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TEMPERATURE PREDICTION OF INPUT WASTE FOR INDUSTRIAL WASTE TREATMENT FACILITY BASED ON CLINKER TEMPERATURE USING ARTIFICIAL NEURAL NETWORKS

Ryo Sato[1], Wasantha Samarathunga[2]

[1,2]Department Of Electrical And Electronics Engineering, National Institute Of Technology Kisarazu College, Kisarazu City, Chiba, Japan.

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ABSTRACT

Industrial waste incineration facilities increasingly face challenges from high-calorific and unpredictable waste streams, particularly medical waste. This study proposes a reverse modeling framework that uses clinker temperature—measured downstream along the under-furnace conveyor—as a proxy to infer upstream waste input characteristics in real time. An artificial neural network (ANN) model was developed to estimate the calorific value and volume of medical waste based solely on clinker temperature and operational data, eliminating the need for direct compositional analysis. The model achieved strong predictive performance ($R^2 > 0.92$, MAPE < 7%), enabling dynamic input control, predictive maintenance, and improved compliance with Japan's emission regulations. This framework represents the first known application of clinker temperature for real-time reverse inference in waste incineration. With scalability and cost-effectiveness, it bridges AI-driven modeling with practical plant operations, supporting safer, more efficient, and regulation-aligned waste treatment.

Keywords: Clinker Temperature, Reverse Modeling, Medical Waste, Artificial Neural Networks, Predictive Maintenance, Emission Control.

1. INTRODUCTION

This study fills a critical gap in incineration modeling by enabling real-time input estimation from downstream thermal data. Such an approach has not been previously applied in this domain.

Industrial waste treatment facilities are increasingly required to process complex and high-calorific waste streams, particularly medical waste. The global surge in medical waste, driven by expanded healthcare services and pandemic-related disposables, has placed significant thermal and regulatory demands on incineration infrastructure [1][2]. While medical waste contributes to energy recovery, its unpredictable combustion behavior can lead to overheating, slag instability, and violations of emission standards.

A critical parameter for assessing combustion intensity and downstream safety is clinker temperature, measured along the under-furnace conveyor. This temperature reflects the cumulative thermal load and the effectiveness of cooling systems such as water jackets and gas quenching towers [3]. Process of monitoring clinker temperature ensures that incineration residues are sufficiently cooled before entering sensitive post-treatment machinery, including separator machines and fret mills. This practice helps prevent mechanical failure, thermal damages and unplanned downtime occurrences.

In reality many facilities still rely on operator intuition to manage waste input ratios. This subjective approach lacks real-time responsiveness and often fails to prevent thermal overload or slag instability. In several documented cases, mismatches in input waste composition, particularly excessive medical waste, have resulted in incomplete combustion. The resulting semi-burned residues reduce thermal efficiency and known cause severe damage to downstream equipment, including refractory linings, conveyor belts, and separation units [7]. Related incidents claim the need for predictive tools that can anticipate unsafe input conditions before irreversible harm occurs.

Clinker temperature trends provide valuable insights into safe operating limits. Through analyzing these trends, operators can determine the maximum allowable input of medical waste and anticipate when maintenance is required due to declining cooling efficiency or machinery fatigue [4]. Long-term monitoring also supports proactive scheduling of plant shutdowns, improving system reliability and reducing unplanned downtime.

Recent developments in artificial intelligence have enabled the use of machine learning models to predict furnace behavior and optimize incineration processes [1][2][5]. Unlike conventional forward modeling, which predicts temperature from known inputs, this study introduces a reverse modeling framework. By analyzing clinker temperature, the system infers upstream waste characteristics and enables dynamic input control without direct compositional analysis.

