Current Applied Science and Technology e-ISSN: 2586-9396

Curr. Appl. Sci. Technol. ….., Vol... (No...), e0270249

Review article

An Integrated Review of Waste-to-Energy Plant Efficiency Enhancement: Fuel Stability, Heat Recovery and Net Power Output Performance

Sooppasek Katruksa*, Suchai Pongpakpian and Patiphan Kerdlap

The Electrical and Energy Engineering Program, School of Engineering, Eastern Asia University Thanyaburi, Pathumthani, Thailand

Received: 21 December 2025, Revised: 23 March 2026, Accepted: 1 May 2026, Published: 13 August 2026

Abstract

Increasing volume of municipal solid waste (MSW) exerts significant pressure on global waste disposal systems and energy security. Waste-to-energy (WtE) technology has consequently emerged as a viable solution to reduce landfill reliance and generate renewable energy. This review examined recent advancements aimed at improving WtE power plant performance, focusing on AI-based combustion control, heat recovery strategies, and hybrid energy integration. Fuel stabilization through artificial intelligence techniques substantially reduces combustion variability and thermal losses, thereby enhancing operational stability. Heat recovery technologies improve energy utilization and boost power generation efficiency by capturing both high- and low-grade waste heat. Furthermore, hybrid integration with renewable energy systems, carbon capture, and smart grid technologies strengthen grid stability, mitigate load fluctuations, and increase overall energy system reliability. These results suggest that achieving high-performance WtE systems requires advancements at both the plant and grid levels. The review also underscores the necessity for integrated intelligent frameworks that combine these strategies to promote sustainable and resilient waste management systems.

Keywords: waste-to-energy (WtE); municipal solid waste; optimization; heat recovery; combustion stability; energy integration; power grid stability

1. Introduction

Increases in urban population, higher consumption rates, and economic expansion have led to a rising amount of community solid waste. Consequently, municipal solid waste (MSW), that is, waste generated by households and businesses, continues to grow globally, with projections reaching 2.2 billion tonnes per year by 2025 and 4.2 billion tonnes per year by 2050 (World Energy Council, 2013, Asian Development Bank, 2020). Pollution then leaks into soil and water, affecting public health, particularly in low-income countries that rely on traditional waste disposal methods such as landfills, open dumping, and open

*Corresponding author: E-mail: sooppasek@eau.ac.th
https://doi.org/10.55003/cast.2026.270249

incineration. These methods all have significant negative impacts (World Energy Council, 2013).

In the face of such a challenge, Waste-to-Energy technology plays an important role in reducing landfill waste, converting it into recyclable resources or energy in the forms of electricity, heat or fuel. It was reported that WtE systems not only serve to dispose of waste safely but also support energy security and reduce the burden of global warming (IEA Bioenergy, 2014)

A systematic review by Maphuhla and Oyedeji (2025) highlighted that WtE has the potential to increase electricity generation rates and reduce landfill demand in the long term and suggested that integrating WtE into national waste management systems could create energy value from non-recyclable waste materials and significantly reduce pollution from traditional waste management. Although the study did not go into technical details of the combustion optimization process, it confirmed the role of WtE as an important engine of the circular economy with more stable electricity generation in densely populated urban areas (Maphuhla & Oyedeji, 2025).

Although many countries have developed various waste management practices, public health, environmental, and space constraints remain major challenges in community solid waste management, especially in urban areas with high population density. As a result, it is necessary to consider waste-disposal methods that can reduce community impact in concrete ways. The waste-to-energy process is recognized as an important method for eliminating waste that cannot be recycled and reducing the risk of germ spread. Moreover, developing waste-to-energy projects requires consideration of many factors, including the suitability of technology, factory environment, citizen participation, which can help reduce conflicts and build confidence in health and environmental impacts (UNEP, 2020).

This study provides a comprehensive review of recent strategies for enhancing the performance of waste-to-energy (WtE) systems, with a particular focus on efficiency improvement and system-level impacts. The review is structured around three primary categories: AI-based control for improving combustion stability, heat recovery strategies for increasing energy utilization and minimizing thermal losses, and hybrid energy integration for facilitating multi-energy generation and overall system optimization. Each approach is evaluated in terms of its contribution to operational stability, energy efficiency, and environmental performance in WtE systems. Furthermore, the study identifies current research gaps and underscores the necessity for more integrated and intelligent frameworks capable of combining these strategies under varying operating conditions and waste compositions.

