Machine Learning-Based High-Resolution Prediction of Low-Resolution Aerosol Data Generated During Metal Cutting

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1. Introduction

During the decommissioning of the nuclear power plant, a cutting process is essential to make the internal metal structure suitable for disposal. The process of cutting radioactive materials contaminated with the surface of the structures generates radioactive aerosols. Most aerosols generated during metal cutting are in the 0.01-1 μm size range. Radioactive aerosols in this size range can generate internal exposure through the inhalation of the worker[1-2]. Previous studies have evaluated aerosols during metal cutting[3-5].

Data resolution improvements are needed to assess worker safety from radioactive aerosols accurately. Min-Ho. Lee (2021) demonstrated the importance of high-resolution aerosol measurements by comparing conventional low-resolution (low measurement range and channel) aerosol measurement data with high-resolution aerosol measurement data[2]. However, high-resolution aerosol measurement equipment varies depending on the specifications, but it is expensive, so it is limited to use in nuclear power plants.

Therefore, this study aims to improve the data measurement limitations of existing low-resolution aerosol data and low-resolution monitoring equipment. This study built data on simultaneous measurements of low-resolution and high-resolution aerosol measurement equipment and improved low-resolution data by synchronizing and analyzing the two data through machine learning.

2. Methods

2.1 Experiments and data collection

Fig. 1 shows the flow from acquiring aerosol data to applying machine learning. First, metal is cut to generate aerosols. Fig. 2 shows the metal cut process and aerosol measured using two measuring equipment. Cut the metal specimens (SUS304 and SS400) using cutting tools (Laser, Plasma, and Flame). Furthermore, measure the aerosol generated during the cutting process using the low-resolution aerosol measuring equipment (OPC, Optical Particle Counter, Grimm Ltd.) and the high-resolution aerosol measuring equipment (HR-ELPI+, High Resolution-Electrical Low-Pressure Impactor, DEKATI Ltd.). The data was collected by simultaneously measuring aerosols using two pieces of equipment positioned in the same location within the experimental space.

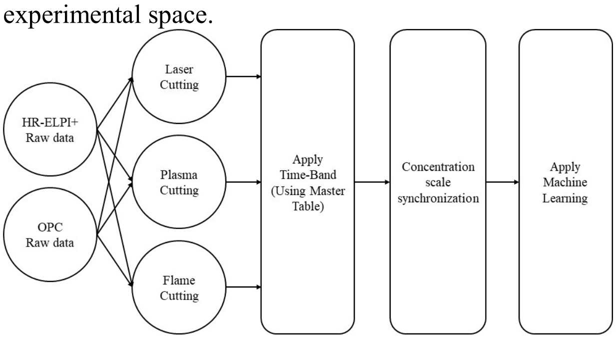

Fig. 1. Aerosol data collect process flow chart

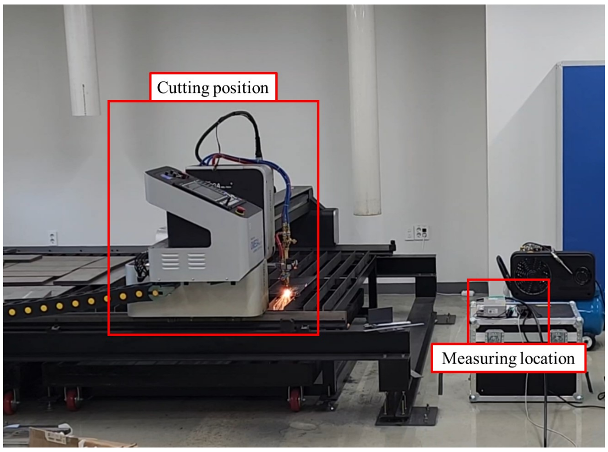

Fig. 2. Metal cutting simulation equipment and aerosol measurement

As shown in Table 1 and Fig 3, both measuring equipment have different specifications. Therefore, the data preprocessing process was conducted to apply the measured aerosol data to machine learning. During the data construction process, since the OPC and HR-ELPI+ data are expressed in different units (#/L and #/㎤ respectively), a unit conversion was performed to standardize the measurements. Additionally, OPC data is sampled every 6 seconds, whereas high-resolution aerosol data is sampled every 1 second. To adjust the measurement intervals, OPC data, measured every 6 seconds, was interpolated over time to match the data intervals of HR-ELPI+.

Table 1: Aerosol measuring equipment specification

Equipment	Detail function
OPC	- Number of diameter channel : 6(0.3-10 ㎛, over 10 ㎛) - Sampling interval : 6 seconds - Aerosol measurement method : optical - Unit of measurement : #/L
HR-ELPI+	- Number of diameter channel : 500(0.006-10 ㎛) - Sampling interval : 1 seconds - Aerosol measurement method : impactor(aerodynamic) - Unit of measurement : #/㎤