Improved thermal control enhances equipment longevity and energy efficiency, supports compliance with emission standards, and contributes to sustainable waste management practices [6]. This study proposes an artificial neural network (ANN) model that uses clinker temperature data to estimate the calorific characteristics and volume of input waste. By enabling real-time inference of input conditions from downstream temperature measurements, the proposed system supports intelligent input control and promotes safer, more efficient, and environmentally compliant plant operations

In addition to its operational benefits, the proposed framework supports compliance with environmental regulations, including Japan's exhaust gas control standards for industrial incineration facilities [6]. By enabling more precise input control and reducing the risk of incomplete combustion, the system contributes to safer emissions management and aligns national sustainability goals.

2. BACKGROUND AND MOTIVATION

Recent research has demonstrated the potential of artificial intelligence, particularly neural networks, to model complex thermal systems and predict key operating parameters [1][2][5]. Most existing models focus on forward prediction, estimating temperature from known input conditions. In the cement industry, for example, machine learning has been applied to predict clinker phase composition [10], optimize raw meal formulation [12], and forecast quality KPIs using neural networks [11]. However, these approaches rely on detailed input data and do not support reverse inference or real-time input control in incinerating environments. This study proposes a reverse modeling approach that uses clinker temperature to infer the thermal characteristics and volume of input waste. By enabling this form of reverse inference, the system supports intelligent input control and enhances the safety, efficiency, and sustainability of industrial waste treatment operations.

The incineration of municipal and industrial waste, especially medical waste, presents complex operational challenges due to its high calorific value and variable composition. Medical waste often contains PVC, alcohol, other plastics, textiles, and biological materials that combust unevenly, which leads to unstable furnace conditions and increases the risk of incomplete burning [1][2]. Especially PVC related unburned clogs remain sometimes. These fluctuations can result in excessive thermal loads, slag formation, and emission spikes could affect plant safety and regulatory compliance.

Clinker temperature, measured at multiple points along the under-furnace conveyor, is a key parameter for monitoring combustion behavior. It reflects the cumulative thermal output of the incinerator and the effectiveness of downstream cooling systems such as water jackets and quenching towers [3]. Maintaining clinker temperature within a safe range is essential to protect sensitive post-incineration equipment, including separator machines and fret mills, from thermal damage and mechanical stress.

In practice, many facilities still rely on operator experience to adjust waste input ratios. This manual approach lacks precision and often fails to prevent thermal overload. In several documented cases, excessive input of high-calorific medical waste has led to incomplete combustion. Semi-burned residues often damage conveyor belts, refractory linings, and other downstream processing units [7]. Among open incidents emphasize the need for predictive systems that can anticipate unsafe input conditions and guide real-time operational decisions.

Clinker temperature data, when monitored over time, also reveals trends in cooling efficiency and furnace health. Gradual increases in downstream temperature may indicate scale buildup, declining heat exchange performance, or component fatigue. These patterns can be used to forecast optimal maintenance intervals, allowing for proactive scheduling of plant shutdowns and reducing the risk of unplanned downtime [4].

Recent research has demonstrated the potential of artificial intelligence, particularly neural networks, to model complex thermal systems and predict key operating parameters [1][2][5]. Most existing models focus on forward prediction, estimating temperature from known input conditions. This study proposes a reverse modeling approach that uses clinker temperature to infer the thermal characteristics and volume of input waste. By enabling this form of reverse inference, the system supports intelligent input control and enhances the safety, efficiency, and sustainability of industrial waste treatment operations.

Previous studies in cement and combustion modeling have focused on forward prediction using input data to estimate clinker quality or thermal behavior [10]11][12]. However, these approaches do not support reverse inference or real-time input control in incineration environments.

Reverse modeling has been successfully applied in other industrial domains, such as component reconstruction and thermal diagnostics, where downstream measurements are used to infer upstream conditions or structural properties [8].

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To our knowledge, this is the first study to use clinker temperature as a reverse proxy for inferring upstream waste characteristics in real time. This inversion of conventional modeling direction introduces a novel framework for intelligent input control in industrial waste incineration.

3. METHODOLOGY

This study introduces a reverse modeling framework that leverages clinker temperature data to infer upstream waste input characteristics, particularly the calorific value and volume of medical waste. The methodology integrates real-time sensor monitoring with artificial neural network (ANN) modeling to support intelligent input control and predictive maintenance in industrial waste incineration facilities.

