Development of an Operation Support System for Emulating Veteran Operators' Burner Operation in Asphalt Plants

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Abstract

A common issue across the manufacturing industry is the challenge of transferring technical skills to the next generation. To support the succession of operational expertise in asphalt plants (hereinafter "plants"), we are working on developing an AI-based operation support system (hereinafter "support system") that makes the operating know-how of veteran operators visible and explicit, enabling novice operators—who lack plant-specific expertise—to operate the plant at a level equivalent to that of veteran operators.

Specifically, focusing on burner operation, we train AI under various conditions using operational data from veteran operators to construct a predictive model of burner opening degree. By comparing the actual measured burner opening degree under each condition with the predicted values from the model and checking the mean absolute error, we verify the optimal conditions for creating the predictive model.

1. Background

The low success rate of skill transfer to the next generation poses a significant challenge in the manufacturing industry[1]. One reason for the low rate is the presence of tacit knowledge in veteran operators' techniques, which are difficult to express or formalize.

To address the challenge, we have applied AI technologies to make the operational expertise of veteran operators visible and explicit in an asphalt plant, so as to develop an operation support system that enables novice operators without specialized plant knowledge to operate the plant with the same proficiency as veteran operators.

2. Objective

This paper focuses on the predictive function of the operation support system, with particular emphasis on the function that emulates burner operations performed by veteran operators, as this operation plays a critical role within the system. The objective is to identify appropriate training data conditions and validate the feasibility of this predictive function during the start-up phase of plant operation—specifically, the period from burner ignition until the aggregate temperature reaches a set temperature (hereinafter "start-up operation"). The burner selected for validation (hereinafter referred to as the "V-burner") is the one used for heating and drying virgin aggregate, where the feed rate, type, and ratio (feed composition) of the aggregate vary. Based on the validation results, the author aims to realize an operation support system that enables even novice operators without specialized knowledge of plant operations to perform operations equivalent to those of veteran operators by following the guidance of the predictive model that emulates veteran operator behavior. In addition, the author is planning to undertake efforts to achieve full automation of the plant including improvements to the PID control system[2] currently used for heating and drying aggregate at the control panel that controls the plant, as well as to establish remote-operation-based plant operation services.

Validation of the feasibility of the predictive function that emulates the operations of veteran operators is essential to enable novice operators without specialized knowledge of plant operations to carry out plant operations at a level equivalent to that of veteran operators. The predictive function will constitute a key foundational technology for the complete automation of plant operations, which we are pursuing.

3. Test Details

3.1 Algorithm Used for the Test

The predictive model used to emulate the burner operation employs Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN).

LSTM is a type of neural network designed to handle time-series data. As a variant of the Recurrent Neural Network (RNN), it addresses the issue of "long-term memory loss" found in conventional RNNs by introducing memory cells that can retain information over extended periods. LSTM adopts a structure that recursively uses "memory cell blocks" in place of the hidden states used in standard RNNs, enabling it to simultaneously leverage both long-term and short-term memory. Within each memory cell, a gating mechanism is learned, which uses the output values of a combination of "the fully connected layer + an activation function" as weighting factors to adjust the values of other pathways[3].

CNN is a type of neural network specialized in extracting local features. This network extracts local features from input data and aggregates them through convolution operations to generate an output. While CNNs are generally used in image processing to extract two-dimensional spatial features, they can also be applied to one-dimensional time series data. In such cases, CNNs are able to make predictions based on historical data within a fixed time window[4].

3.2 Validation Items and Test Results

To evaluate the appropriate conditions for constructing a high-accuracy predictive model, the following validations were conducted:

1. Validation of training period
2. Validation of seasonality
3. Validation of input parameters
4. Validation of use of only start-up operation
5. Validation of manual start-up operation
6. Validation of adding temperature parameters
7. Validation of use of limited training data

Validation 5 is similar to Validation 4 in that both use only the start-up operation as training data. However, while Validation 4 includes both manual and automatic operations, Validation 5 uses only manual operations. It should be noted that "automatic operation" refers to the burner opening operation performed at the control panel, whereas "manual operation" refers to the same operation performed directly by a veteran operator.

