Power Consumption Optimization for Electric Arc Furnace with Time Series Prediction

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ABSTRACT

Optimizing power consumption for electric arc furnace (EAF) has a critical impact for maximizing productivity. To achieve the goal, we propose an AI based algorithm that determines optimal timing for recharging scrap to EAF. More specifically, we predict power consumption and time duration required for melting scrap considering scrap types and amounts of each type of scrap. Furthermore, with the advance in explainable AI, we offer guidance for the optimal timing of recharging scrap. We evaluate the performance on a real site and successfully reduce scrap charging time of 3% and power consumption of 7.1%, 53,802 Japanese Yen.

1. INTRODUCTION

Steel is one of the most important material in many fields such as construction and manufacturing industries (Torquato, Martínez-Ayuso, Fahmy & Sienz, 2021). However, even both private steel making companies and governments try to achieve a net-zero carbon goal, steel making is responsible for almost 5% of greenhouse gas emissions of entire emissions of the world, making it one of the highest-carbon emitting industries (Coskun, Sarikaya, Buyukkaya & Kucuk, 2023). In order to reduce the carbon emission, electric arc furnaces (EAF) have been gradually replacing the traditional fuel based furnaces (Bae, Nam & Moon, 2022, Zhang, Yi, Guo & Zhu, 2022). EAF is mainly used for melting scrap steel and others scrap metals in general for recycling. However, EAF-based steel making is a highly energy-demanding procedures (Bisio, Rubatto & Martini, 2000). The production and recycling of steel require a great deal of electric energy and the significant energy losses have always been a bottleneck for minimizing the cost (Ameling, Strunck, Pottken, & Strohschein, 1983). With the number of skilled engineers in the electric furnace steel making industry decreasing, it is necessary to introduce an automatic control system that can make important decisions automatically or can help operator's decision makings (Yi, Lee, Lee, & Kim, 2021). Furthermore, since the increasing cost of fuel makes temperature managements of EAF become more expensive, a growing interest is attracted to development of automation system (Andonovski & Tomažič, 2022).

In usual melting processes of EAF, recharging additional scrap into EAF is one of main reasons that bring major heat loss. For the recharging, operators need to determine when open EAF and begin recharging the EAF (meltdown time). While meltdown time depends on the composition of the scrap, early beginning of the recharging brings an additional process for securing room in EAF for the additional scrap, in which major heat loss occurs. In contrast, a late beginning of the recharging makes the runtime of EAF even longer, a waste of electric power occurs. Consequently, determining the meltdown time is one of the most important decision-makings to optimize melting processes of EAF. Operators usually consider the total weight and composition of scrap metals to determine the meltdown time. However, the scrap metal composition is approximated by samples or the visual of the scrap so that the decision making is highly dependent on the operator's experience.

The goal of this paper is to improve energy efficiency of EAF by correctly predicting the electric power requirements for melting all the scrap in EAF. By accurately predicting the power consumption, we guide the meltdown time so that the heat loss of EAF can be minimized.

This paper is organized as follows. Section 2 briefly reviews the existing work for optimizing EAF. In section 3, we explain scrap melting processes and the data collection system for an EAF of the real steel-making company, Hangook Jaegang. Section 4 gives problem descriptions of the real steel-making site. In Section 5, we show prediction results while section 6 explains our strategy for saving electric energy utilizing the predictions. Then, we conclude in section 7.

2. Related Work

In this section, we briefly review existing works for EAF optimization. Early works focus on building mathematical models for the dynamics inside EAF considering domain knowledge while recently more interests have been attracted to data driven based dynamics analysis and EAF modeling for optimizations.

Nikolaev, Kornilov, Anufriev, Pekhterev & Povelitsa (2014) presents a detailed control mechanism used to optimize EAF. In the work, the authors develop a mathematical model to analyze electrical characteristics of EAF and the dynamic behavior of the automatic control system. With the model, the authors develop a system for identifying the phases of smelting according to the harmonics of the arc currents and have increased 5% of mean productivity by decreasing the highest operating cost of an EAF, the power consumption. In MacRosty & Swartz (2005), melting processes and chemical reactions are analyzed. As in Nikolaev et al. (2014), the authors explore mathematical modelling techniques to analyze steel-making processes of EAF and develop a dynamic model for the processes. Data driven analysis has been conducted for parameter estimation with real site data such as off-gas composition, but it seems like the volume of collected data is rather limited. In addition, the authors carry out a sensitivity analysis in order to identify the effect of each parameters in the model.

