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Intelligent Combustion Control in Waste-to-Energy Facilities: Enhancing Efficiency and Reducing Emissions Using AI and IoT

Dongmin Shin [1,2], Jaeho Lee [1], Jihoon Son [1], Yongkeun Yun [1], Yoonchan Song [1] and Jaeman Song [2,*]

[1] SKecoplant Co., Ltd., Seoul 03143, Republic of Korea; dm.shin@sk.com (D.S.); jhleec@sk.com (J.L.); sjh1005@sk.com (J.S.); yongkeun.yun@sk.com (Y.Y.); chan1003@sk.com (Y.S.)

[2] Department of Mechanical Engineering, College of Engineering, Kyung Hee University, Yongin 17104, Republic of Korea

* Correspondence: jaemansong@khu.ac.kr

Abstract: Expanding waste-to-energy (WtE) facilities is difficult, and with tightening incineration regulations, improvements in WtE facility operations are required to dispose of waste that is increasing by an average of 4.8% annually. To achieve this, an intelligent combustion control (ICC) system was studied using digital technologies such as the Internet of Things and artificial intelligence to improve the operation of WtE facilities. The ICC system in this study is composed of three modules: perception, decision, and control. Perception: collecting and visualizing digital data on the operating status of WtE facilities; Decision: using AI to propose optimal operation methods; Control: automatically controlling the WtE facility according to the AI-suggested optimization methods. The ICC system was applied to the "G" WtE facility, a solid waste WtE facility operating in Gyeonggi province, Republic of Korea, and the digital data collected over six months showed high quality, with low delay and a data loss rate of only 0.12%. Additionally, in January 2024, the ICC system was used to automatically control the second forced draft fan and induced draft fan over a four-day period. As a result, the incinerator flue gas temperature decreased by 0.66%, steam flow rate improved by 2.41%, power generation increased by 3.09%, CO emissions were reduced by 60.72%, and NOx emissions decreased by 7.33%. Future research will expand the ICC system to include the automatic control of the first forced draft fan and the operation time of the stoker.

Keywords: waste-to-energy (WtE); intelligent combustion control (ICC); artificial intelligence (AI); internet of things (IoT)

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1. Introduction

To manage the increased waste resulting from economic growth and improved living standards, expanding waste-to-energy (WtE) facilities is necessary, but implementing this is difficult. Globally, if current waste policies and technologies are maintained, municipal solid waste is expected to increase by approximately 77% from 2126 million tons in 2020 to 3782 million tons in 2050 [1]. In China, waste transportation volume is projected to increase by about 55% from 228.02 million tons in 2018 to 353.20 million tons in 2025, while incineration treatment is expected to grow by approximately 120% from 101.85 million tons in 2018 to 223.93 million tons in 2025 [2]. Japan incinerated 78% of its waste in 2019, with an expected increase to 79.5% by 2025, a 1.3% rise [3]. According to the 2021 Waste Generation and Treatment Status Report [4], Korea's waste generation in 2021 was 197.38 million tons, with an annual average increase of 4.8% over the past five years. The amount of waste incinerated for disposal also increased from 9.65 million tons per year in 2016 to 9.79 million tons per year in 2021, a 1.5% rise, and starting in 2026, the direct land-filling of municipal solid waste will be banned, leading to further increases in waste incineration. However, by 2026, 50% of the national WtE facilities will have exceeded their 20-year lifespan [4], resulting in reduced operating hours and decreased incineration efficiency, causing a shortage in WtE facility capacity. Consequently, while the government and private incineration companies are attempting to expand WtE facilities, concerns about the risks of air pollutants emitted during the incineration process are making project implementation difficult.

Regulations on air pollutants and greenhouse gas emissions from WtE facilities are being strengthened. Nitrogen oxides (NOx) and carbon dioxide (CO_2), emitted during the waste incineration process, are subject to emission regulations as air pollutants and greenhouse gases. Europe (50–120/150 mg/Nm^3), Japan (114 mg/Nm^3), and Korea (144 mg/Nm^3) have strict emission standards for air pollutants released during the incineration process. In China (300 mg/Nm^3), as incineration expands, it is expected that air pollutant emissions will become more stringent [5]. In particular, in the case of Korea, the Korea Ministry of Environment has set goals in the Third Comprehensive Plan for Air Environment Improvement (2023–2032) to reduce nationwide NOx emissions by 33.3% by 2027 and by 45.4% by 2032 compared to 2021 levels [6]. Consequently, NOx emission regulations for WtE facilities are also being tightened. Additionally, various greenhouse gas reduction policies and regulations are being implemented across industries to respond to the climate crisis. WtE facilities, which account for 39.4% (6.593 million tons CO_2eq in 2020) of greenhouse gas emissions in the waste sector, are also required to reduce their greenhouse gas emissions [7].

Several countries are aiming to achieve carbon neutrality by recovering heat generated during the incineration process. China is implementing policies to achieve carbon neutrality by reducing greenhouse gases generated during waste landfilling and utilizing energy recovered from the incineration process as a means to replace coal-fired power plants. Various technology developments and policies are being implemented for this [2]. Japan's Ministry of the Environment has established and is implementing a plan to expand electricity production per ton of waste from 213 kWh in 2019 to 321–382 kWh by 2025 and 359–445 kWh by 2030 as a measure against global warming [3]. In Korea, energy recovery from waste incineration in private WtE facilities increased by 37% from 4,245,000 Gcal/year in 2015 to 5,830,000 Gcal/year in 2020, resulting in a reduction effect of 3,263,000 tons CO_2eq [8].

Therefore, research on improving the equipment and operation of WtE facilities is required to enhance their efficiency of energy generation and reduce air pollutant emissions. Equipment improvements involve enhancing the structure, shape, and processes of WtE facilities to improve the combustion process and efficiency. Many WtE facility manufacturers and research institutions are conducting studies on this. Operational improvement involves enhancing the procedures and methods of operating WtE facilities, which are implemented through systems such as the Automatic Combustion Control (ACC) system.

Improving the operation of WtE facilities using digital technology offers high accessibility and significant benefits. Improving the equipment involves high investment costs and risks, and the return on investment (ROI) is long, making project implementation challenging. However, improving operations using digital technology can be applied to in-serviced WtE facilities, requires relatively low investment, and offers a short ROI, making it highly accessible. Recently, intelligent combustion control (ICC) systems, which use digital technologies like the Internet of Things (IoT) and Artificial Intelligence (AI) to enhance existing ACC systems, have been studied. ICC systems are reported to be very effective not only in their economic advantages for implementation and operation but also in improving combustion efficiency and reducing pollutants [9–15]. Most WtE facilities currently operate simply to comply with environmental regulations, relying on empirical and conventional methods. Therefore, the effectiveness of operational improvements is expected to be high when ICC systems are utilized.

Waste has a very high degree of uncertainty in its combustible component composition, which has been reported as a limitation in the waste combustion control of ACC systems using traditional control methods. Unlike fossil fuels, waste does not have consistent combustible components (carbon, hydrogen, and sulfur) and moisture content, and it is impossible to determine the changing combustible composition and moisture content of waste in real time during the incineration process. Therefore, automatically controlling the appropriate oxygen supply to fully combust with uncertain combustible composition and moisture content has been shown in past studies to be limited by traditional control methods such as PID (Proportional–Integral–Derivative) control or sequential control [16–18]. Hwang et al. [19] modeled these nonlinear combustion processes as a multivariable linear process using AutoRegressive with eXogenous inputs (ARX) to predict steam production, O_2, CO, NOx, SOx, and dust emissions, and studied adaptive control using these predictions.

Studies have been conducted to overcome the limitations of existing ACC systems by using AI control algorithms such as fuzzy logic and metaheuristic methods. Song et al. [18] studied a fuzzy logic expert control system using steam production, incinerator pressure, CO concentration, and O_2 concentration. This research developed a combustion control system that responds to changes in steam production and waste combustible composition by controlling the timing of waste feed, stoker speed, air supply amount, and air supply temperature. Jang et al. [17,20] studied an expert system using fuzzy control as an auxiliary system to a PID control system. This system confirmed that exhaust gas temperature, CO concentration, O_2 concentration, and incinerator pressure were stabilized compared to manual operation by auxiliary control of waste feed weight, air supply amount, and auxiliary fuel amount. However, the target incinerator in the study had a small capacity of 5 tons/day and was a rotary kiln type, which differs in type and capacity from the WtE facilities targeted in this study. Park et al. [16] used fuzzy logic to predict incinerator operating conditions and researched optimal operation using a genetic algorithm. Through this, waste feed weight and primary air supply were controlled to stabilize steam production compared to manual operation. Chang et al. [21] conducted research on controlling waste feed weight, primary/secondary air flow/temperature, and superheated steam flow using fuzzy logic and genetic algorithms. Yu et al. [22] confirmed through simulation that Fuzzy Neural Networks (FNNs) achieve stable control more quickly and with less overshoot compared to PID control and fuzzy control.