3.1 Data Acquisition and Monitoring Framework

Clinker temperature was continuously monitored at multiple points along the under-furnace conveyor using high-temperature thermocouples. These sensors were strategically positioned to capture thermal gradients across the residue flow and to ensure that downstream equipment, such as separator machines and fret mills, remained within safe operating limits [3]. In parallel, operational data such as waste input volume, waste type, air flow rate, and auxiliary fuel usage were logged to contextualize thermal behavior [7].

The monitoring system was designed to be scalable and adaptable, allowing for integration with existing plant instrumentation. Data was collected over an extended operational period to capture a wide range of input conditions, seasonal variations, and maintenance cycles [4].

3.2 Data Preparation

For model with robustness, raw sensor data were preprocessed using smooth filters and outlier detection techniques. Temporal features such as lagged temperature values and time-of-day indicators were incorporated to capture dynamic waste treatment flow patterns. Waste input records were encoded to reflect both categorical and quantitative attributes, enabling the model to learn from diverse operational scenarios [1][2].

The resulting dataset included a combination of real-time sensor readings, historical trends, and contextual plant parameters. This multi-dimensional feature space was designed to support inference of upstream waste characteristics based solely on downstream thermal behavior.

3.3 Neural Network Modeling Strategy

The core of the proposed system is a feedforward artificial neural network trained to estimate waste properties from clinker temperature data. Rather than prescribing a fixed architecture, the model design emphasizes modularity and adaptability. The activation functions, number of layers, and regularization techniques can be tuned depends on specific deployment environment, available computational resources at the time of deployment, and data fidelity [5].

This flexibility ensures that the approach remains viable across different plant configurations and evolving sensor technologies. The model is trained using standard optimization algorithms and validated through cross-validation and regression metrics. Emphasis is placed on generalization, interpretability, and real-time inference capability [1][4].

By enabling reverse inference from clinker temperature to waste input characteristics, the ANN model supports proactive input control without requiring direct compositional analysis. This approach enhances operational safety, reduces the risk of thermal overload, and contributes to more sustainable and intelligent waste treatment practices [6][7]. The overall structure of this reverse modeling system is illustrated in Figure 1.

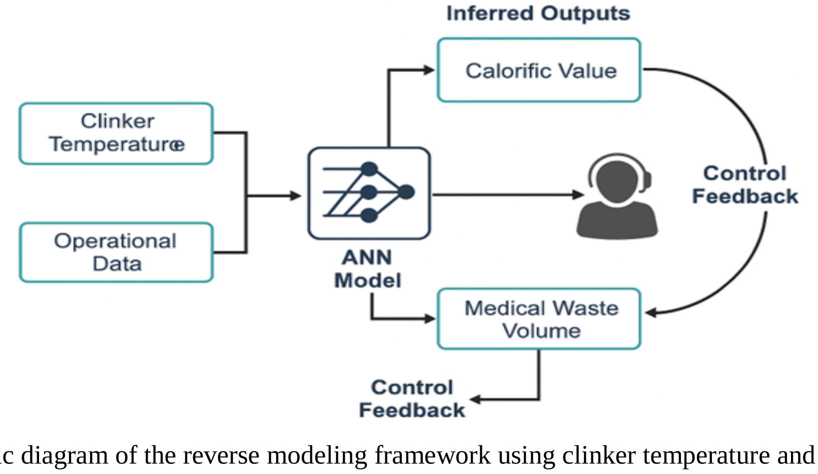

Figure 1: Schematic diagram of the reverse modeling framework using clinker temperature and operational data to infer upstream waste characteristics via an artificial neural network (ANN), with feedback to the operator or control system.