3.2.1 Validation of Training Period

To identify the appropriate training period conditions, we varied the training period of the predictive model (i.e., the durations of the training and validation data periods) and examined the behavior of the Mean Absolute Error (MAE). MAE represents the average of the absolute differences between the true values and the predicted values, which allows us to evaluate the prediction accuracy. It is commonly used when the goal is to minimize error, as a smaller MAE indicates a smaller discrepancy between the true and predicted values. In this study, MAE was adopted as an index to validate the prediction accuracy of the burner opening degree, representing the difference between the predicted burner opening and the operation performed by a veteran operator. The average of the MAE values obtained in each validation run was referred to as "average MAE" and was used as the performance evaluation metric for the predictive model.

Table 3.1 presents the relationship between the training period and the average MAE. Overall, the table indicates that the longer the training period, the lower the average MAE—in other words, the performance of the predictive model improves as the training period increases.

The improvement in average MAE was particularly significant when the training period ranged from two weeks to one month. However, when the training period exceeded one month, the degree of improvement became more gradual. Based on this result and considering the goal of minimizing the time required for implementation, we determined that a one-month training period is appropriate, as it achieves 84% of the improvement seen with a six-month training period.

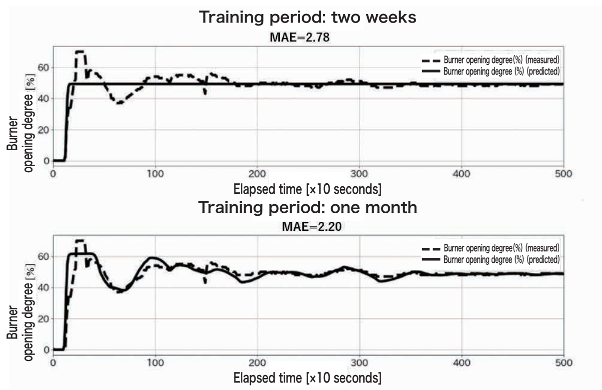

Figure 3-1: Trend graphs of burner opening degree compared between models trained for two weeks and one month

Table 3.1 Relationship Between Training Period and Average MAE

Training Period	Two weeks	One month	Two months	Three months	Six months
Average MAE [%]	10.5	5.93	5.87	5.44	4.99

Table 3.2 Relationship Between Gaps in Training-Validation Period and Average MAE

Gaps in timing between the training and validation periods (Data acquisition period used for model validation)	One week (2021/ 5/6~12)	Two weeks (2021/ 5/6~18)	One month (2021/ 5/6~31)	Two month (2021/ 6/1~30)	Three month (2021/ 7/1~31)	One year (2022/ 4/1~30)	Two years (2023/ 4/1~28)
Average MAE [%]	7. 80	8. 54	9. 48	8. 73	9. 11	7. 67	6. 51

Figure 3-1 presents trend graphs of the predicted burner opening degree using models trained over two weeks and one month. In the graphs, the solid line represents the predicted values, while the dashed line represents the actual measured values. These graphs also confirm that the one-month model yields smaller errors relative to the actual values and produces more accurate prediction results than the two-week model.

3.2.2 Validation of Seasonality

We assumed that the prediction accuracy might vary depending on the difference in ambient temperature between the data used to train the predictive model and the data used for validation. Therefore, we validated the prediction accuracy by varying the data acquisition period used for model training (hereinafter referred to as the "training period") and the data acquisition period used for model validation (hereinafter referred to as the "validation period"). In this validation, the training period was fixed from April 1 to April 30, 2021, while the validation period was varied to observe the behavior of the MAE.

Table 3.2 presents the relationship between the gap in timing between the training and validation periods and the average MAE. According to the table, when the time gap between the training and validation periods ranged from one week to three months, the average MAE tended to increase as the time gap widened. However, for gaps of one year and two years, the average MAE was equal to or even lower than that of the one-week gap.

These results indicate the presence of an annual cycle and suggest that the prediction accuracy is strongly correlated with the similarity in ambient temperature between the training and validation data. Therefore, we concluded that the predictive model needs to be updated for each season.