Recently, studies have been conducted to improve incinerator combustion and ACC systems using machine learning (ML)-based AI on operating data from WtE facilities. Chen et al. [23] predicted furnace temperature, ember stage temperature, flue gas oxygen content, and steam flow in a stoker incinerator using CNN (Convolutional Neural Network) BiLSTM (Long Short-Term Memory). Compared to traditional models such as LSSVM (Least Squares Support Vector Machine), CNN, and LSTM, the CNN-BiLSTM model showed higher prediction accuracy and applicability. Tang et al. [24] reviewed various AI algorithms and methods that could be used in WtE facilities and projected that AI-based incinerator combustion control will become a future research trend due to its advantages in overcoming the limitations of manual control, reducing costs, improving energy efficiency, and decreasing pollutants. However, they noted that the reviewed AI studies face difficulties in direct application to actual industrial sites due to the closed nature of the DCS (Distributed Control System). Lee et al. [25] estimated the heat value of waste using LSTM and reported that when operating a WtE facility based on the estimated results, compared to operation based on operator experience, there was a 70% reduction in response time and a 20% improvement in power system stability, enhancing operational stability by 44%. Tskamoto et al. [9] studied a system that uses 91 digital data points collected at 1 s intervals in a DCS and neural network algorithms to predict steam production and automatically control primary air flow. They reported that while manual operation achieved 80% of the target steam production, using this automatic control system increased it to 89%. Fujiyoshi et al. [10] and Yamase et al. [11] used AI to understand waste combustion status through flame images and fuzzy logic learned from operator experience to predict steam production and CO emissions. They reported that applying these predictions to the existing ACC system improved the steam production variation coefficient from 1.5 to 0.9 and reduced CO emissions by 24%. Egusa et al. [12] and Terasawa et al. [13] used ML to predict the calorific value of waste, steam production, and CO emissions 3 min in advance and AI to understand waste combustion status through flame images, improving the ACC system. They reported that this reduced manual operation by 90% and stabilized steam production. Tsuda et al. [14] and Kojima et al. [15] applied AI to understand waste combustion status through flame images to the existing ACC system. They reported a 4% increase in power generation, a 52% reduction in CO concentration, a 30% reduction in ammonia usage, and an over 30% improvement in the steam production variation coefficient.

However, previous studies on waste combustion control using AI had limitations when applied to WtE facilities. Most research on improving incinerator combustion and control using fuzzy logic, metaheuristic methods, and ML-based AI confirmed their effectiveness only through simulations in labs without verifying their expansion to ICC systems or their effectiveness in in-serviced WtE facilities. Specifically, the ML-based AI systems developed by WtE facility manufacturers were studied as auxiliary systems to the ACC system, making them inapplicable to WtE facilities that do not use the incinerator manufacturer's ACC system. Moreover, previous studies focused on AI for controlling combustion and did not explore data collection methods or control systems to enhance AI learning and inference accuracy.

Therefore, this study aimed to research an intelligent combustion control (ICC) system using ML-AI to enhance energy recovery and reduce air pollutant emissions from WtE facilities. The ICC system developed in this study is composed of (1) operating data collection, (2) AI to propose optimal incinerator operation methods, and (3) automatic control of the incinerator based on the AI-suggested methods. This system is more effective in controlling the combustion of waste with high uncertainty compared to traditional automatic control methods implemented in existing ACC systems. Additionally, the ICC system, utilizing the latest digital technologies, minimizes investment and operational costs while enhancing usability, ensuring its applicability to in-serviced WtE facilities and effectively achieving the study's objectives.

2. Methods

A study was conducted on an ICC system that automatically controls the airflow of a stoker incinerator using AI. Among the various types of incinerators, the research focused on the most widely operated stoker-type WtE facility. Of the representative operational variables of stoker incinerators—waste feed rate, airflow, and stoker speed—the study explored the method of automatically controlling airflow using AI, as it has the greatest impact on the combustion process. The waste combustion process in the stoker-type WtE facility targeted in this study is presented in Figures 1 and 2.

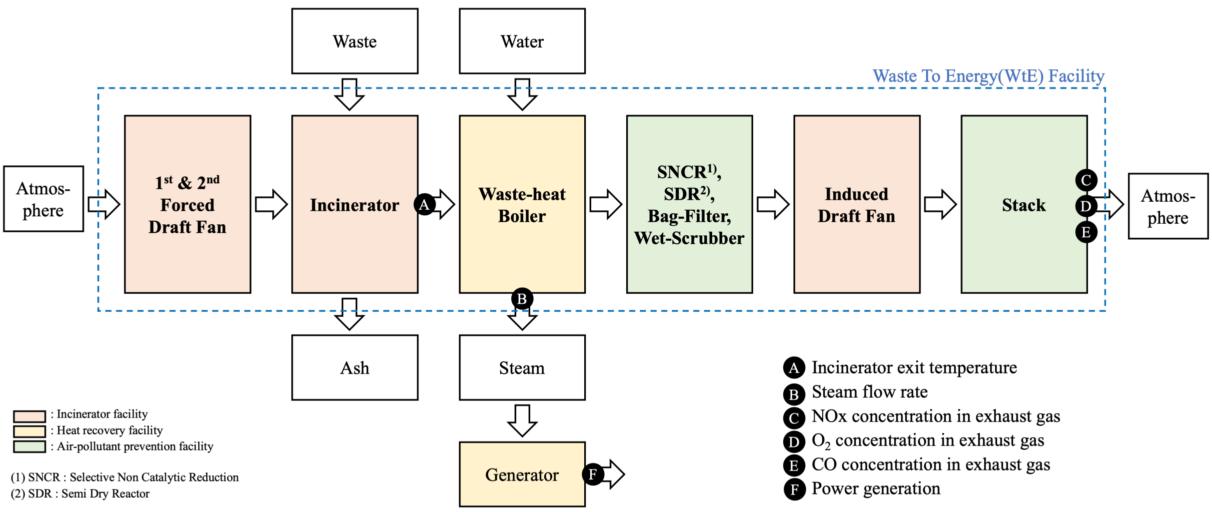

Figure 1. Overall incineration process of the WtE facility.

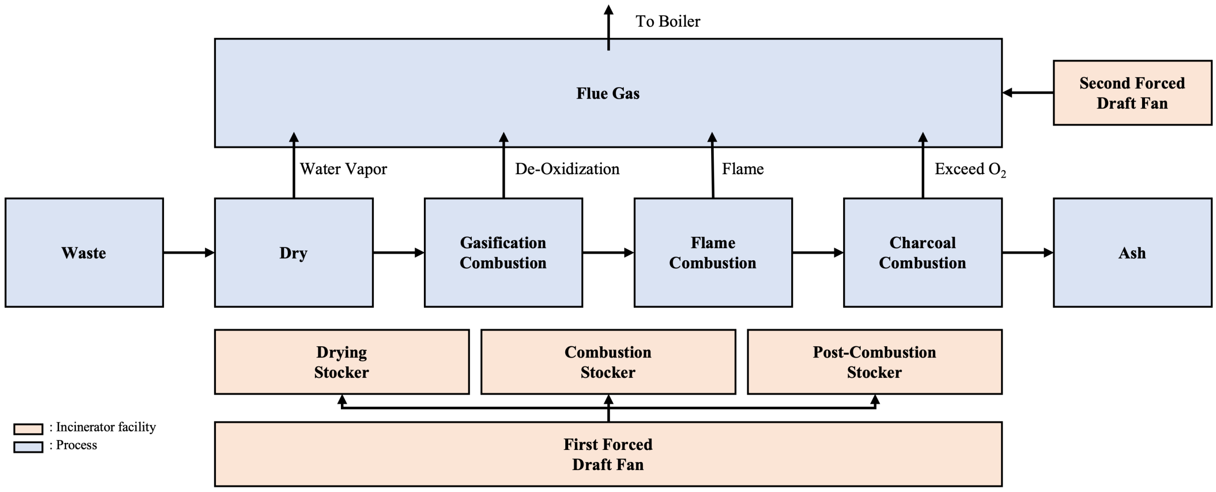

Figure 2. Overall combustion process in stoker-type incinerator [26].