2. Structure and Operating Principle of a Municipal Solid Waste Incineration Power Generation System

Figure 1 shows an example of an industrial-scale municipal solid waste incineration (MSWI) power plant, which includes steam and power generation systems, as well as treated flue gas vents. The overall structure reflects the process of converting energy from waste to electricity, with waste being burned in a furnace to produce hot gas for steam generation and the rotation of electric turbines. The exhaust gases are passed through a pollution control system before being released into the atmosphere through the chimney shown in the image, demonstrating the concept of waste management alongside energy production on an industrial scale. (Doka, 2003; ESWET, 2017).

Figure 1. Photograph of a municipal solid waste incineration power plant illustrating the main process units for energy generation

Figure 2 shows the structure of the combustion and boiler buildings, which are the main components of the process of converting energy from solid waste into thermal energy. Inside this building, combustible materials in the garbage are burned under proper temperature and air intake control. This results in the oxidation of both the volatile gases released from waste and the remaining solid carbon, occurring simultaneously in the gas and solid phases. The combustion temperature is 850-1450°C, which is suitable for the stable release of thermal energy (GIZ, 2017).

The heat generated by such a combustion process is transferred to the boiler system. The boiler is usually installed in the same building to generate high-pressure, high-temperature steam for the next power generation process. Therefore, the combustion building and the boiler are considered the core of the system. Waste-to-Energy relies on the continuous conversion of waste chemical energy into thermal and mechanical energy (GIZ, 2017).

Figure 2. Incineration furnace and steam boiler building of a waste-to-energy power plant

Figure 3 shows steam turbines and generators in the waste-to-energy building of the power plant. This system converts thermal energy from waste incineration into commercial electricity (Syam, 2023). The steam turbine receives high-pressure, high-temperature steam from the boiler and directs it into a multi-stage impeller, continuously expanding the steam and transferring energy to the shaft. The generator converts this mechanical energy to electricity through the rotation of the rotor inside the stator's magnetic field. This setup enables a continuous, stable waste-to-energy system suitable for industrial use (Syam, 2023).

Figure 3. Steam turbine and electric generator units used for converting thermal energy from high-pressure steam into electrical power

3. Approaches and Techniques for Enhancing the Efficiency of Waste-to-Energy Power Plants

3.1 Application of artificial intelligence techniques to enhance the operational performance of waste-to-energy power plants

Artificial intelligence (AI)-based approaches have been extensively implemented to improve combustion stability and operational performance in waste-to-energy (WtE) systems. These techniques seek to minimize fuel variability, enhance process control, and facilitate data-driven optimization in response to dynamic operating conditions.

Figure 4 shows the framework of an artificial intelligence training system for an incinerator power plant, which connects historical operational and calorific data with camera-captured images of garbage inside the bunker. Both numerical and visual data go through a joint process of data preparation and processing to be used in model training for assessing waste uniformity and predicting calorific values. The model results are presented through the interface to support the decision to adjust the fuel feed. This model guided fuel feed adjustment improves combustion stability and overall efficiency of waste-to-energy systems (Lee et al., 2024).

