system that can be applied to actual EAF sites even after the research is complete, the model was developed using only features that can be ensured during operation.

Moreover, the operator’s workload was reduced by developing an AI operation system that automatically controls the operation based on the tap temperature predicted by TTPM and applying it to the site. The system that was developed as a result of this research verified the effect of a reduction in electrical power and costs by analyzing the operational data for 49 days during a field application test of five months. In addition, it can be differentiated from other studies in that it can be applied to the actual production site and assist the operator.

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