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TEMPERATURE PREDICTION OF INPUT MEDICAL WASTE FOR AI-BASED INTEGRATION OF INDUSTRIAL WASTE TREATMENT FACILITIES

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ABSTRACT

Medical waste, due to its high calorific value, has a pronounced effect on furnace temperature in industrial waste treatment facilities. While it contributes to energy recovery, uncontrolled input volumes can lead to overheating, equipment degradation, and regulatory violations. This study introduces a lightweight, data-driven artificial neural network (ANN) model that predicts furnace temperature based on medical waste input quantity. Trained on operational data, the model achieves approximately 80% prediction accuracy, particularly within the critical 1250–1400°C range. Unlike rule-based or deep learning approaches, the ANN model offers fast convergence and low computational overhead, making it suitable for real-time deployment in control room environments. Proposed model is ready to be integrated into a practical assistive system that includes temperature forecasting, input waste recommendations, alerts. Further well aligned with Japan's 2024 exhaust gas regulations, enhances operational safety, combustion efficiency, and environmental compliance. This research bridges academic modeling and industrial application, offering a regulation-ready solution which also brings profit to plant.

Keywords: Medical Waste, Furnace Temperature, ANN Model, Real-Time Prediction, Assistive System, Emission Compliance

1. INTRODUCTION

High-temperature incineration and melting processes are central to industrial waste treatment. These processes enable volume reduction and material stabilization. Among various waste types, medical waste is particularly influential due to its high energy content, which enhances combustion efficiency and supports power generation. However, excessive input can cause furnace overheating, leading to equipment strain and non-compliance with emission regulations [1].

Currently, input decisions are largely based on operator experience. This approach lacks predictive tools and quantitative guidelines. The present study aims to model the relationship between medical waste input and furnace temperature using AI. The goal is to enable real-time control and integration into automated plant systems [2].

This study offers more than just a predictive model—it introduces a practical tool designed for real-world incinerator control. By focusing on medical waste, which has a strong thermal impact, the proposed ANN model helps operators anticipate temperature changes before they occur. Its lightweight design makes it easy to deploy in control rooms, and its accuracy supports safer, more efficient input decisions. What makes this work stand out is its integration into a broader assistive system that includes input recommendations, temperature forecasting, and alert mechanisms. The newly proposed framework in this research is also aligned with Japan's 2024 emission regulations, making it not only technically sound but also policy awareness. In short, this research bridges the gap between academic modeling and operational control, offering a smart, regulation-ready solution for industrial waste management.

This work advances existing research in several keyways. First, it introduces a lightweight, data-driven ANN model specifically tailored for short-term furnace temperature prediction based on medical waste input volume. Unlike fuzzy neural networks [2][4], which depend on rule-based logic and require expert-defined parameters, the proposed model learns directly from operational data. This improves adaptability and reduces setup complexity. Second, while prior studies have explored deep learning architectures such as LSTM and hybrid BiLSTM-DBCNN models [3][7], these approaches often demand large datasets and high computational resources. On contrary, the ANN model achieves comparable accuracy with faster convergence and lower computational overhead. This makes it suitable for real-time deployment in control rooms. Finally, the integration of this predictive model into an assistive system that includes input recommendations, temperature forecasting, and alert mechanisms provides a practical framework for proactive incinerator control. This system supports operational safety, emission compliance, and automation readiness beyond what has been demonstrated in earlier AI-incineration studies [1][6].

The following sections describe the model's development, evaluate its predictive performance, and outline its integration into a feasible control system.

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2. BACKGROUND AND OPERATIONAL CHALLENGES

2.1 Characteristics of Medical Waste

Medical waste typically includes plastics, textiles, and organic materials with high calorific values. While its combustion efficiency supports energy recovery, improper blending with lower-calorific waste can destabilize furnace temperature and increase operational risks [5].

2.2 Monitoring the actual furnace and Control Limitations

As a general condition industrial incinerators operate at temperatures exceeding 1300 degrees Celsius. To clear government regulatory standards, these temperatures are maintained by auxiliary burners.

In Japan, strict regulations have been imposing time to time on exhaust gas for industrial waste treatment facilities. Recently the 2024 legal revision has strengthened measures against mercury emissions [8]. Regulated substances include sulfur oxides (SOx), nitrogen oxides (NOx), cadmium, lead, and hydrogen chloride. In addition, mercury regulations on mercury also gained much concern after recent court cases. require incineration facilities to implement emission control measures, conduct regular monitoring, and report to administrative authorities. These regulations are coordinated with related laws such as the Air Pollution Control Act, the Chemical Substances Control Law (PRTR system), and the Special Measures Law for Dioxins, and they also influence facility design reviews and the preparation of technical documentation.