An EAF simulation based on computational fluid dynamics is presented in Yigit, Coskun, Buyukkaya, Durmaz & Güven (2015). In this work, the thermal effect of the coal particle combustion is analyzed. With the computational fluid dynamics approach, this work analyses the flow field inside EAF which severely affects both temperature distribution and performance of EAF. Then, CO and CO_2 emissions are estimated according to the distribution of temperature inside EAF. The work presented in Sandberg (2005) optimizes energy consumption and proposes scrap selection for EAF using multivariate data analysis. In this work, authors learn models from real site data to predict chemical composition of the steel, electrical energy consumption and metallic yield. The prediction for certain chemical elements shows the most accurate results while carbon was found to be one of the most difficult elements to predict. In addition, the authors suggest the optimization of scrap recipes. In Sandberg, Lennox & Undvall (2007), the authors continue their study, but focus more on estimating scrap properties based on the evaluation of historical process data.

In Wang (2012), a linear model is created in order to optimize the scrap recipe with a focus on cost reduction and scrap transportation and loading operations to increase the production rate. According to the experimental evaluations of the work, the authors have achieved both a reduction of the scrap feedstock cost by between 2% and 6% and the charging time by between 2 and 10 minutes. The research presented in Bai (2014) also uses linear modeling to optimize key performance variables such as the electric power consumption, electrode consumption, percentage of scrap melted, average arc current, oxygen input, gas input and carbon input. The ultimate goal is to optimize the production cost while maintaining quality and efficiency. Reductions between 7% and 22% were achieved in terms of production cost. A study presented in Gajic, Savic-Gajic, Savic, Georgieva & Di Gennaro (2016) uses deep neural networks to learn the effect of fluctuations in the chemical composition on electrical energy consumption. In this study, the authors learn a mapping function between the input variables (such as the content of carbon, chromium, nickel, silicon and iron) and target variable (electrical power consumption). The authors also show that the chemical composition, especially, carbon content is the most relevant parameter for electric power consumption. Recently, a novel study that optimizes EAF processes by predicting the tab temperature and by minimizing the deviation of the tab temperature in Choi, Seo & Lee (2023). In the work, the authors develop a tap temperature prediction model with a machine learning-based support vector regression algorithm and have achieved the tap temperature deviation decreased by 17% and the average power consumption decreased by 282 kWh.

The optimization techniques mentioned in this section, exploit mathematics and deep neural networks to model the melting processes of EAF. However, these studies usually assume no variance of EAF processes and data limitation, thus may become less effective when applied to real steel-making sites. Meanwhile, we analyze the EAF process and limitations on data collection system of real steel-making company, and propose power consumption prediction based EAF process optimization strategy that is applicable to a variety of real steel-making companies.

3. System description

In this section, we will briefly describe the actual processes of EAF and the data collection system of real steel-making company, Hangook Jaegang. The focus in this section is to point out the processes that make the procedures become less energy-efficient in order to find proper approach to optimize the melting processes of EAF.

3.1. Scrap melting procedures and issues

The melting procedure of EAF consists of the following 4 phases.

1. Charging phase: loads scrap into EAF.
2. Melting phase: melt the scrap inside EAF.
3. Recharging phase: loads additional scrap into EAF.
4. Tapping phase: tapping the liquid steel.

In charging phase, various kinds of scraps are loaded into EAF and the quantity of each kind of scrap is approximated. Only total weight are accurately measured. In melting phase, operators run EAF to melt the scrap. Before all of the scrap in EAF melt, operators load additional scrap (Recharging phase). For recharging phase, operators need to decide meltdown time and the decision making depends on the experiences of operators.