Through literature and field surveys, the current status and problems of incinerator operation and ACC systems were identified, and research directions for improvement were derived. The ICC system that meets the research directions was studied in three stages: perception, decision, and control. The developed ICC system was experimented at the stoker-type "G" WtE facility in Gyeonggi Province, Republic of Korea, to evaluate the feasibility and appropriateness of the study.

2.1. Field Survey

From February 2021 to March 2023, a field survey and interviews were conducted at 14 WtE facilities with operators, facility managers, and general managers to investigate the current status and issues of incinerator operations and ACC systems. The 14 WtE facilities surveyed included 2 municipal solid waste WtE facilities operated by public entities, 8 municipal/industrial soild waste WtE facilities operated by private incineration companies, 3 private medical soild waste WtE facilities, and 1 overseas industrial/medical solid/liquid waste WtE facility. Thirteen of these WtE facilities used stoker-type systems, and one used a rotary kiln–stoker combination.

The survey revealed that the utilization rate of ACC systems was low, and WtE facilities were primarily operated based on operator experience. Due to the high uncertainty in the waste combustion process, existing ACC systems are known to face difficulties in achieving optimal combustion control of the incinerator. For these reasons, the utilization rate of ACC systems installed at the 2 public WtE facilities was low, and the 12 private WtE facilities did not have ACC systems installed. Operators visually monitored the incinerator's operating status displayed on the Machine–Human Interface (HMI) and manually adjusted operational variables based on their judgment and experience of the waste combustion situation. Due to the manual adjustments, there were physical limitations in responding to the rapidly changing waste combustion patterns, leading operators to fix operational variables at empirical values without making adjustments. Additionally, the level of experience among operators varied, resulting in differing levels of judgment, and the transfer of experience to improve judgment was not effectively conducted.

This reliance on operator experience and manual adjustments led to missed opportunities for further improving energy recovery and reducing pollutant emissions. Most WtE facilities operated empirically and conventionally within the limits of environmental regulations rather than focusing on enhancing energy recovery and reducing air pollutant emissions. Consequently, the operation of WtE facilities focused more on complying with legal regulations and increasing revenue through waste incineration rather than actively achieving social goals.

2.2. Research Directions for Improvement of WtE Facility

Based on the findings from literature reviews and field surveys, the study aimed to improve the identified issues in the operational methods of WtE facilities, focusing on three key directions: safety, technicality, and commercial viability.

1. Safety: Ensuring that the technology developed in this study does not pose any threat to the operation of the incinerator.
2. Technicality: Considering reliability, scalability, maintainability (simplicity, evolvability, operability).
3. Commercial Viability: Ensuring standardization, investment cost, and openness, allowing many incineration companies to adopt the technology.

2.3. Study of the ICC System

It was assumed that AI could optimally control the incinerator fans for airflow. The AI would be trained using operating data collected during the waste incineration process, and it was assumed that the trained AI could automatically control the incinerator based on the optimal fan operation methods it determined. It was expected that, with this automatic operation, steam production would increase, and air pollutant emissions would decrease compared to operations based on the operator's experience, judgment, and manual adjustments. The validity of these assumptions was confirmed through similar studies [18–24].

The ICC system was studied in three stages: perception, decision, and control. In the perception stage, the collection and visualization of digital data on the WtE facility's operating status were researched. This enabled the AI to accurately understand the WtE facility's operating status and make appropriate decisions. In the decision stage, the AI capable of making decisions based on the perceived data was researched. The AI determined the optimal incinerator operation method to enhance energy recovery and reduce pollutant emissions from the WtE facility. Finally, in the control stage, methods for automatically controlling the incinerator based on the AI-determined operation methods were studied. The architecture of the ICC system configured in these stages is presented in Figure 3.

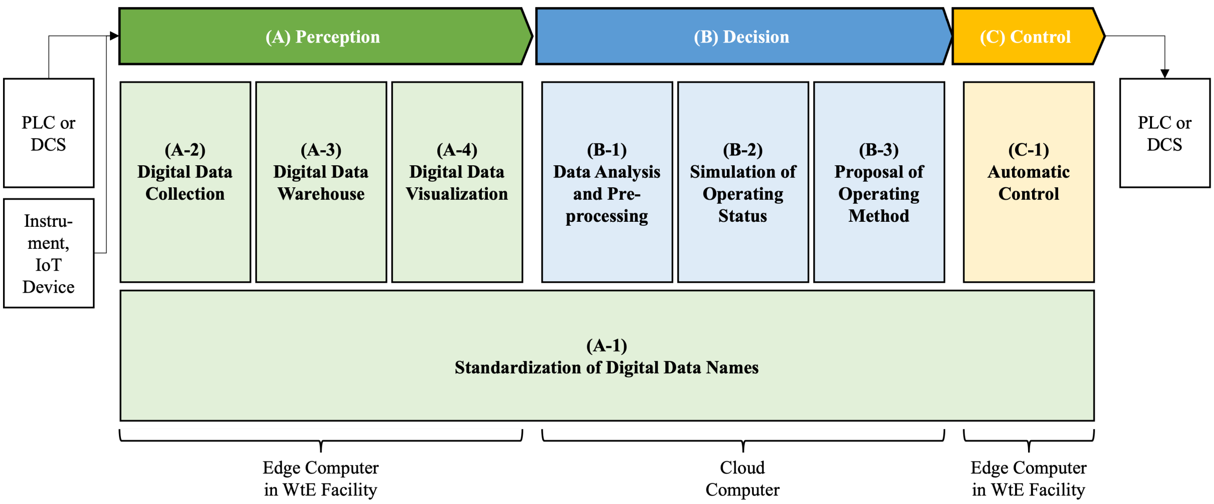

Figure 3. Architecture of the ICC system.

2.3.1. Perception

The digital data previously collected on the operating status of WtE facilities were of low quality and thus unusable in the ICC system of this study. In some WtE facilities surveyed, HMI software collected the operating status of the WtE facility as digital data. However, the number of collected digital data points was small, and they were collected as hourly or daily averages, resulting in low-quality digital data that were inadequate for predicting the operating status of the incinerator and determining optimal operation methods in the ICC system of this study.

Therefore, a study was conducted to collect high-quality digital data on the operating status of WtE facilities. An edge server installed at the WtE facility collected real-time operating status from the control system, converted it into digital data, and transmitted it to a cloud computer. The digital data transmitted to the cloud computer were processed and stored to improve their quality and usability. To achieve this, studies were conducted on (A-1) standardization of digital data names, (A-2) digital data collection, (A-3) digital data warehouse, and (A-4) digital data visualization. The quality of the collected digital data was assessed based on the rate of delay and data loss to evaluate the adequacy of the study.

(A-1) Standardization of Digital Data Names. To enhance the scalability and cost effectiveness of the ICC system, the standardization of digital data names for collecting operating status of WtE facilities was studied. Instrument tag names, which were differently assigned at each of the 12 WtE facilities surveyed, were analyzed, and standardized digital data names for collecting operating status of WtE facilities were developed. Standardized digital data names classified WtE facilities by company code, functionally divided incineration equipment by facility code, and categorized measurement targets and items by function code. By using standardized digital data names in the ICC system, the need for improvements due to different instrument tag names at each WtE facility was minimized, thereby enhancing the scalability and cost effectiveness of the ICC system.

(A-2) Digital Data Collection. The standardization of methods for collecting operating status from WtE facility control systems was studied to improve the scalability and stability of the ICC system. The survey of 12 WtE facilities revealed that the configurations of control systems varied. Researching digital data collection methods for each differently configured control system is inefficient. Therefore, standardized methods for collecting WtE facility operating status were studied using standard control protocols and IoT communication protocols, even if the control system configurations differed. Particularly, using standard control protocols improved the stability of the ICC system by preventing interference with the control systems of operational WtE facilities during data collection.