Temperature, emission, and operational data have continuously been monitored in a central control room. However, a consistent time lag of approximately 25 minutes exists between waste input and temperature detection. This delay complicates real-time control and limits the effectiveness of reactive adjustments [2][4]

3. RESEARCH OBJECTIVES

This study is guided by the following objectives:

To quantify the relationship between medical waste input volume and furnace temperature

To develop a predictive model using artificial neural networks and supervised learning

To evaluate the model's accuracy and operational relevance

To propose an AI-integrated assistive system for real-time input control

4. METHODOLOGY

Unlike fuzzy neural networks [2][4], which rely on rule-based logic and are sensitive to parameter tuning under uncertain conditions, the proposed ANN model uses purely data-driven learning to capture nonlinear relationships between medical waste input and furnace temperature. This reduces reliance on expert-defined rules and improves generalizability across operational scenarios.

Compared to LSTM-based models [3][7], which are designed for sequential time-series prediction and require large datasets to capture long-term dependencies, the ANN model focuses on short-term temperature forecasting. It uses fewer parameters and achieves faster training convergence. This makes it more suitable for real-time integration in control rooms with limited computational resources.

4.1 Data Collection

Operational data were collected from a stoker-type incinerator. The dataset included:

Medical waste input volume (kg/hour)

Furnace temperature readings (degrees Celsius)

Auxiliary burner status

Emission metrics (NOx, SOx, dioxins)

4.2 Model Development

An artificial neural network was constructed using supervised learning. Input features included medical waste quantity, time of input, and burner status. The target output was the predicted furnace temperature. The dataset was divided into training and validation sets to assess model performance [3].

Figure 1: Conceptual flow of the AI-based assistive system.

The diagram illustrates the end-to-end process from medical waste input through ANN-based temperature prediction to real-time operator guidance via the assistive system.

5. RESULTS

The ANN model achieved approximately 80 percent prediction accuracy in estimating furnace temperature based on medical waste input. Predictions were most reliable within the 1250 to 1400 degrees Celsius range, which is critical for slag formation and emission control [1][4].

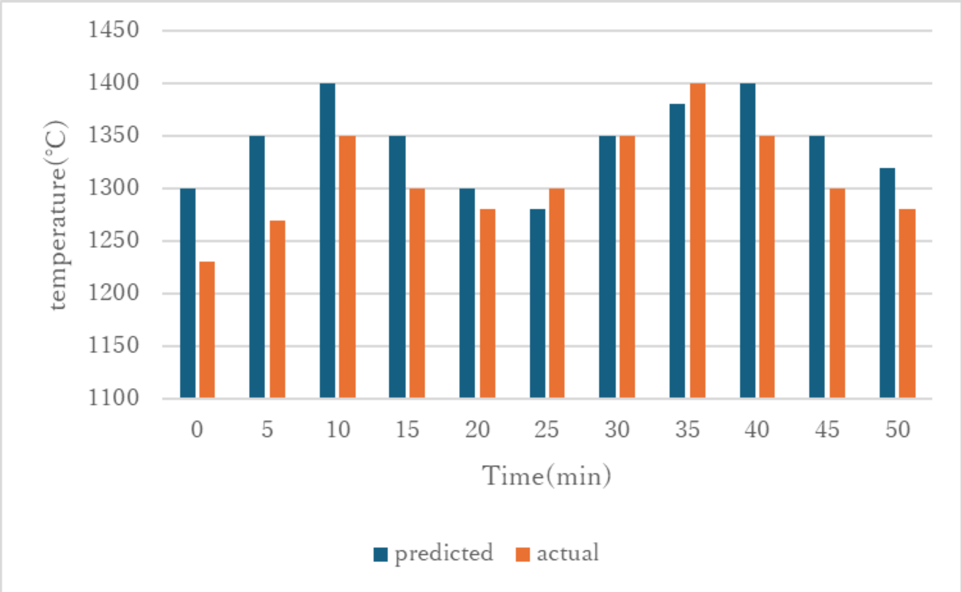

Figure 2: Temperature Prediction vs Monitoring

Figure 2 compares predicted and monitored furnace temperatures over time. The blue line represents temperature forecasts generated by the AI model. The orange line shows actual temperature readings from the incinerator. A consistent 25-minute time lag is evident, reflecting the physical delay in heat propagation and sensor response. The model's anticipatory capability enables proactive input control. This helps prevent overheating and maintain emission compliance [2].