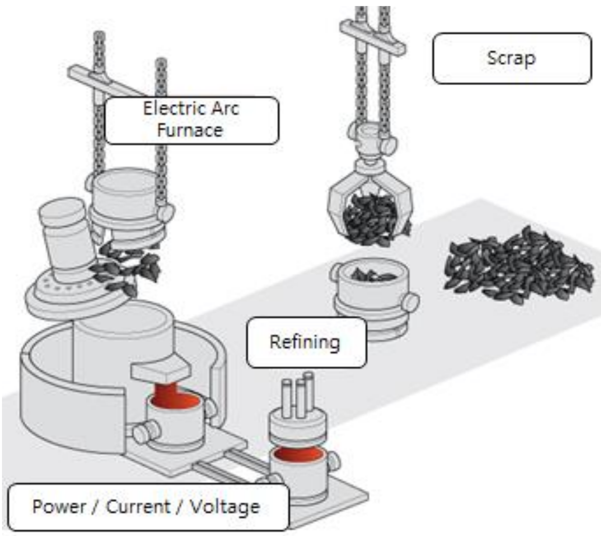


Figure 1. Electric Arc Furnace of Hangook Jaekang

As mentioned earlier, the amount of heat loss depends on the decision making for the timely recharging phase. If the scrap is melt well so that enough room for the additional scrap is already secured, the heat loss is minimal. Otherwise, an additional unnecessary procedure for securing the room by rearranging and pressing scrap in EAF occurs, which in turn indicates massive heat loss in recharging phase.

Table 1. Data description

No.	Data	Data type
1	Voltage	TAP
2	Current	Norch, KA
3	Power	MVA
4	Sensitivity	BIG/MIDDLE/SMALL
5	Scrap types	Ratio of Fe, Cu, ...
6	Total weight	Ton
7	Temperature	°C, Cooling water temperature

3.2. Data collection

Since the steel-making company is in the middle of introducing a data collection system, only limited number of sensors are available as shown in Table 1. The steel-making company measures total weight of scrap, electric power usages and so on. For the data collection, the company employs InTouch MES system. Although the steel-making company is not systematic, the company collects and analyzes various data to make important decisions such as the meltdown time.

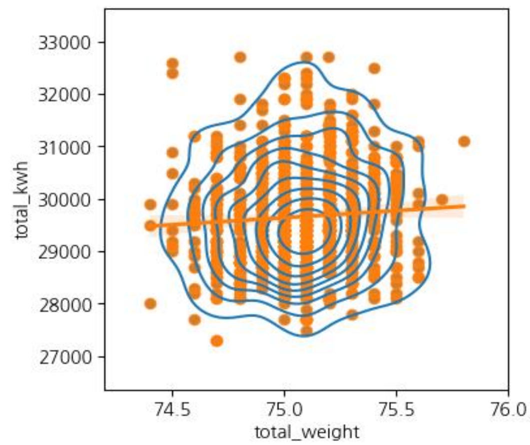


Figure 2. Total power consumption as a function of total weight of scrap. Near zero correlation is observed between the two variables. This indicates that EAF operators decide the required power regardless of the weight of the scrap.

4. Problem Description

We found from interviews that EAF operators of the steel making company usually consider “Scrap types”, "Total weight" and "Time" to estimate the power requirements (=”Power” * “Time”) for melting the current batch of scrap. Especially, the operators consider total weight as the most important variable, which makes us expect strong linearity with the power requirements. Figure 2 shows the total power consumption as a function of the total weight of scrap. As shown in the figure, however, even though the total power consumption is dependent on the composition of scrap as well, almost zero linearity is observed between the total weight and the power consumption while on average, 30,000 KW is used to melt 75 tons of scrap. This further indicates that the decision making on “Power” is severely dependent on experiences of EAF operators and thus, the decision making may vary even for the same conditions. Considering that the number of skilled operators is decreasing, it may result in severe waste of electrical power.

Another problem is that the decision making for meltdown time severely depends on the operators experiences as well. With the decreases of skilled operators, this may result in massive heat loss since early beginning of the recharging may bring the unnecessary process, securing enough room for the additional scrap. In contrast, late beginning indicates waste of electrical power in melting phase. In the steel making company, the operators begin the recharging phase after 80% of scrap have been melt, then additional scrap, which is 80% of the scrap loaded at the charging phase, is loaded. Thus, energy efficiency of the EAF severely depends on correct prediction of the meltdown time, the beginning of recharging phase. In order to address these problems, we develop an AI based prediction model for total power requirements and an guidance model to suggest the timely meltdown time so that occurrences of the unnecessary processes are minimized.