The optimization of the digital data conversion cycle for the collected WtE facility operating status was studied. The operating status collected from control systems is continuous analog information over time. Therefore, a study on the optimal conversion cycle for converting this information into discrete digital data was necessary. A short digital data conversion cycle improves the continuity of digital data and enhances the performance of the AI, but it increases the computational resource costs for transmitting, storing, and processing the digital data. Conversely, a long conversion cycle reduces computational resource costs but decreases the continuity of digital data, lowering the accuracy of the AI. Thus, this study researched the optimal digital data conversion cycle to maximize the accuracy of the AI and minimize computational resource costs based on various conversion cycle experiments and combustion theory.

A method for transmitting converted digital data to the cloud computer without loss was studied. The survey revealed that outdated network equipment at the 12 WtE facilities caused network interruptions. As a result, the transmission of converted digital data to the cloud computer was interrupted, leading to decreased data quality. Therefore, this study explored a method to temporarily store collected/converted digital data on the edge server during network interruptions and transmit the stored data to the cloud computer once the network was restored. This addressed the issue of degraded data quality due to network problems. Additionally, network firewalls were applied to enhance data transmission security over public internet connections, and the data collection-edge server and data transmission-edge server were physically separated. All digital data transmitted to and received from the cloud computer were encrypted.

(A-3) Digital Data Warehouse. The processing and storage methods for WtE facility digital data using cloud computing services were studied to improve the cost effectiveness and scalability of the ICC system. Digital data transmitted in real time from WtE facilities to the cloud computing service are stored simultaneously in the data storage service and the time-series database. The digital data stored in the data storage service are periodically processed through ETL (Extract, Transform, Load) processes to improve their quality and then used for AI training. The data stored in the time-series database are used for AI inference and real-time data visualization. For this, the study utilized cloud computer infrastructure as a service (IaaS) and software as a service (SaaS) to ensure the cost effectiveness and scalability of the ICC system.

(A-4) Digital Data Visualization. Intuitive data visualization was studied to ensure that the collected digital data are utilized for improving the operation of WtE facilities. The operating status required by WtE facility operators/managers was selected and visualized over time. Important operating status was configured to be visible on a single screen, and the relationships between digital data were visualized. Through this visualization, operators/managers could intuitively assess the operating status of WtE facilities and utilize these data to improve WtE facility operations.

2.3.2. Decision

Reliance on the operator's experience and manual adjustments in incinerator operation resulted in missed opportunities for improving energy recovery and reducing pollutant emissions. Operational variables were fixed at empirical values and were not adjusted. The levels of experience among operators varied, leading to different levels of judgment, and the transfer of experience to improve judgment levels was not effectively carried out. Consequently, this reliance on operator experience and manual adjustments led to missed opportunities for additional energy recovery and pollutant reduction.

Therefore, AI to propose the optimal incinerator operating methods was studied. AI capable of simulating the operating status of the incinerator and exploring the optimal operating methods through trial and error was researched. To achieve this, studies were conducted on (B-1) data analysis and pre-processing, (B-2) simulation of operating status, and (B-3) proposal of operating methods. The validity of the study was evaluated based on the operational results of the incinerator determined by AI. The interaction and operational sequence of the perception–decision–control stages in the ICC system are presented in Figure 4.

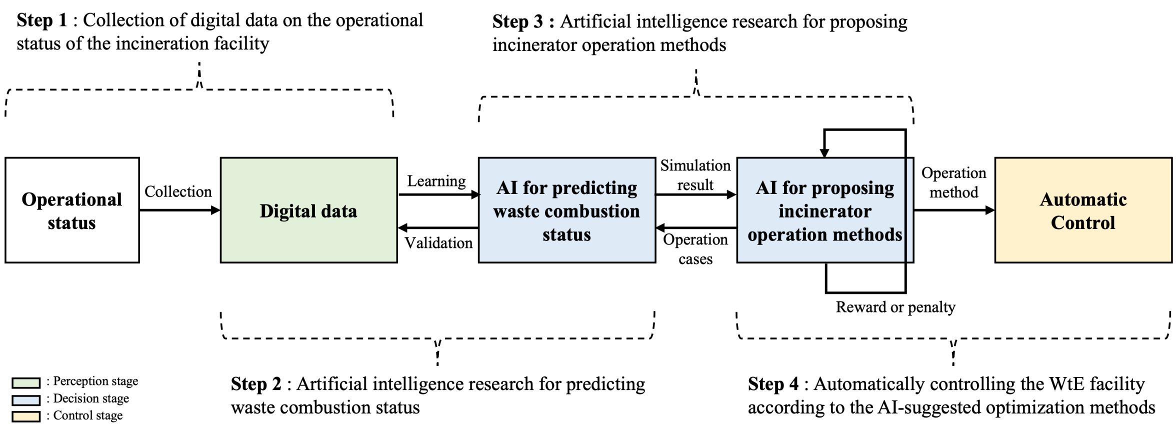

Figure 4. Operational sequence of the perception–decision–control stages in ICC system.

Data analysis and AI study were conducted using the latest version of PyTorch, and an NVIDIA DGX A100 was utilized for training.

(B-1) Data Analysis and pre-processing Operational variables, observational variables, and target variables for AI on incinerator combustion control were selected. Each variable was chosen based on combustion and thermal fluid dynamics theory to ensure that the physical phenomena are reflected in the AI under study. This approach improved the prediction and decision accuracy compared to AI implemented with simple data analysis. Operational variables were selected as variables manipulated for incinerator operation, including waste feed weight, waste feed timing, first forced draft (FD) fan, second forced draft (FD) fan, induced draft (ID) fan, and stoker speed. Observational variables, influenced by operational variables, included incinerator temperature, incinerator pressure, and other related parameters. Finally, target variables, which the AI aims to achieve, included steam flow rate, pollutant emissions, and other relevant metrics.

The selection and optimization of each operational variable followed a comprehensive procedure:

(1) Initial selection of variables based on expert knowledge and combustion/thermal fluid theory;
(2) Feature engineering, including correlation analysis and data analysis;
(3) AI modeling and evaluation;
(4) Update of variable selection;
(5) AI model update;
(6) Experimental validation;
(7) Performance evaluation;
(8) Further refinement of variable selection.

This iterative process ensured that the most relevant and impactful variables were identified and incorporated into the AI model.

Data pre-processing procedures for AI training were also studied. Methods to exclude measurement errors and outliers in the collected digital data on WtE facility operations were developed to shorten AI training time and improve accuracy. Additionally, correlations between the selected variables were analyzed to add or delete variables for AI training based on the types and quality of the collected digital data, enhancing AI performance and reducing training and inference times.

(B-2) Simulation of Operating Status. AI to simulate the operating status of the incinerator was researched. Experimentally verifying the changes in observational and target variables with changes in operational variables requires significant time and cost. Therefore, this study developed AI to simulate changes in observational and target variables with changes in operational variables using Recurrent Neural Network (RNN) ML. RNN is an artificial neural network specialized in predicting time-series data, with a structure that improves network performance on current and future inputs using past information. An AI simulating 10 variables, including incinerator flue gas temperature, incinerator pressure, and steam flow rate, was studied. After implementing the initial incinerator operating status simulation AI, hyper-parameters were repeatedly adjusted to improve the accuracy of the simulation AI. The adjustment of hyper-parameters involved evaluating the AI's prediction performance using calculated MAE and visualized results and then modifying various aspects of the AI algorithm to improve performance. These modifications included changes to data features, data averaging methods, scalers, subsequence size, epochs, sampling parameters, sequence length, and hidden layer size.

(B-3) Proposal of Operating Method. AI to propose the optimal incinerator operating methods was studied. Determining the optimal operating methods based on the incinerator operating status is very difficult, and experimentally verifying it involves many risks. Therefore, this study aimed to find the optimal operational variables by having the operating status simulation AI simulate the observational and target variables according to changes in operational variables. This exploration of the optimal incinerator operating methods was implemented using Reinforcement Learning (RL) ML. RL is a learning method where an agent interacts with the environment and learns actions that maximize rewards, with the agent learning the optimal policy through trial and error. The concept diagram of the RL algorithm is shown in Figure 5.