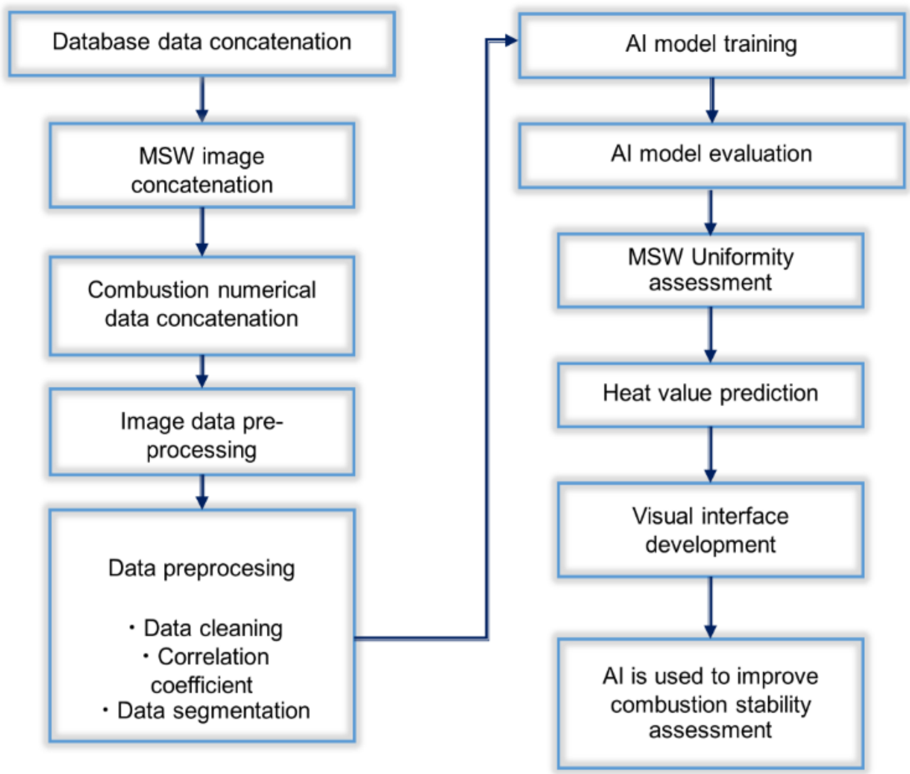


Figure 4. Workflow of the artificial intelligence–based framework for combustion stability assessment in a waste-to-energy system

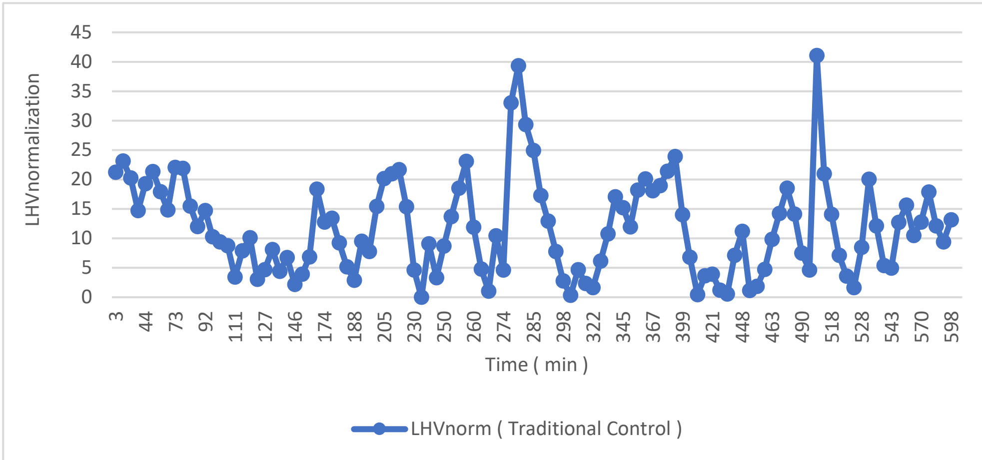
Figure 5 compares the fluctuation behavior of normalized low heating values (LHV) between traditional combustion control and AI-based MSW uniformity control over approximately 10 h. In this AI-driven MSW uniformity assessment, image recognition and predictive modeling were used to control waste feeding and combustion parameters (Lee et al., 2024).

The LHV value data used in the analysis were standardized (normalized LHV) to compare relative changes in fuel quality over time, which are independent of the absolute calorific value of the fuel at each moment. Such standardization helped to more clearly highlight the volatility and stability of the combustion process. Normalization of low calorific values was carried out according to equation 1:

$$\mathrm{LHV}_{norm}\,(\%) = \frac{|\mathrm{LHV}-\mu|}{\mu}\mathrm{x}100 \qquad (1)$$

where LHVnorm represents the normalized lower heating value as a percentage. Here, LHV denoted the instantaneous lower heating value at a given time, and μ was the mean lower heating value of the dataset over the operating period. The normalized value, LHVnorm, was thus calculated as LHV divided by μ, expressed as a percentage (Lee et al., 2024).

a)



b)