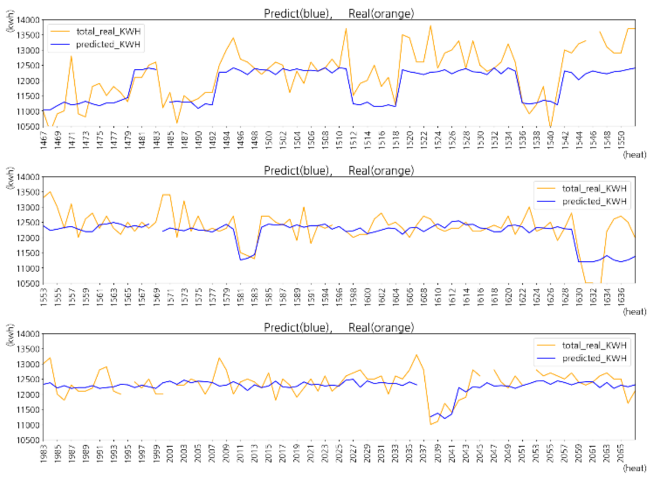


Figure 3. Prediction of Electric power requirement shows that the prediction model successfully learns the long-term dependencies while local vibrations are ignored.

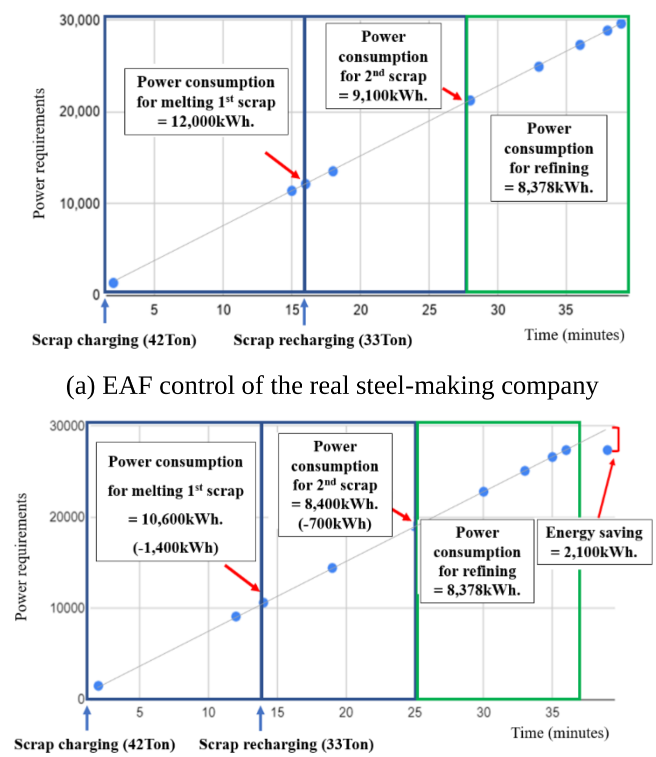
5. AI BASED PREDICTION OF POWER REQUIREMENTS

We develop a software module, *AI Guidance Predict*, that, automatically learns the best prediction model for time series forecasting problems. The aim of AI Guidance Predict is to accurately predict important factors for manufacturing processes so that the process controls can be optimized. To achieve the goal, AI Guidance Predict automatically finds the best prediction model by exploring the given bellows.

1. Linear model (Geladi & Kowalski, 1986): It learns linear prediction model and offers online predictions.
2. Decision tree: It learns tree-structured prediction model and offers online predictions. The resulting prediction models could vary according to the training dataset.
3. XGBoost (Chen et. al. 2015): By sequentially applying Decision tree and learning the formers prediction error, it offers more accurate predictions.
4. Deep temporal neural network: Artificial neural network based time series forecasting models are developed. The models include Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez,... & Polosukhin (2017) and Yoo, Lee, Ju, Chung, Kim, & Choi, J. (2021).
5. Adaptation learning: It analyzes differences between already seen training dataset and unseen online dataset to keep the prediction model up-to-date.