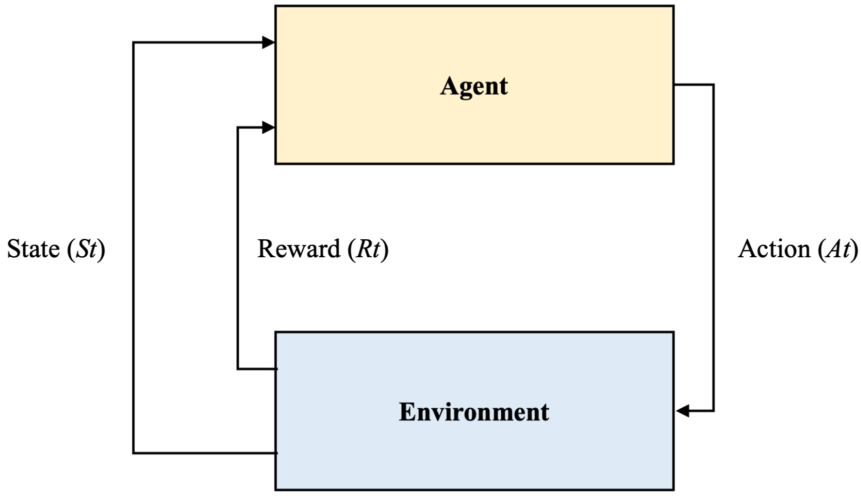

Figure 5. Concept of Reinforcement Learning (RL) algorithm.

The RL algorithm was studied to determine the optimal range of operational variables by assigning rewards and penalties based on whether the simulated observational and target variables met WtE facility operating standards and legal requirements and whether steam flow rate increased. The range of operational variable changes was conservatively applied by analyzing the experiences of operator managers and the operating distributions of the collected digital data.

2.3.3. Control

An automatic control system was configured to ensure that the incinerator fans operate automatically according to the AI-proposed incinerator operating methods. The optimal incinerator operating methods suggested by the AI in the cloud computer environment were transmitted to the WtE facility control system in the reverse direction of the incinerator operation data collection process. The existing automatic control system of the operational WtE facility was analyzed and improved so that the second FD and ID fans would be automatically controlled according to the AI-suggested optimal operating methods. In particular, to prevent operational disruptions of the WtE facility due to errors in the suggested results or during the data transmission process, maximum/minimum control ranges and interlocks, along with other safety devices, were supplemented.

The results of this study are applicable only to stoker incinerators and have not been verified for rotary kiln incineration facilities. Additionally, because the first FD fan is not automatically controlled by AI, if an operator manipulates it outside the operating range used in the AI learning process, disturbances in the combustion process or equipment failure may occur. Consequently, an interlock system was studied to prevent disturbances in the combustion process (e.g., excessive pollutant generation, rapid temperature fluctuations) and equipment failures due to first FD fan operation and unexpected situations.

The interlock was implemented across the perception, decision, and control stages. In the perception stage, information on incinerator operation and data collection status (e.g., operation, stoppage, calibration) was collected to allow verification in the decision/control stage of the context in which data were collected. In the decision stage, potential operational data that could cause disturbances (e.g., abnormal measurements, irregular data) were excluded through expert assessments using information on incinerator operating status and data collection status, and this was used in AI learning considering safety factors. The operating range that AI could propose was limited, and operational methods causing disturbances were penalized in the Reinforcement Learning (RL) process. In the control stage, if operational data excluded in the decision stage were received by the control system, if AI proposed an operational method outside the operating range, or if system abnormalities (e.g., AI malfunction, data loss, data collection/transmission issues) were detected, automatic operation was immediately halted.

3. Result and Discussion

The performance of the studied ICC system was evaluated through experiments at the "G" WtE facility located in Gyeonggi province, Republic of Korea which has a capacity of processing 72 t of municipal/industrial solid waste per day.

3.1. Perception

Out of approximately 3600 instrument tags at the "G" WtE facility, 176 tags were selected based on combustion and thermal fluid dynamics theory to monitor the WtE facility's operating status and to be used in AI learning and decision. These tags were converted into digital data names. The operating status of the WtE facility was collected by connecting seven PLC controllers and one Continuous Environmental Monitoring System (CEMS) using standardized control communication protocols and IoT communication protocols. The operating status collected according to the digital data conversion cycle was converted into digital data and transmitted to the cloud computer. The digital data on the WtE facility's operating status, transmitted from the seven PLC controllers and one CEMS, were subjected to ETL on a daily basis to integrate the collected digital data into a single reference and improve their quality.

It was confirmed that the collected digital data were of high quality. The quality of the collected digital data was evaluated based on accuracy and timeliness. Data accuracy was assessed by comparing the measurement data received by the control system with the collected digital data for errors and data loss. When comparing the digital data collected over six months, from September 2023 to February 2024, for the representative state value of the incinerator flue gas temperature, no errors were found, and approximately 0.12% of the data was lost. The data loss rate was calculated as (1 − (actual number of collected digital data/number of digital data that should have been collected according to the data collection interval)). However, since the data loss was not continuous, it was determined that there were no issues with utilizing the data in the AI. Timeliness was evaluated by examining the time taken for the WtE facility's operating status, received by the control system, to be collected as digital data. Analyzing the time differences among the measurement data received by the control system, the collection time of the operating status, the conversion time to digital data, the transmission time of the digital data, and the reception time of the digital data revealed no significant differences. The temporal changes in the representative WtE facility operating statuses collected as digital data, such as (a) incinerator flue gas temperature, (b) steam flow rate, (c) NOx concentration in exhaust gas, and (d) O_2 concentration in exhaust gas, were standardized using Z-score normalization and presented in Figure 6. Z-score normalization is a technique used to standardize the values of a dataset to have a mean of zero and a standard deviation of one. The formula for Z-score normalization is given by

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

where

- z is the Z-score,
- x is the value to be standardized,
- μ is the mean of the dataset.
- σ is the standard deviation of the dataset.

Figure 6 demonstrates that the WtE facility operating statuses are collected as digital data without data loss and can be utilized in the desired form and period through data visualization technology.