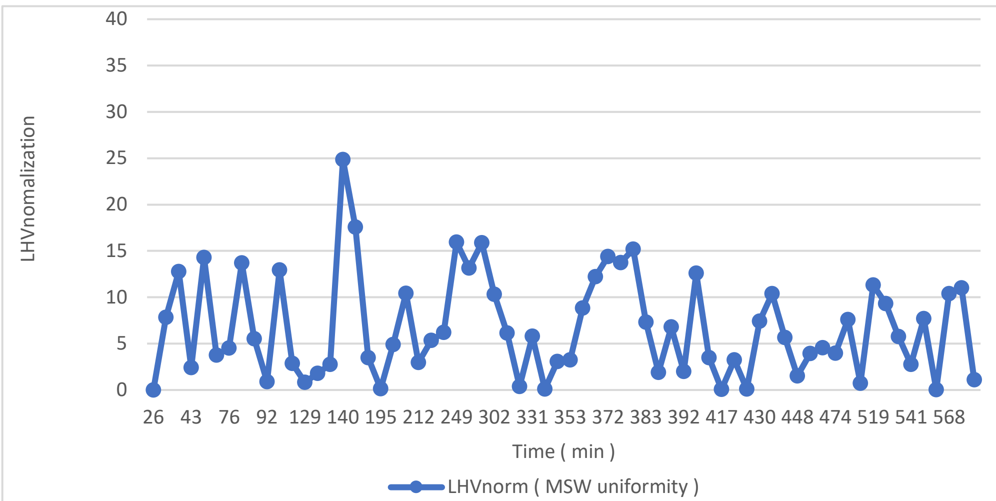


Figure 5. Comparison of normalized lower heating value (LHV) fluctuations under a) conventional control and b) AI-based MSW uniformity–based control

According to the analysis, traditional combustion control exhibited pronounced fluctuations in LHV values, reflecting irregular waste distribution in the incinerator (Figure 5a). In contrast, controls utilizing municipal solid waste uniformity assessments substantially reduced these fluctuations, resulting in a more stable combustion process, as demonstrated in Figure 5b.

The results demonstrated that waste mass uniformity directly governed the consistency of calorific value. Implementing a uniformity-based control strategy significantly reduces variability in combustion thermal energy, enabling more efficient and stable waste-to-energy plant operations (Lee et al., 2024).

Figure 6 compares the performance of traditional combustion control and model predictive control (MPC) in maintaining the LHV within a ±10% tolerance band around the design value of 2,070-2,530 kcal/kg (Lee et al., 2024). The graph in Figure 6 shows that the traditional control's LHV value deviated outside the tolerance band for an extended period, especially early in the run, reflecting its reactive nature, which relied on adjustment after the deviation had occurred. This could lead to instability in the combustion process. On the contrary, MPC control could more consistently keep the LHV within the tolerance band, supporting stable operations by reducing both the size and duration of deviations outside the specified range (Lee et al., 2024). This research confirms that artificial intelligence can significantly improve the stability and control of combustion processes in waste-to-energy plants using low-calorific-value waste. These advances reduce system response time, minimize fluctuations in calorific value during combustion, and lead to more uniform operation. As a result, energy recovery becomes more efficient, frequent control adjustments are reduced, and operational performance is enhanced. This approach provides a strong foundation for future progress in waste management technologies and sustainable energy production (Lee et al., 2024).

Figure 7 shows the framework of the intelligent control system for a waste-to-energy plant, which comprises a multivariate reinforcement learning algorithm (data-driven prediction) and real-time detection of abnormal combustion conditions (abnormal condition recognition and sensing). To improve the accuracy of control of the waste feed rate, the timing of the sieve's movement needed to be taken into account. Primary–secondary air supply rates and coolant supply reduced exhaust temperatures and helped to control NO_x and SO_2 concentrations within legal emission limits. Such a system helped to maintain the furnace temperature in the optimal range, reduce combustion fluctuations and increase heat exchange efficiency. The system stabilized steam power and overall power generation (Zhu & Zhang, 2024). The intelligent control framework improved combustion stability and heat exchange efficiency, thereby enhancing the overall operational performance of the waste-to-energy plant.