For the prediction of power requirements for melting scrap, we use AI Guidance Predict and collect dataset for 3 months since the real site has recently introduced the automated data collection system. More specifically, we collected 6,642,700 samples and each sample consists of 8 features representing the status of furnace and scrap from 2021-02-23 to 2021-05-23. Since the real site has 10 operators who has their own strategies, we split our dataset into train set of the first 2 months and test set of the last month. This guarantees that the both datasets have similar distributions and thus we can expect decent online real site predictions.

Figure 3 shows the prediction results. While the average power requirement is 12,500KWh, we achieve prediction error of 391.86KHh in terms of mean absolute error (MAE), which is 3% of mean absolute percent error (MAPE). More specifically, the predictions (blue line) are successful for global patterns while local vibrations are ignored. This is partially because sampling scrap composition may fail to represent the true scrap compositions.



(a) EAF control of the real steel-making company

(b) AI based EAF control

Figure 4. Prediction of electric power requirement and offering guidance for meltdown time reduces 3% of runtime and 7.1% of electric power consumption.

6. ENERGY EFFICIENT EAF CONTROL

While AI Guidance Predict provides predictions for decision making of control units, *AI Guidance Explain* offers explanations on predictions and thus, on the decision makings. AI Guidance Explain quantifies the effects of the changes of input variables to the target variables so that control units can decide optimal control of EAF. In addition, the explanations helps operators to understand reasons for the optimal controls and to determine that the optimal control is proper or not. To offer such explanations, AI Guidance Explain explores the given bellows.

1. Analyzing the resulting decision tree structure to offer explanations of predictions of the decision tree.
2. Estimating each feature's effect on predictions of deep neural network models to offer explanations.

With AI Guidance Explain, we guide meltdown time, the begging of the recharging phase as shown in Figure 4. In Figure 4(a), 12,000kWh of electric power is consumed before the beginning of the recharging phase and another 9,100kWh is required for finishing the melting process. In contrast, only 10,600kWh and 8,400kWh are required for melting 1st and 2nd scrap in Figure 4(b) and thus 2,100kWh of electric power is saved. Furthermore, the overall run time is reduced from 28minutes to 25minutes. This is because accurate prediction of power requirement and timely beginning of recharging phase minimize overheating and occurrences of unnecessary process for securing room for 2nd scrap. One another concern of the proposed prediction is the uncertainty of the estimation of the scrap composition since inappropriate estimations may bring severe deterioration of prediction accuracy. For this, we further investigate the feature importance using AI Guidance Explain. As shown in Figure 5, the prediction model considers the weight of the scrap much more than the scrap composition. This indicates that the predictions may become even more robust for the real applications.

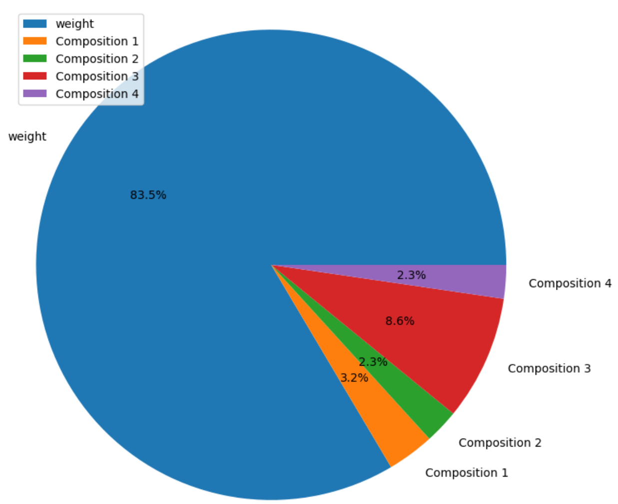


Figure 5. Feature importance: scrap weight and composition.

7. CONCLUSION

In this paper, we propose a novel approach that employs artificial intelligence for predicting the total electric power required for melting scrap in electric arc furnace and for offering the timely beginning of recharging phase. Unlikely to the existing work that may become less effective on real world problems, we successfully predict the total amount of electric power requirements and offer the timely beginning of recharging phase so that the occurrences of the unnecessary processes of securing room inside EAF is minimized. With the predictions and guidance, we have proved that the proposed approach successfully achieve energy saving of 7.1% of total electric power usage and reduce the run time by 3%, which saves 53,802 Japanese Yen.

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