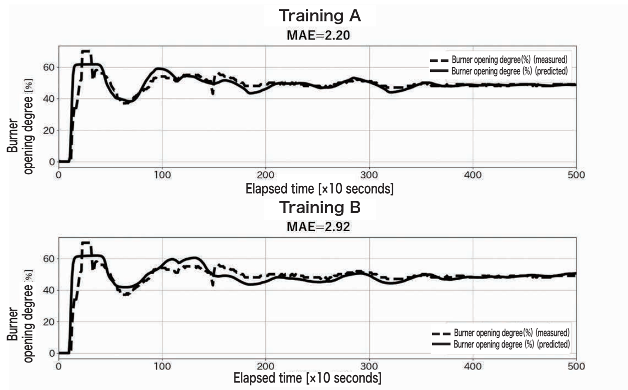

Figure 3-2: Trend graphs of burner opening degree compared between Conditions A and B

Table 3.3 Relationship Between Input Parameters and Average MAE

Conditions	A	B	C	D
Input Parameters	· Aggregate temperature [℃] · Set temperature [℃] · Total feed amount [×0. 1 t/h]	· Aggregate temperature [℃] · Set temperature [℃] · Total feed amount [×0. 1 t/h] · Feed amount of each feeder (No.1–10) [×0. 1 t/h]	· Aggregate temperature [℃] · Set temperature [℃] · Total feed amount [×0. 1 t/h] · Sand feeder feed amount [×0. 1 t/h]	· Aggregate temperature [℃] · Set temperature [℃] · Sand feeder feed amount [×0. 1 t/h]
Average MAE [%]	5. 93	7. 16	6. 54	8. 90

3.2.3 Validation of Input Parameters

To improve prediction accuracy, we validated whether the prediction accuracy could be improved by modifying parameters such as aggregate temperature (hereinafter referred to as "input parameters") that are used to create the predictive model.

Table 3.3 presents the relationship between input parameters and the average MAE. In the previous validations, three parameters: aggregate temperature, set temperature, and total feed rate were used as input parameters. These were set as the default condition, referred to as Condition A. We further defined Condition B with the addition of the feed rate of each individual feeder to Condition A, Condition C with the addition of only the sand feeder's feed rate to Condition A, and Condition D, which is similar to Condition C but excludes the total feed rate from Condition A. We then calculated the average MAE for each condition.

According to the table, Condition A resulted in the lowest average MAE, indicating that increasing the number of input parameters tends to degrade prediction accuracy. As an example, **Figure 3-2** presents trend graphs of the predicted burner opening degree using the models from Conditions A and B. In the graphs, the dashed line represents the actual measured values, while the solid line represents the predicted values. The graphs also confirmed that the model using Condition A produced prediction results that were more closely aligned with the actual measurements. However, the moisture content in the supplied sand is considered to have a significant impact on burner opening control. Therefore, we will continue further validation on the input parameters.

3.2.4 Validation Using Only Start-Up Operation Data

In previous validations, the model was trained on the entire burner operation—from ignition to shutdown (hereinafter referred to as "entire burner operation"). Since this development focuses specifically on the burner' s start-up operation, we conducted a validation using only start-up operation data to examine whether it would improve the performance of the predictive model. In this validation, both automatic and manual operations during start-up were included as training data. The range of start-up operation was defined as the period from burner ignition until the aggregate temperature converges. The convergence condition was defined as "when the consecutive extrema fall within ±8°C of the set temperature (hereinafter referred to as the settling range) three times in series or when the temperature remains within the settling range continuously for six minutes." A diagram of the convergence condition is shown in **Figure 3-3**. In the example in **Figure 3-3**, the gray-shaded area is considered to represent the period during which the aggregate temperature has converged. This convergence condition was defined by the author, based on