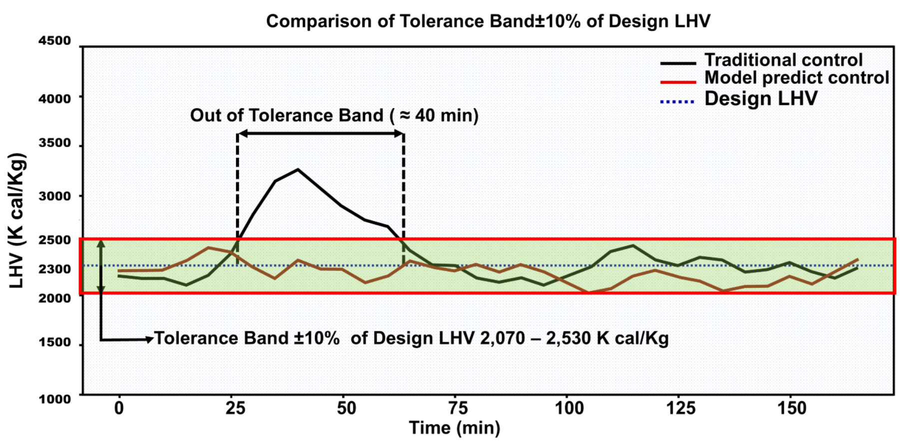


Figure 6. Comparison of traditional and model predictive control performances with respect to the design LHV tolerance band

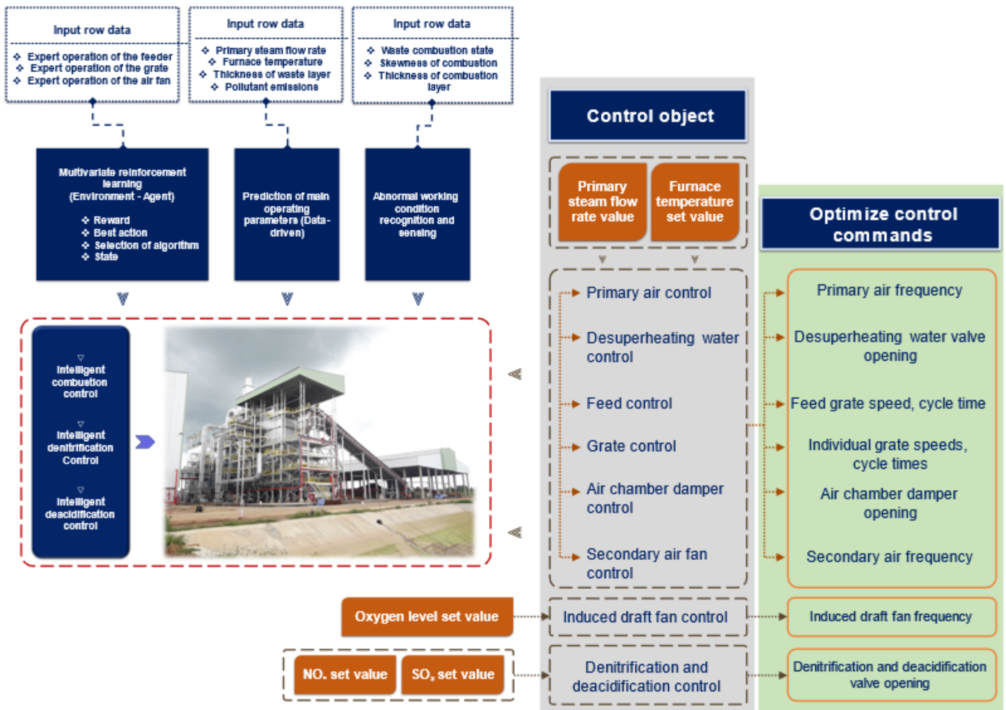


Figure 7. Architecture of an intelligent control system for combustion regulation, nitrogen oxides (NO_x) reduction, and acid gas removal in a waste-to-energy power plant

Table 1 presents the changes in key performance and economic indicators of a waste-to-energy (WtE) plant before and after the implementation of the intelligent control system. The comparison covers two operating periods: April–June 2022 (pre-implementation) and January–March 2023 (post-implementation). The results indicate that the electricity generation rate per unit of waste increased from 322.1 kWh/t to 335.5 kWh/t. This represented a 4.2% improvement. In addition, the plant's internal power consumption ratio decreased from 14.1% to 12.0%. This reflected enhanced operational efficiency and reduced demand for auxiliary electricity within the process (Zhu & Zhang, 2024).