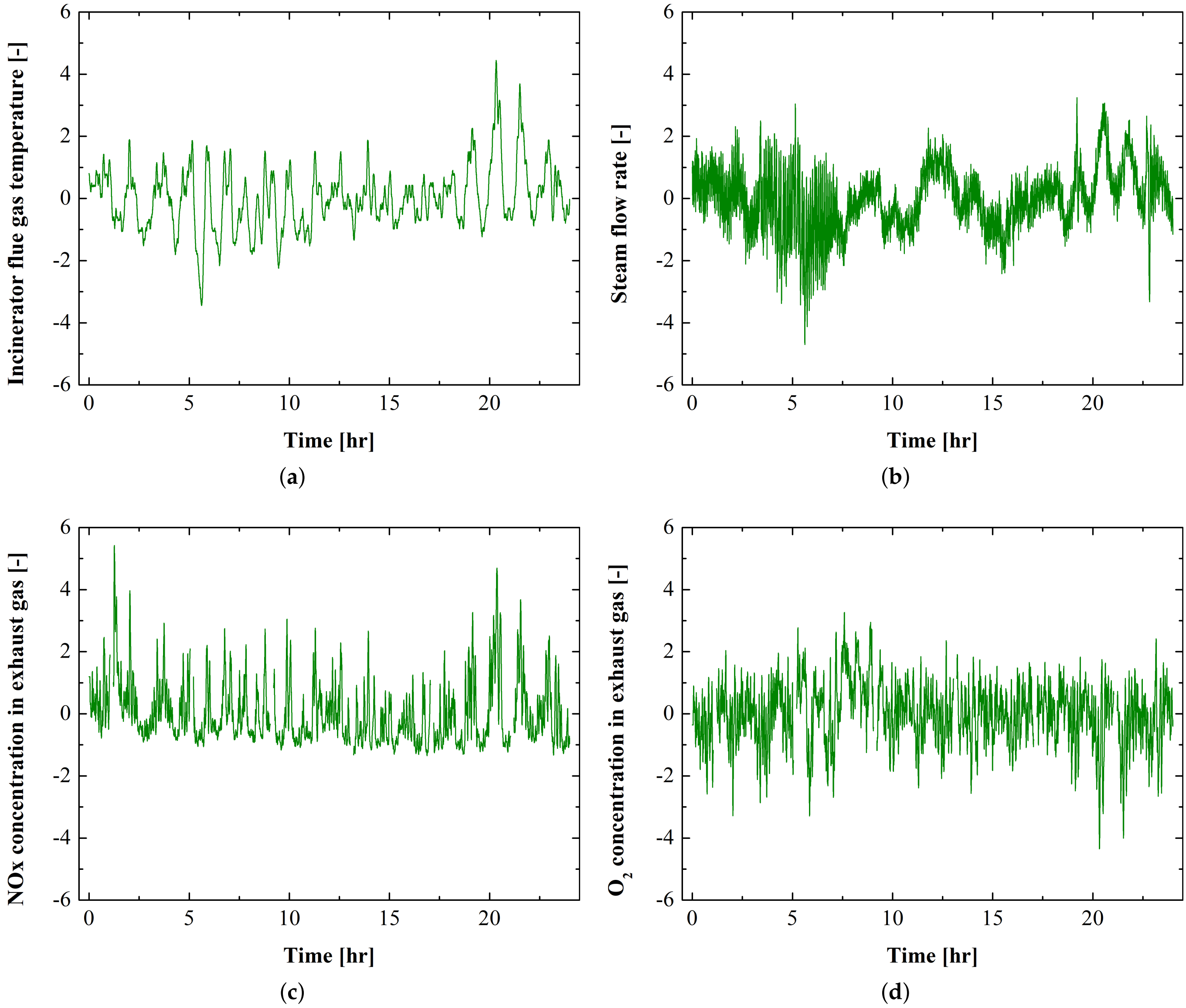

Figure 6. The digital data collected from the "G" WtE facility for one day out of six months (Z-score normalization). (**a**) Incinerator flue gas temperature. (**b**) Steam flow rate. (**c**) NOx concentration in exhaust gas. (**d**) O_2 concentration in exhaust gas.

3.2. Decision

The second FD and and ID fan were selected as control variables for optimal operation at the "G" WtE facility, as suggested by the AI. Correlation analysis of the collected digital data from the "G" WtE facility, following the data analysis procedures of this study, revealed no significant changes in the observational and target variables with the manipulation of the first FD fan. Therefore, the second FD and ID fans were chosen as the control variables to be proposed by the AI for the "G" WtE facility.

The operating status of the "G" WtE facility's observational variables, such as incinerator flue gas temperature, NOx emission concentration, O_2 emission concentration, the target variable of steam flow rate, etc., was simulated by the AI. The accuracy of these simulations was evaluated using the Mean Absolute Error (MAE). MAE is a measure used to quantify the accuracy of a predictive model. It provides a straightforward way to measure the accuracy of a model by averaging the absolute errors between the predicted and actual values. It is defined as the average of the absolute differences between the actual (ground truth) and predicted values. The MAE of the AI-simulated steam flow rate was assessed as 1.48 for the validation set and 1.56 for the test set. Table 1 presents the MAE for the key observational and target variables simulated by the AI, and Figure 7 compares the actual values (ground truth) over time with those simulated by the AI. The relatively low MAE of the test set, the small difference between the MAE of the validation and test sets, and the similar trends between the AI-simulated and actual operating status indicate that the AI simulations in this study are significant.

Table 1. MAE of the AI-simulated operating status.

Title 1	(a) Incinerator Flue Gas Temperature [°C]	(b) Steam Flow Rate [Ton/h]	(c) NOx Concentration in Exhaust Gas [ppm]	(d) O_2 Concentration in Exhaust Gas [%]
Validation set	12.73	0.22	4.11	0.73
Test set	12.40	0.23	4.41	1.00

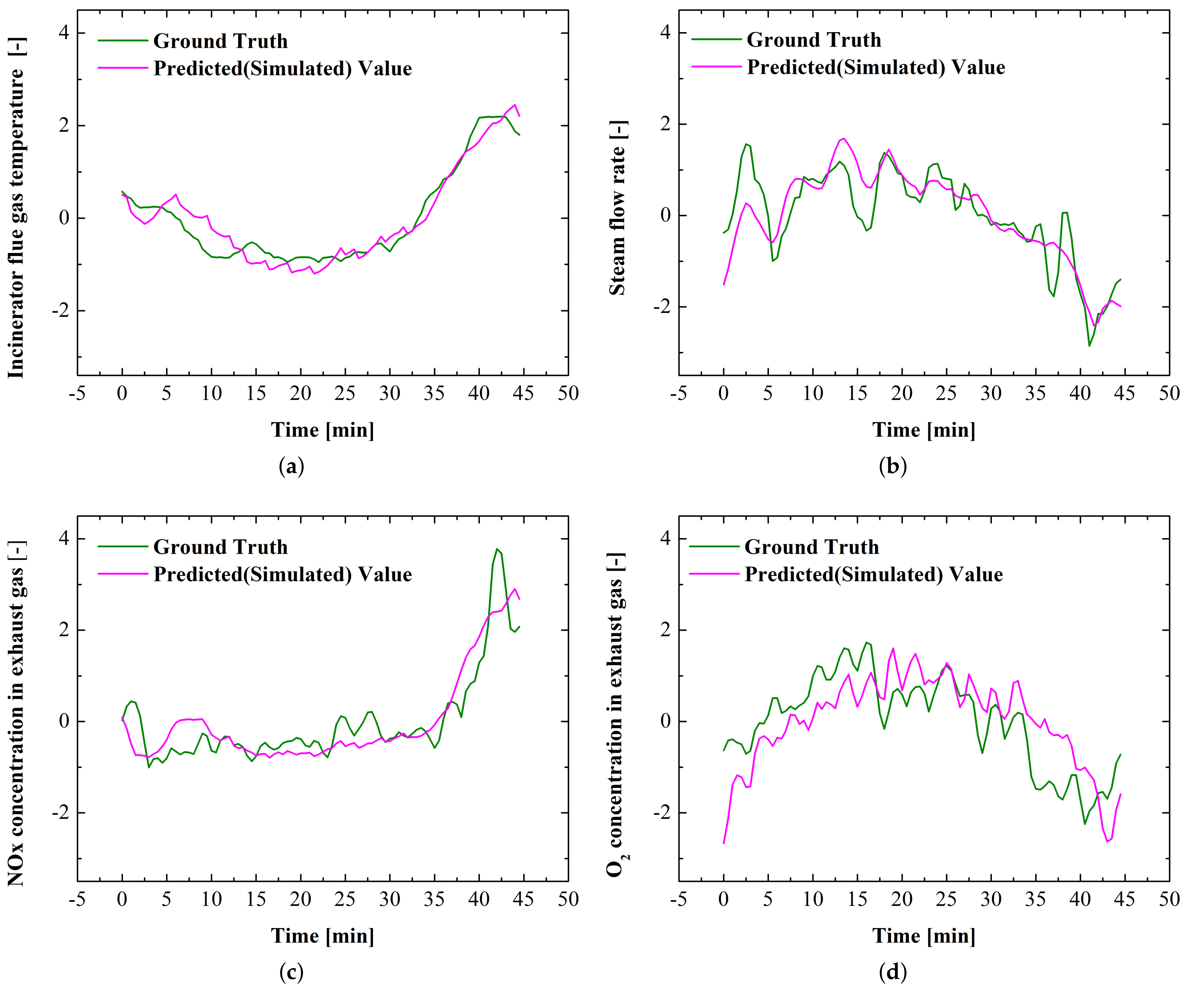

Figure 7. Comparison between AI-simulated operating status and actual values (ground truth) for 45 min of test set (Z-score normalization). (**a**) Incinerator flue gas temperature. (**b**) Steam flow rate. (**c**) NOx concentration in exhaust gas. (**d**) O_2 concentration in exhaust gas.

An RL to determine the optimal operating methods for the second FD and ID fans was studied. The changes in observational and target variables with changes in the control variables, within their historical operating ranges, were predicted. The RL predicted a

2.10% improvement in steam flow rate for the validation set and a 1.14% improvement in steam flow rate for the test set.

3.3. Control

3.3.1. Performance Evaluation of AI Combustion Control

Operating the fans according to the method proposed by the AI resulted in a 3.04% increase in steam flow rate. An experiment was conducted over eight days in September 2023 at the "G" WtE facility to evaluate the combustion control performance of the AI. The operator manually adjusted the the second FD and ID fans according to operating methods proposed by the AI at 10 min intervals. All incinerator operational variables, except for the operational variables proposed by the AI, were fixed, and waste was fed into the incinerator according to a consistent rule based on the incinerator's operating status. To eliminate other experimental disturbances (such as weather, calorific value of waste, and incinerator condition), performance of combustion control was evaluated on a daily basis. The experimental results, shown in Figure 8, indicate that compared to operation based on operator experience, AI-driven operation increased the incinerator flue gas temperature by 0.37%, steam flow rate by 3.04%, and power generation by 2.97%, while CO emission concentration decreased by 29.88% and NOx emission concentration increased by 15.69%. Although NOx emissions slightly increased, they remained within the legal emission limit of 42.5 ppm.