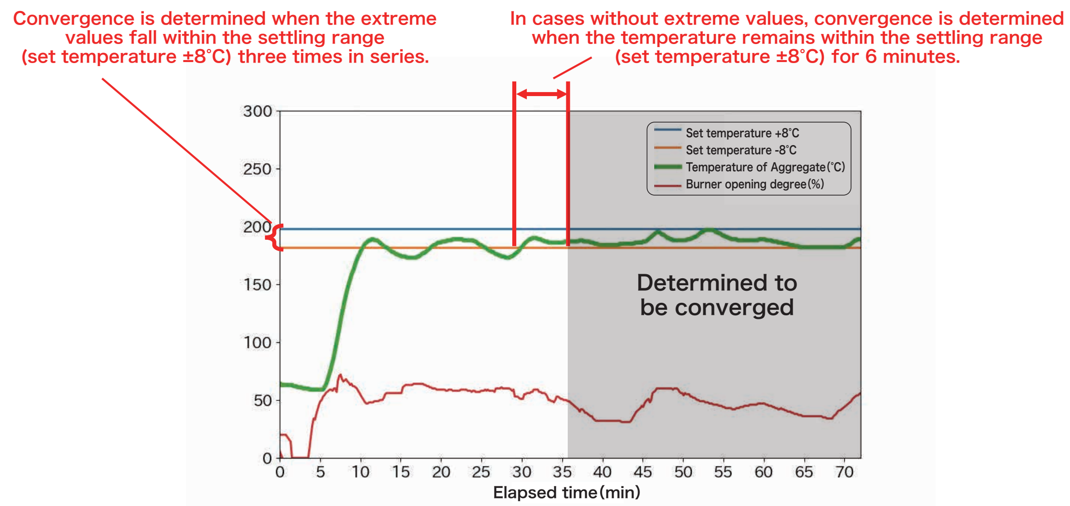

Figure 3-3: Illustration of Convergence Conditions

Table 3.4 Comparison of Average MAE Before and After Extracting Start-up Operation

Training Range	Average MAE [%]	Data volume
Entire burner operation	5. 93	81
Only start-up operations where aggregate temperature converged	9. 99	21

the judgment that it ensures sufficient reproducibility, quality of operation, and availability of operational data for validation.

Table 3.4 presents the relationship between the average MAE when training on the entire burner operation and when training only on the start-up operation where the aggregate temperature converged. According to the table, training using only the start-up operation where the aggregate temperature has converged results in a higher average MAE, indicating reduced prediction accuracy.

Figure 3-4 presents trend graphs of the predicted burner opening degree using two models: one trained on the entire burner operation and the other trained only on the start-up operation at converged temperature. In the graphs, the dashed line represents the actual measured values, while the solid line represents the predicted values. The trend graphs also confirm that the model trained on the entire burner operation produces prediction results that more closely align with the actual values. In general, prediction accuracy tends to decrease with a smaller amount of training data. In this study, focusing only on the start-up operation reduced the training volume by 74%.

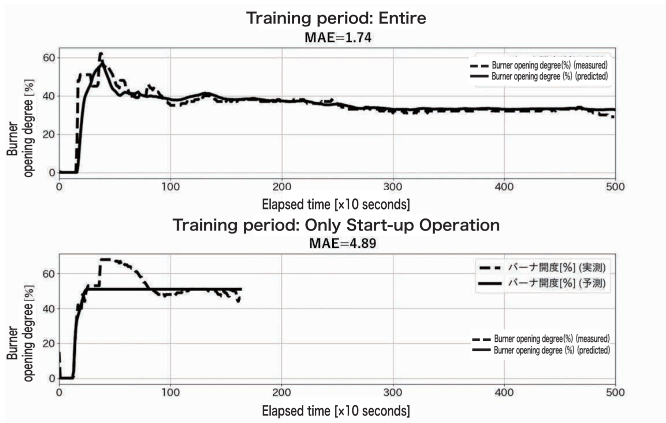

Figure 3-4: Trend graphs of burner opening degree compared between Entire Period and Only Start-up Operation Period