From an environmental and economic perspective, ammonia consumption for NO_x control was significantly reduced from 2.9 kg/t to 1.8 kg/t. This represented a 38.2% decrease. The use of slaked lime for acid gas neutralization declined from 14.3 kg/t to 11.0 kg/t, equivalent to a 23.2% reduction. These improvements were due to more stable combustion control. This control mitigated temperature fluctuations and excess oxygen levels, which suppress the formation of NO_x and SO_2. Consequently, demand for air-pollution-control reagents was substantially reduced. This resulted in lower operating costs and improved overall system performance (Zhu & Zhang, 2024). Building upon the performance improvements observed in Table 1, Table 2 presents optimization-based approaches for enhancing combustion efficiency and emission control in waste-to-energy systems.

Table 1. Comparison of key operational performance indicators before and after intelligent control implementation in a waste-to-energy power plant

Indicator	2022 (average, Apr-Jun)	2023 (average, Jan-Mar)	Change (%)
Net electricity generation (kWh/t MSW)	322.1	335.5	↑ 4.2%
Internal electricity consumption (%)	14.1	12.0	↓ 2.0%
Ammonia consumption (kg/t MSW)	2.9	1.8	↓ 38.2%
Lime consumption (kg/t MSW)	14.3	11.0	↓ 23.2%

Note: The observed changes were mainly associated with improved operational control.

Table 2. Comparison of combustion efficiency improvement and NOx reduction of MCOO-TR with other optimization methods

Method	CE Improvement (%)	NOx Reduction (%)
NSGAII-RBF	↑12.55	↓6.10
SMPSO-RBF	↑13.08	↓13.08
MS-RV	↑88.69	↓19.05
MOPSO-TA-RBF	↑24.59	↓13.08
MOPSO-RBF	↑22.17	↓14.64

Note: Results are based on a representative operating condition from the original study. Positive values indicate CE improvement, while NOx values represent emission reduction.

Table 2 demonstrates a substantial improvement in combustion efficiency, ranging from 12.55% to 88.69%, resulting from the integration of multi-objective optimization with adaptive knowledge transfer. This integration enhanced system responsiveness under variable operating conditions. Regarding emission control, NOx emissions were reduced by 6.10% to 19.05% through optimized air distribution and improved furnace condition management, which promoted more complete combustion and suppressed pollutant formation. Nevertheless, the method's effectiveness was sensitive to input data characteristics and site-specific conditions, suggesting that further validation is necessary to confirm scalability and robustness in full-scale applications (Cui et al., 2023).

Table 3 presents efforts to improve modeling accuracy through the application of artificial intelligence techniques. It indicates that CNN-BiLSTM achieves higher prediction accuracy than CNN, LSSVM, and LSTM, with respective error reductions of 82.5%, 71.3%, and 22.7%. These improvements suggest that CNN-BiLSTM more effectively captured the nonlinear dynamics characteristic of MSWI combustion processes, resulting in enhanced combustion control and more stable plant operation (Chen et al., 2022). To clarify the practical significance of these results, it is necessary to specify the evaluation metric and operational variable employed, which would facilitate direct comparison with established benchmarks in the field.

In addition to predictive accuracy, the relationship between model performance and measurable operational outcomes warrants further examination. A reduction in prediction error does not fully demonstrate the engineering value of the approach unless it is linked to quantifiable improvements in plant efficiency or emission stability. Establishing this connection would enhance the study's contribution and improve the interpretability of the results for both academic and industrial stakeholders (Chen et al., 2022). Furthermore, Table 4 presents an analysis of fault detection performance in waste-to-energy systems.

Table 4 indicates that the SCN-CBR model achieved the highest fault detection accuracy across various operating conditions when compared to conventional and hybrid models. This improved performance demonstrated the SCN-CBR approach's ability to effectively capture the nonlinear characteristics of the MSWI incineration process, resulting in enhanced fault detection reliability and greater operational stability of the system (Ding & Yan, 2021). In addition, Table 5 presents a comparison of different models for predicting key process variables.