6. DISCUSSION

6.1 Sensitivity of Temperature to Input Volume

Analysis revealed a nonlinear relationship between medical waste input and temperature rise. Inputs exceeding 150 kilograms per hour consistently led to temperature spikes above 1350 degrees Celsius. These spikes triggered emission control alerts [1].

6.2 Operational Implications

Excessive input volumes caused thermal stress on refractory linings and post-treatment equipment. Elevated temperatures were associated with increased formation of NOx and dioxins. Blending medical waste with lower-calorific waste proved effective in mitigating temperature surges and stabilizing combustion [2][5].

6.3 Uniqueness of Approach

This study distinguishes itself by introducing a lightweight, data-driven artificial neural network (ANN) model tailored for short-term furnace temperature prediction based solely on medical waste input volume. Unlike rule-based fuzzy neural networks that require expert-defined logic, or deep learning architectures such as LSTM and BiLSTM-DBCNN that demand extensive datasets and computational resources, the proposed ANN model achieves comparable accuracy with faster convergence and lower overhead. Its integration into a real-time assistive system aiming practical input recommendations, temperature forecasting, and alert mechanisms. Thus offers a practical, deployable framework for proactive incinerator control. By focusing specifically on the thermal impact of medical waste and addressing the operational lag in temperature detection, this approach enables anticipatory adjustments that enhance safety, efficiency, and regulatory compliance.

6.4 Comparative Evaluation of AI Approaches

This comparative table summarizes how the proposed ANN-based approach stands apart from existing AI models used in waste incineration control. Unlike fuzzy neural networks or deep learning architectures, this study directly addresses the operational challenges posed by medical waste input—particularly its impact on furnace temperature.

The proposed lightweight model design makes it suitable for real-time deployment, a finite advantage in central control room environments where computational resources are limited and updatability is costly. While other models may offer theoretical precision, they often require extensive datasets and tuning, making them less practical for day-to-day operations.

Table 1: Comparative Evaluation of AI Approaches for Furnace Temperature Prediction

Feature	This Study	Fuzzy Neural Networks [2[4]	Deep Learning Models (LSTM, BiLSTM-DBCNN) [3]7]
Focus on medical wase input	✅ Yes	❌ No	❌ No
Real-time deployability	Lightwegght ANN	⚠️ Rule-based tuning	⚠️ High computational cost
Input--temperature impact modeling	Explicitly modeled	❌ Not addressed	⚠️ Implicitly handled
Integrated assistive system	✅ Yes 2024	❌ Yes	❌ Not incluled
Regulatory alignment	mercury rules	⚠️ General emissions	⚠️ General emissions General emissions

Moreover, this study goes beyond prediction by proposing an integrated assistive system that includes input recommendations, temperature forecasting, and alert mechanisms. This practical operator friendly thinking reflects a shift from academic modeling to applied engineering, offering promising benefits for plant operators.

It should be mentioned that complying with Japan's updated 2024 exhaust gas regulations, the proposed model demonstrates environmental relevance and policy awareness. This regulatory alignment enhances acute credibility and positions it as a forward-looking solution for sustainable waste management.

7. AI-BASED INTEGRATION SYSTEM

Based on the model's predictive capabilities, an integrated assistive system is proposed. Key components include:

Input recommendation engine for optimal medical waste quantity

Temperature forecasting module that predicts furnace temperature 25 minutes in advance

Alert mechanism to flag potential overheating scenarios

Operator interface for real-time guidance and feedback

This system supports proactive decision-making. It reduces reliance on manual judgment and facilitates integration with automated plant operations [4].

8. CONCLUSION

This study demonstrates that furnace temperature in industrial waste treatment facilities is highly sensitive to medical waste input quantity. AI-based prediction enables real-time control and supports integration into automated systems. The proposed assistive system offers a practical solution for optimizing combustion, ensuring emission compliance, and protecting equipment [1][3]. By addressing limitations in rule-based and deep learning models, this work contributes a deployable, interpretable, and efficient framework for incinerator control.

9. FUTURE WORK

As Future research extensions the focus will naturally expand toward dataset to include seasonal and compositional variations in waste streams. Additional efforts will be made to integrate real-time sensor feedback for closed-loop control and to validate model performance across multiple facilities. Hybrid modeling approaches that combine ANN with physical simulations will also be explored to enhance predictive accuracy [3][5].

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