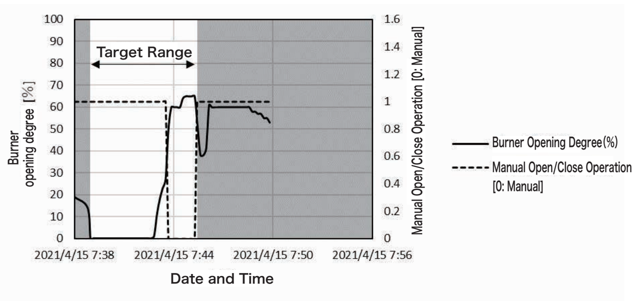

Figure 3-5: Target Range of Manual Start-Up Operation

This significant reduction in data volume is considered a major factor contributing to the decline in prediction accuracy. Moreover, by limiting the evaluation target to only the start-up operation, the portion of the data following temperature convergence—which is easier to predict—was excluded. This condition likely resulted in the decreased MAE. Since this validation focuses on start-up operations, we conducted further verification of methods to improve their prediction accuracy in the subsequent sections.

3.2.5 Validation of Manual Start-up Operation

In previous validations, both automatic and manual operations during the start-up phase were used as training data. However, the automatic operation does not reflect the decision-making of any veteran operator. To emulate the operation of a veteran operator, which is the objective of the operation support system, we compared a predictive model that includes both the automatic and manual operation phases during start-up with another predictive model that uses only the manual operation phase, which reflects the intention of the veteran operator, so as to verify whether performance improves. The targeted range for manual start-up operation is shown in **Figure 3-5** and defined as the period from the operation start until switching from manual to automatic control. It should be noted that the same data were used with only the training range modified, and the data volume remained constant. **Table 3.5** shows the average MAE before and after limiting the training range to manual start-up operation only.

Figure 3-6 shows trend graphs of the predicted burner opening degree using the predictive model that includes both automatic and manual operations, and a predictive model using only the manual operation. In the graphs, the solid line represents predicted values, and the dashed line indicates actual values.

The table and graphs show that limiting the training data to manual start-up operation reduced the average MAE, indicating improved predictive model performance. This result suggests that, to enhance prediction accuracy, the predictive model should be trained exclusively on the operation intended for emulation, thereby improving the quality of the training data.

Table 3.5 Comparison of Average MAE Before and After Extracting Manual Start-up Operation

Training Range	Average MAE [%]
Entire	12. 5
Only Manual Operation	6. 8

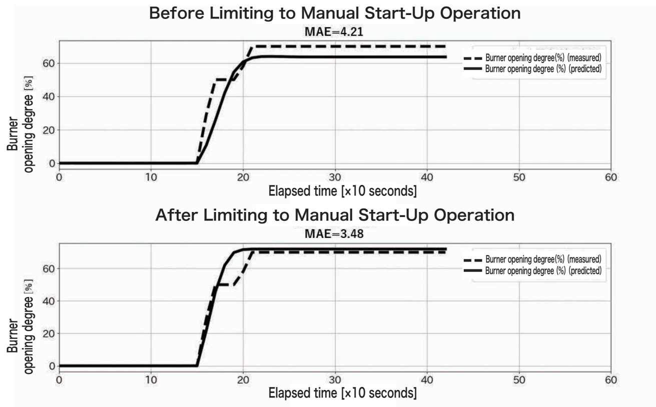

Figure 3-6: Trend Graph of Burner Opening Degree Before and After Limiting to Manual Start-Up Operation

3.2.6 Validation with Temperature Parameters Added to Input Parameters

To improve prediction accuracy, we considered adding ambient temperature as an input parameter. However, since ambient temperature is not measured in existing plants, we used bag inlet temperature and flue gas temperature (hereinafter referred to as "temperature parameters") to indirectly incorporate ambient temperature into the model. We then validated whether this approach would improve the performance of the predictive model. The temperature parameters are highly dependent on the plant' s operating conditions and are believed to approach the ambient temperature after a sufficient cooling period following the end of aggregate supply. However, to ensure a sufficient volume of data, we did not perform validation using only data that had undergone sufficient cooling time. Instead, we validated the model by including the temperature parameters as additional input parameters.