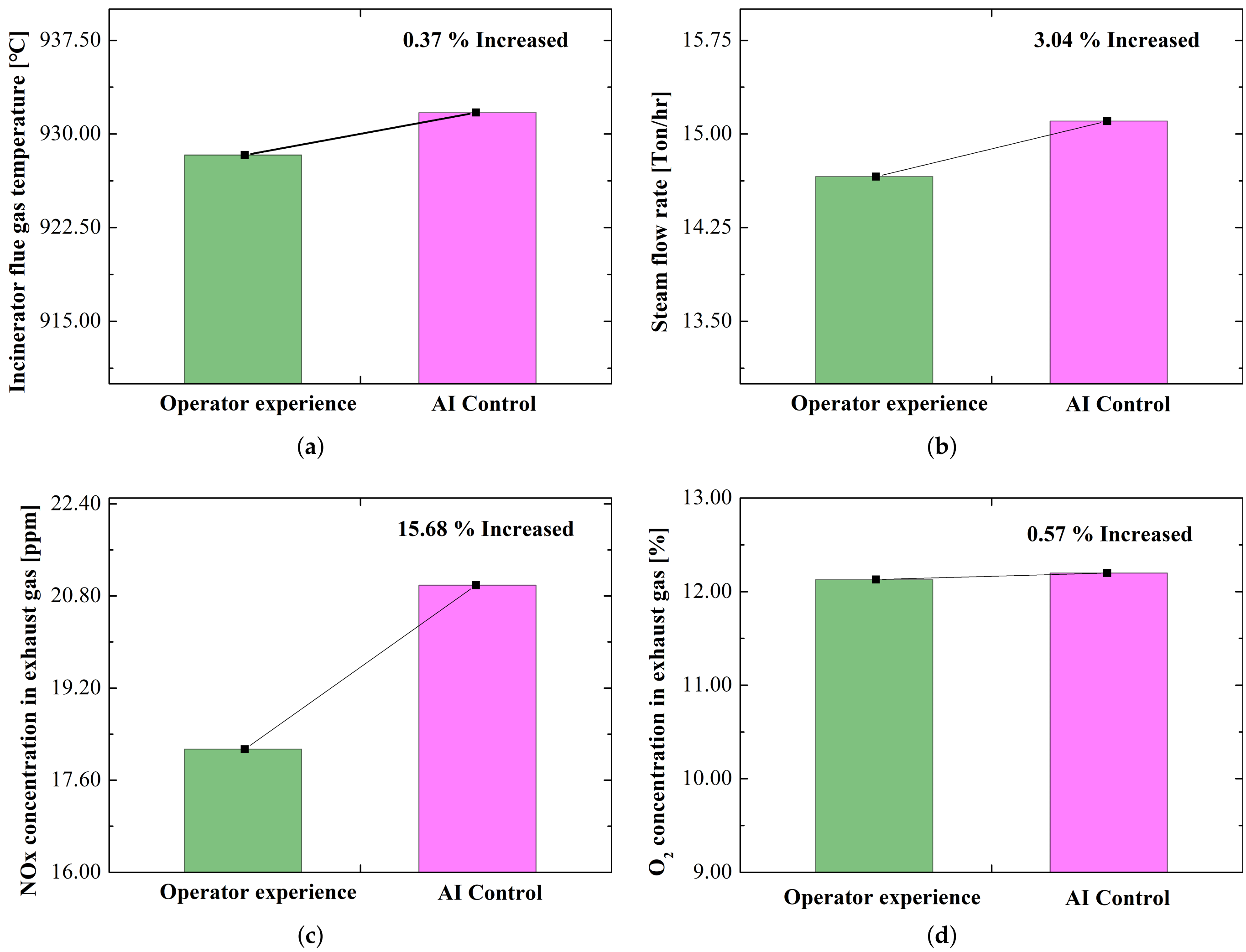

Figure 8. *Cont.*

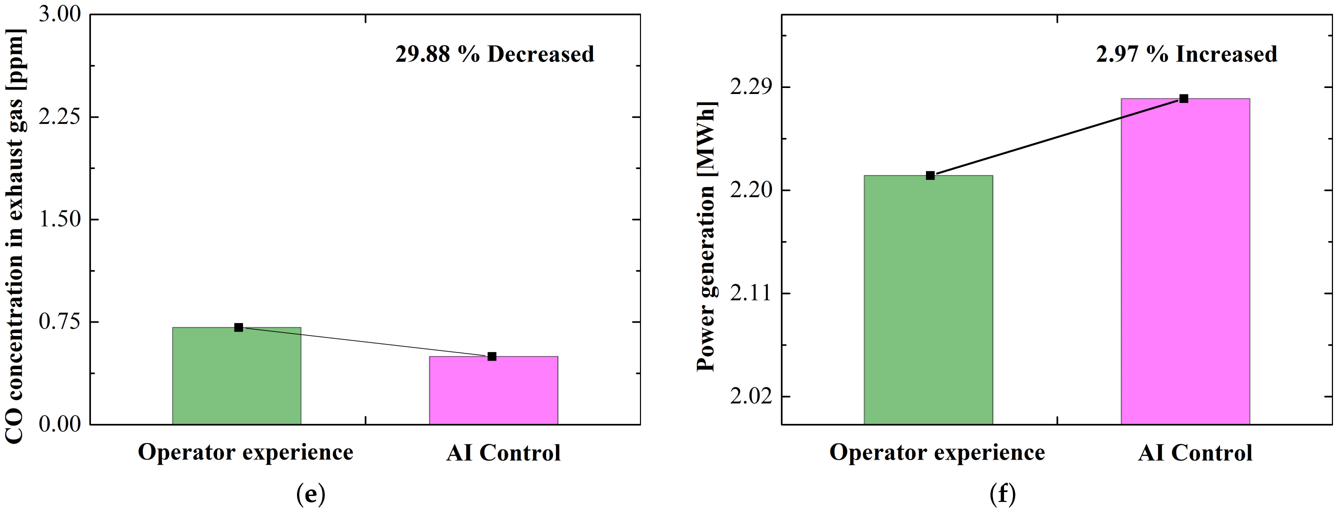

Figure 8. Evaluation of AI combustion control for eight days. (**a**) Incinerator flue gas temperature. (**b**) Steam flow rate. (**c**) NOx concentration in exhaust gas. (**d**) O_2 concentration in exhaust gas. (**e**) CO concentration in exhaust gas. (**f**) Power generation.

It was confirmed that AI can control incinerator combustion. During the experiment, no anomalies or malfunctions occurred in the WtE facility, and it operated stably. Un-burned residues were fully combusted with the appropriate supply of secondary combustion air, resulting in a 29.88% reduction in CO concentration and a 3.04% increase in steam flow rate. However, the rapid change from the current airflow to the AI-suggested airflow caused a 139.79% fluctuation in internal incinerator pressure. Due to the 10 min intervals at which the airflow was suggested, the airflow could not be adjusted quickly enough to match changes in combustion conditions, leading to increased combustion instability. This instability likely caused localized over-supply of O_2, resulting in increased NOx emissions.

3.3.2. Performance Evaluation of the ICC System's Combustion Control

Experiments confirmed that the automatic control of the studied ICC system resulted in a 2.41% increase in steam flow rate and a 7.33% reduction in NOx emissions. In January 2024, a four-day experiment was conducted to evaluate the automatic control of the ICC system under the same conditions as the performance evaluation of AI combustion control. To address the issue of increased NOx emissions observed in previous experiments, the AI was updated to suggest the operating method at 5 min intervals, and the second FD and ID fans were automatically controlled to gradually transition from the current airflow rate to the AI-suggested airflow. The results, shown in Figure 9, indicate that the incinerator flue gas temperature decreased by 0.66%, steam flow rate increased by 2.41%, power generation increased by 3.09%, and CO emission concentration decreased by 60.72%. Additionally, unlike in the performance evaluation of AI combustion control, NOx emissions decreased by 7.33%. These results are similar to those found in previous studies conducted by incinerator manufacturers [19–25].