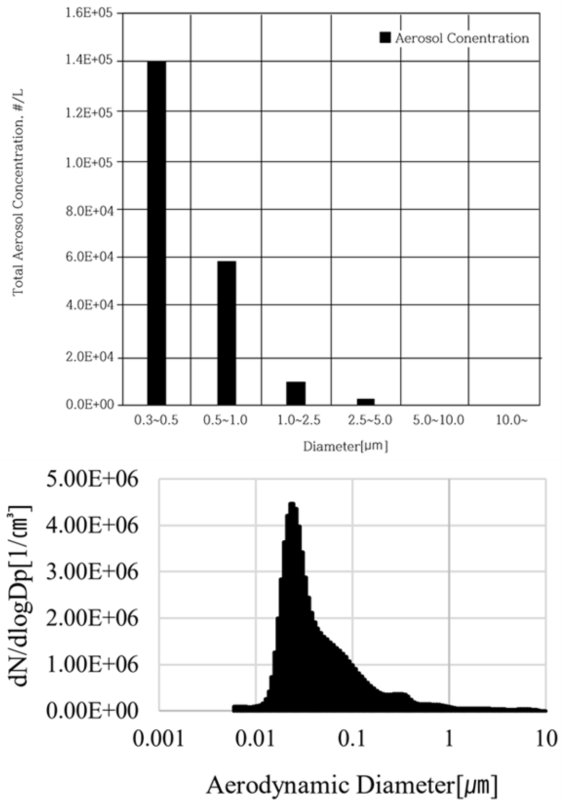

Fig. 3. Examples of OPC and HR-ELPI+ measurement data

2.2 Machine Learning Using Aerosol Data

Based on the data obtained from the simultaneous measurement of the two instruments, machine learning was performed to upscale the OPC data to 500-diameter channels, similar to HR-ELPI+, by treating the OPC data as part of the HR-ELPI+ data. The machine learning was conducted using supervised learning with an Artificial Neural Network (ANN) model. Machine learning was performed using the Keras package in Python, as shown in Table 2. The ANN model utilized three hidden layers, as depicted in Figure 5. The hidden layers were configured with 25, 128, and 500 units, respectively, the number of which was determined through manual search.

Table 2: Python and Keras usage parameters

Pakage	*Version*	*Parameter*
Python	3.8.5	-
Keras	2.4.3	Layer : Dense Initializer : normal Activation : relu, softmax(only unit 500) Compile : mean squre error optimizer : adam

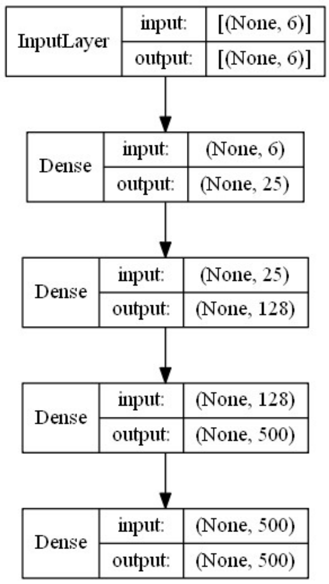

Fig. 5. ANN Dense layer(Hidden layer :6, 25, 128)

The number of data points used for machine learning is shown in Table 3. A separate data frame was constructed for each cutting method to reflect the differences in the cutting methods and machine learning was performed accordingly. For each cutting method, 90% of the obtained data was used for training, while 10% was used for validating the machine learning model. The predictive accuracy of the machine learning model was evaluated by calculating R-squared(R^2), Root Mean Square Error (RMSE), and Mean Absolute Error(MAE. Additionally, the Count Median Aerodynamic Diameter (CMAD) was calculated to determine whether the actual distribution was accurately predicted..

Table 3: Number of data used for machine learning

Cutting Method	*Learning Data*	*Test Data*	*Total Data*
Laser	6,598	734	7,332
Plasma	32,130	3,570	35,700
Flame	28,187	3,132	31,319

The number of X and Y are same in machine Learning

3. Result and Discussion

Fig. 6 shows the results of predicting low-resolution data into high-resolution data using the ANN model. A narrower predicted data range was observed compared to the observed data range. This result is because most of the data applied in the machine learning process includes distributions that peak at 0.1 after cutting, likely a consequence of supervised learning based on a large amount of data.

The model's predictive accuracy was analyzed by calculating the R^2, RMSE, and MAE between the observed data and the predicted data. The R^2 value was calculated to be 0.88, while the RMSE and MAE were calculated to be 0.012 and 0.005, respectively. Additionally, similar values were observed when comparing the CMAD between the observed data range and the predicted data range. The results, with an R^2 value above 0.8, RMSE and MAE values close to zero, and similar CMAD outcomes, indicate the high accuracy of the machine learning model.

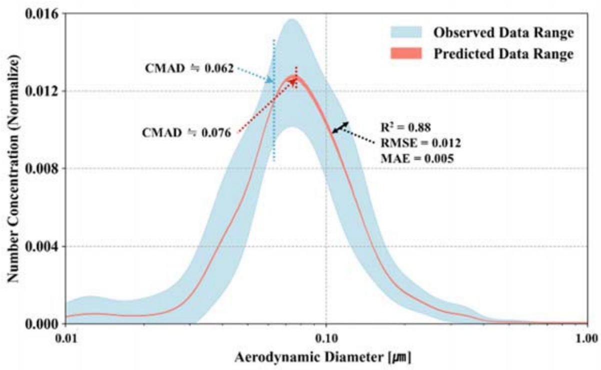

Fig. 6. HR-ELPI+ Simultaneous observed data distribution (Blue) and Prediction data distribution (Red)

4. Conclusion

This study shows that the distribution of high-resolution aerosol data through upscaling from low-resolution data shows sufficient predictive value and demonstrates the practicality and usefulness of machine learning in aerosol monitoring. The results suggest converting existing low-resolution measurement technology and data from previous studies into high-resolution using the simultaneous measurement data established in this study.

Further research can address the predicted data range's limitations and enhance the model's accuracy by applying various models and refining machine learning parameters. By achieving precise high-resolution distribution predictions and characteristics, this approach can effectively evaluate the safety of nuclear power plant decommissioning workers in the future.

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