Table 3.6 Relationship Between Average MAE Before and After Adding Temperature Parameters

Training Range	Average MAE [%]
Before Addition of Temperature Parameter	7. 31
After Addition of Temperature Parameter	6. 69

Table 3.6 compares the average MAE before and after adding temperature parameters as input variables. The results show that the inclusion of temperature parameters led to a reduction in the average MAE, confirming improved predictive model performance.

Figure 3-7 presents trend graphs of burner opening predictions generated by the models with and without the addition of temperature parameters to the input parameters. In the graphs, the solid line represents predicted values, while the dashed line represents actual measurements. The graphs also confirm that the model incorporating temperature parameters produces predictions that more closely align with the actual values. Furthermore, it is suggested that using only data with sufficiently confirmed cooling time may further enhance prediction accuracy by improving the quality of the training dataset.

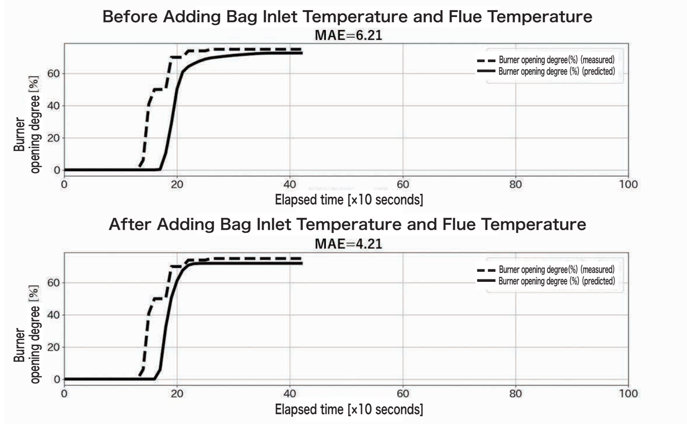

Figure 3-7: Trend Graph of Burner Opening Degree Before and After Adding the Temperature Parameters

3.2.7 Validation with Limited Training Data

Since seasonal variations in ambient temperature are considered to affect the performance of the predictive model, training and testing were conducted using data from a period with minimal temperature fluctuations to validate improvements in the model' s performance. **Figure 3-8** shows temperature variations from November 2020 to March 2021. As temperatures varied significantly from November to December but remained relatively stable from December to February, the period for obtaining operational data was set to December 2020 through February 2021. The training period covered two weeks in January 2021, and the data used for testing were from December 2020 to February 2021.

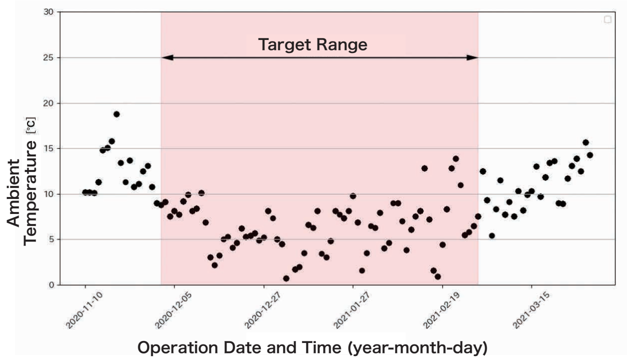

Figure 3-8: Temperature Variations from November 2020 to March 2021

The timing of the first manual adjustment of the burner opening after ignition (hereinafter referred to as "the initial burner adjustment timing") is expected to vary due to human factors and may have an adverse effect on the performance of the predictive model. Therefore, to eliminate the negative impact of such variation, a validation was conducted to determine whether focusing on the initial burner adjustment timing and narrowing the training data—by selecting 80% of the dataset as indicated by the shaded area in **Figure 3-9**—would improve predictive model performance. The proportion of data used was determined by the author, based on the judgment that a sufficient volume of operational data could be secured.