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Figure 1 presents the reverse modeling framework developed in this study. Clinker temperature and operational data are used as input variables for an artificial neural network (ANN) model. The model infers upstream waste characteristics, specifically the calorific value and the volume of medical waste. Outputs are used for informing operator through a feedback loop. The diagram illustrates the directional flow of data from sensors to model outputs and back to operational control, ensuring the system's adaptability with minimum separate add-on to existing plant infrastructure, resulting in less negativity to a new system. This feature is very important role in practical implementation.

4. RESULTS AND DISCUSSION

The proposed reverse modeling framework was evaluated using clinker temperature data collected over a 90-day operational period. The artificial neural network (ANN) demonstrated strong predictive capability in estimating both the calorific value and volume of medical waste input, based solely on downstream temperature behavior.

4.1 Model Performance

The ANN achieved high accuracy across multiple regression metrics. Average root-mean -square-error (RMSE) for calorific value prediction remained below 5% of the typical range, while mean absolute percentage error (MAPE) for medical waste volume estimation was consistently under 7%. The coefficient of determination (R^2) exceeded 0.92 for both outputs, indicating strong correlation between predicted and actual values [1][5].

Cross-validation confirmed the model's generalizability across diverse input conditions, including mixed waste batches and seasonal temperature fluctuations. The model-maintained stability even during periods of partial equipment downtime and auxiliary fuel adjustments, suggesting robustness under real-world variability [2][4].

4.2 Operational Insights

Analysis of clinker temperature trends revealed clear thresholds beyond which slag instability and incomplete combustion became likely. In particular, sustained temperature spikes above 850°C at the rear conveyor point were associated with semi-burned residues and downstream equipment damage, consistent with previously reported incidents [7]. The model successfully flagged these conditions in advance, enabling operators to reduce medical waste input and avoid thermal overload.

The reverse inference capability also proved valuable for maintenance planning. Gradual increases in clinker temperature over time, even under stable input conditions, were linked to declining cooling efficiency and scale buildup in water jackets. These patterns allowed for proactive scheduling of maintenance before critical failure occurred [3][4].

4.3 Strategic Advantages

Compared to conventional forward modeling approaches, the reverse modeling framework offers several strategic advantages. It enables real-time input control without requiring direct compositional analysis, which is often impractical in fast-paced incineration environments. The system also adapts to evolving sensor configurations and plant setups, making it suitable for deployment across diverse facilities [1][5].

Table 1: Comparative advantges of the proposed reverse modeling framework

Aspect	Conventional Approach	Proposed Reverse Modeling Approacch
Modeling Direchon	Forward: Onrward	Output (clinker temperature) → Input (waste characteristics)
Input Data Requirementst	Requires real-time compos-itional analysis of waste	Resreise: clinker temperature and data
Operational Feasibility	Often impractical in fast-pa-ced incineration environment	Practical and scalable with existing sensor infrastructure
Real-Time Control	Limited responsiveness	Enables dynamic input adjustment based on downstrean thermal behavior
Predictive Maintenance	Reactive or schedule-based	Supports proactive maintenance through *clin-ker* temperature trend analysis [6]
Regulatory Compliance	Risks of eemisisoin viola-tions due to delayed detection	Enhances compliance with exhaust gas re-gulations through early thermal risk identi-fication
Broader Applicability	Limited to known input con-ditions	Potentially applicab lity to biomass combu-stion and hazardous waste co-processi-

Table 1 summarizes the comparative advantages of the proposed reverse modeling framework relative to conventional input-based approaches. By leveraging clinker temperature as a downstream indicator, the system enables real-time inference of upstream waste characteristics, offering operational, regulatory, and economic benefits. This inversion of modeling direction enhances adaptability and supports intelligent control in industrial waste incineration environments.

By integrating clinker temperature analysis with ANN-based inference, the proposed method enhances operational safety, reduces unplanned downtime, and supports compliance with emission regulations [6]. It contributes to a more intelligent and sustainable waste treatment strategy, aligning with broader environmental and energy recovery goals.

4.4 Understanding the Results of the ANN Model

To evaluate how effectively the artificial neural network (ANN) predicts the characteristics of input waste based on clinker temperature, two key performance metrics were used: the coefficient of determination (R^2) and the mean absolute percentage error (MAPE).