It was confirmed that incinerator combustion control is possible through AI-based automatic control. As with the previous experiment(3.3.1. Performance Evaluation of AI Combustion Control), no anomalies or failures occurred at the WtE facility during the AI-based automatic control, and the facility operated stably. The appropriate supply of combustion air resulted in the full combustion of un-burned residues, leading to a 60.72% decrease in CO emissions and an increase in steam flow rate. The shortened interval for determining airflow and the incremental changes in airflow reduced the internal pressure of the incinerator by 25.2%, which likely increased combustion stability, resulting in reduced NOx emissions compared to the AI combustion control performance evaluation.

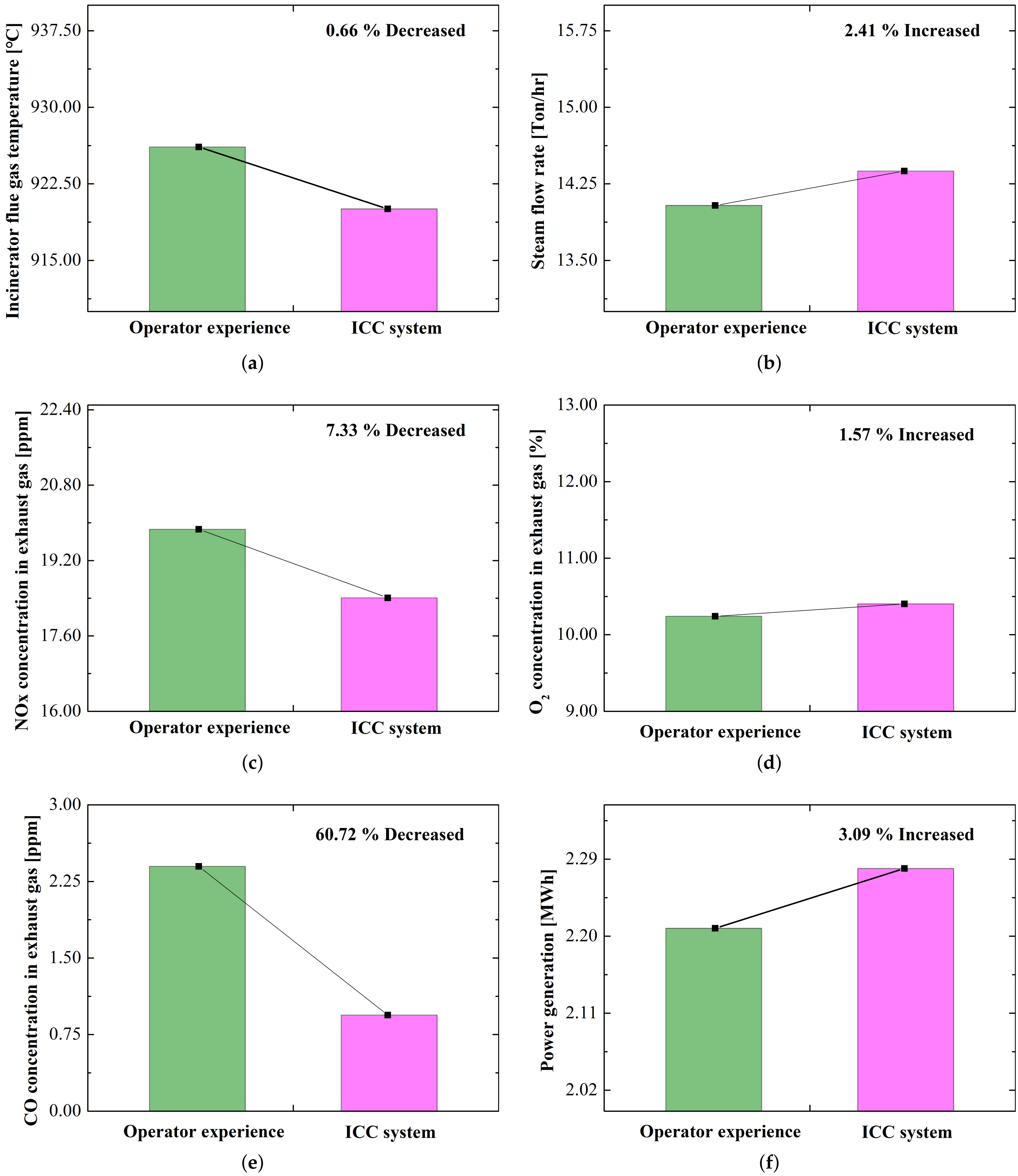

Figure 9. Evaluation of ICC system's combustion control over four days. (**a**) Incinerator flue gas temperature. (**b**) Steam flow rate. (**c**) NOx concentration in exhaust gas. (**d**) O_2 concentration in exhaust gas. (**e**) CO concentration in exhaust gas. (**f**) Power generation.

Future study will focus on advancing the AI-based ICC system. During the research study, it was confirmed that the AI for proposal of the operating method was influenced by the performance of the AI for simulation of the operational status. Therefore, additional studies on hyperparameters and AI algorithms will be conducted to improve the performance of the operational status simulation AI. Furthermore, experiments will be conducted to obtain operational data changes by modifying the first FD fan and stoker timing, which were excluded from this study due to insufficient operational data, to include them in the ICC system. This represents the aim to enable automatic control of the first FD fan and stoker timing in the ICC system. Lastly, studies will be conducted to optimize the interval at which AI proposes operational methods. This study confirmed improved combustion control performance when changing from a 10 min interval to a 5 min interval. We aim to further shorten the AI operational method proposal interval within a range that does not strain the fans. Through the follow-up studies, it is expected that the performance and stability of the ICC system will be further improved, and its application range expanded.

4. Conclusions

This study aimed to enhance energy recovery and reduce air pollutant emissions from waste-to-energy (WtE) facilities by developing an intelligent combustion control (ICC) system using artificial intelligence (AI), Internet of Things (IoT), and cloud computing. Through literature review and investigation of 14 operating WtE facilities, it was confirmed that the existing Automatic Combustion Control (ACC) systems have limitations in controlling the combustion of waste with very high uncertainty.

The study sought to overcome these limitations by utilizing AI. Unlike previous studies that used AI to predict the operating status of incinerators to support decision-making in ACC systems, this study is distinctive in that it not only predicts operating status through Deep Learning (DL) but also determines and proposes optimal combustion control methods using Reinforcement Learning (RL). Furthermore, the study investigated methods for collecting operational data to improve the accuracy of AI learning and inference, as well as an ICC system that automatically controls the incinerator based on AI-proposed operational methods. The ICC system was developed to address social, economic, and environmental issues of WtE facilities internationally, even for those without ACC. To expand its applicability, the ICC system was standardized for use in many in-service WtE facilities, with economic feasibility and openness secured through IoT and cloud computing.

Experimental results confirmed that the ICC system can achieve optimal combustion control of waste with very high uncertainty, improving energy recovery and reducing air pollutant emissions compared to operator operation. The effectiveness of the ICC system was confirmed through experiments at the "G" WtE facility in Gyeonggi province, Republic of Korea. In January 2024, a four-day automatic control of the second forced draft fan and induced draft fan resulted in significant improvements: a 0.66% decrease in flue gas temperature, a 2.41% improvement in steam flow rate, a 3.09% increase in power generation, and reductions of 60.72% in CO and 7.33% in NOx emission concentrations. The ICC system continues to be applied and utilized in the "G" WtE facility.

Future studies will focus on enhancing the ICC system through improvements in AI performance, AI proposals for the first FD fan and stoker operation methods, and optimization of AI operation proposal intervals. These studies are expected to further improve the performance and stability of the ICC system and expand its range of application.

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Abbreviations

The following abbreviations are used in this manuscript:

ACC	Automatic Combustion Control
AI	Artificial Intelligence
ANN	Artificial Neural Network
ARX	AutoRegressive with eXogenous inputs
CEMS	Continuous Environmental Monitoring System
CNN	Convolutional Neural Network
CO_2	Carbon Dioxide
DCS	Distributed Control System
ETL	Extract, Transform, Load
FD	Forced Draft
HMI	Human–Machine Interface
IaaS	Infrastructure as a Service
ICC	Intelligent Combustion Control
ID	Induced Draft
IoT	Internet of Things
MAE	Mean Absolute Error
ML	Machine Learning
NOx	Nitrogen Oxides
LSSVM	Least Squares Support Vector Machine
LSTM	Long Short-Term Memory
PID	Proportional–Integral–Derivative
PLC	Programmable Logic Controller
RL	Reinforcement Learning
RNN	Recurrent Neural Network
SaaS	Software as a Service
SOx	Sulfur Oxides
WtE	Waste-to-Energy

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