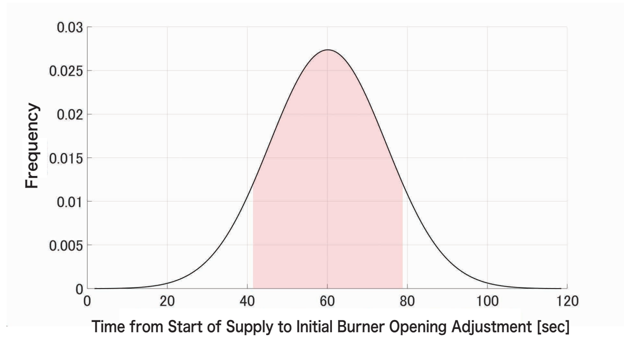

Figure 3-9: Schematic Diagram of Data Used for Validation

Table 3.7 presents the relationship between the burner opening in the data actually used for validation and the average MAE before and after narrowing the training data. The table confirms that narrowing the training data to records with minimal temperature fluctuations and closely aligned initial burner adjustment timings results in a lower average MAE, indicating improved predictive model performance.

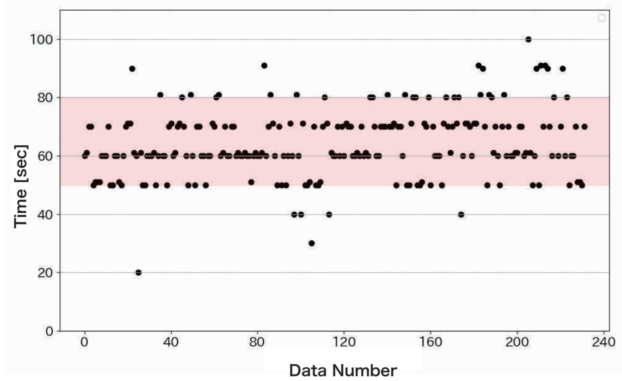

Figure 3-10: Time from Start of Supply to Initial Burner Opening Adjustment from December 2020 to February 2021

Table 3.7 Comparison of Average MAE Before and After Narrowing Training Data

Training Range	Average MAE [%]
Before Narrowing Training data	6. 80
After Narrowing Training data	4. 13

Figure 3-11 presents trend graphs of burner opening predictions generated by the models before and after narrowing the training data. The solid line represents predicted values, while the dashed line represents actual measurements. The graphs also confirm that the model trained with the narrowed dataset produces predictions that more closely align with the actual values.

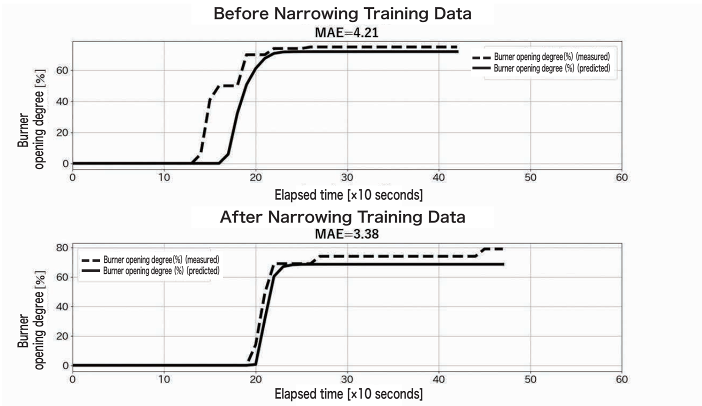

Figure 3-11 Trend Graph of Burner Opening Degrees Before and After Narrowing Training Data

4. Conclusion

In this paper, we developed a predictive model for V-burner opening based on the operations of a veteran plant operator and evaluated the appropriate conditions for the training data.

The conditions identified through testing as appropriate involve focusing on manual start-up operations, selecting data under stable ambient temperature conditions, and choosing data in which the timing of the initial burner adjustment is similar. On the other hand, challenges remain in making accurate predictions during seasons with large temperature fluctuations and in maintaining prediction accuracy when the model is applied to seasons different from those used for training. These issues will need to be addressed in our future work.

5. Future Outlook

We plan to verify the accuracy of the developed predictive model through field testing. Furthermore, we will work on improving the model so that it can adapt to changes in ambient temperature due to seasonal variations. Through these efforts, we aim to reduce the amount of data required for the operation support system and figure out a method for enabling its early implementation in real-world applications.

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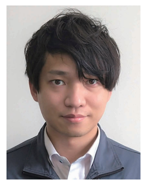

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