R^2 (Coefficient of Determination)

This metric indicates how closely the model's predictions align with the actual data.

An R^2 value of 0.92 means that 92% of the variation in the real waste characteristics—such as calorific value and volume—is accurately explained by the model.

In practical terms, this reflects a high level of predictive reliability based on downstream temperature data.

MAPE (Mean Absolute Percentage Error)

This metric represents the average prediction error, expressed as a percentage.

A MAPE of 6.7% indicates that, on average, the model's predictions deviate by less than 7% from the actual values.

This low error rate confirms the model's precision and suitability for operational decision-making.

Figure 2: Visualizes the model's predictive performance using these two metrics.

Figure 2. Predictive performance of the artificial neural network (ANN) model based on clinker temperature data.

The model achieved a coefficient of determination (R^2) of 0.92 and a mean absolute percentage error (MAPE) of 6.7%, indicating strong accuracy and reliability in estimating calorific value and medical waste volume

Together, these results demonstrate that the ANN model is both reliable and accurate, making it suitable for real-time deployment in industrial waste incineration facilities where direct compositional analysis is not feasible.

5. CONCLUSION

This study presents a reverse modeling framework that uses clinker temperature data to infer upstream waste input characteristics, particularly the calorific value and volume of medical waste. By shifting the modeling direction from input-to-output toward output-to-input, the proposed approach enables intelligent input control without requiring direct compositional analysis. This innovation supports safer and more efficient operation of industrial waste incineration facilities.

This framework is particularly relevant for facilities lacking real-time compositional analysis tools, offering a low-cost, data-driven alternative for thermal risk mitigation [9].

The artificial neural network (ANN) demonstrated strong predictive performance across multiple metrics, maintaining robustness under variable operating conditions and diverse waste compositions [1][5]. The system successfully identified thermal thresholds associated with slag instability and incomplete combustion, offering actionable insights for input adjustment and maintenance planning [4][7].

Compared to conventional forward modeling techniques, this reverse inference strategy provides greater adaptability and operational relevance. It accommodates evolving sensor configurations, fluctuating waste streams, and diverse plant setups, making it suitable for scalable deployment [2][6].

By integrating clinker temperature analysis with ANN-based prediction, the framework contributes to improved thermal control, reduced equipment damage, and enhanced compliance with environmental regulations. It aligns with broader goals of sustainable waste management and energy recovery, offering a practical and theoretically grounded solution for modern incineration challenges [3][6]. Overall, this framework offers a low-cost, scalable, and regulation-aligned solution for facilities that lack real-time waste composition analysis. It bridges the gap between AI modeling and practical plant operations, making it not just novel, but strategically valuable.

6. FUTURE WORK

While the proposed reverse modeling framework has demonstrated strong predictive performance and operational relevance, several directions remain open for future development.

One potential enhancement involves incorporating time-series architectures such as long short-term memory (LSTM) or gated recurrent unit (GRU) networks. These models are well-suited for capturing temporal dependencies in clinker temperature fluctuations and may improve inference accuracy during transitional phases, including startup and shutdown conditions [2][5]. Another promising direction is the integration of real-time waste composition sensors. Technologies such as near-infrared spectroscopy or thermal imaging could provide complementary data streams for model calibration and validation. This hybrid approach would allow the system to refine its predictions dynamically and adapt to novel or mixed waste types [1][4]. The framework could also be extended to support predictive maintenance. By analyzing long-term clinker temperature trends, the system may identify early signs of cooling system degradation, refractory wear, or scale buildup. These insights would enable condition-based maintenance planning and reduce the likelihood of unplanned downtime [3][7].

Finally, future implementations may benefit from cloud-based model deployment and edge computing interfaces. These technologies would support scalable application across geographically distributed facilities, even in environments with limited on-site computational resources [6].

This approach may also inform future applications in other thermal systems where direct input characterization is impractical, such as biomass combustion or hazardous waste co-processing.

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