Table 3. Percentage improvement in modeling accuracy of CNN-BiLSTM compared with conventional models

Model (Baseline)	MAE	CNN-BiLSTM MAE	Improvement (%)
CNN	0.292	0.051	↑82.5
LSSVM	0.178	0.051	↑71.3
LSTM	0.066	0.051	↑22.7

Note: The improvement percentages were calculated based on the reduction in mean absolute error relative to each baseline model. The CNN-BiLSTM model consistently showed lower prediction error, indicating enhanced modeling accuracy and improved capability in capturing nonlinear behavior in the MSWI incineration process.

Table 4. Comparison of fault detection accuracy for different models in MSWI process

Model	Accuracy Range (%)	Performance Summary
BP	~68–78	Lowest accuracy among all models
SVM	~75–85	Moderate accuracy, better than BP
ED-CBR	~80–88	Improved performance with case-based reasoning
BP-CBR	~85–92	Higher accuracy due to hybrid approach
SCN-CBR	~90–95	Highest accuracy across all case compositions

Note: The accuracy values were estimated from graphical results presented in the original study. SCN-CBR consistently demonstrated superior fault detection performance across different case compositions. Higher accuracy indicated better capability in identifying faults within the MSWI incineration process.

Table 5 demonstrates that the MIMO-TSFNN model attained the highest prediction accuracy for key MSWI variables. Enhanced modeling accuracy facilitates more precise regulation of furnace temperature, oxygen content, and steam flow, resulting in more stable combustion, reduced energy loss, and improved overall plant efficiency (Ding et al., 2022). In addition to modeling, Table 6 assessed control performance from a dynamic perspective.

Table 6 demonstrates that the QDRNN-PID controller achieved superior control performance, characterized by reduced tracking error and enhanced system stability. These improvements led to more consistent combustion conditions, decreased fluctuations, and lower emissions, including NOx. As a result, the operational efficiency and reliability of the MSWI plant are substantially enhanced (Ding et al., 2022). Furthermore, Table 7 presents the effectiveness of advanced data-driven models in capturing multivariable process behavior, extending the analysis from control to predictive system optimization.

Table 5. Comparison of modeling performance for MSWI process

Model	Furnace Temperature	Flue Gas O_2 Content	Main Steam Flow	Overall Performance
MIMO-TSFNN	Highest accuracy	Highest accuracy	Highest accuracy	⭐ Best
TSFNN	High	High	Moderate	Good
RBFNN	Moderate	Moderate	Low	Fair
BPNN	Moderate	Low	Low	Fair

Note: The performance levels were qualitatively summarized based on the reported prediction errors, including RMSE and APE, for key MSWI variables. Lower error values indicated higher modeling accuracy, reflecting improved capability in capturing nonlinear and multivariable process behavior.

Table 6. Comparison of control performance for MSWI process

Controller	Error (ISE/IAE)	Stability	Overshoot	Response Speed	Overall Performance
QDRNN-PID	Lowest	Highest	Lowest	Stable	⭐ Best
DRNN-PID	Moderate	High	Moderate	Stable	Good
PID	Highest	Lower	Highest	Slower	Fair

Note: The performance levels were qualitatively derived from error indices and dynamic response trends reported in the original study. Lower ISE and IAE values indicated improved control accuracy, whereas reduced overshoot and faster settling reflected enhanced system stability and efficiency in MSWI operation.

Table 7 demonstrates that the proposed TR-LRDT model consistently outperformed conventional methods, including CART, RF, and BPNN, across all key variables in the MSWI process. Notable reductions in RMSE and MAE were achieved for furnace temperature, boiler steam flow, flue gas oxygen content, and pollutant emissions such as NOx, CO, and CO_2. These results suggest that the proposed model offered more accurate prediction of multivariable nonlinear dynamics in the waste-to-energy process.

Enhanced modeling accuracy improves the effectiveness of combustion control by enabling more precise regulation of critical variables. This leads to reduced fluctuations, lower pollutant emissions, and increased combustion efficiency. Consequently, the overall operational stability and energy efficiency of the MSWI plant were enhanced, supporting more reliable and optimized waste-to-energy system performance (Wang et al., 2024b). Table 8 further illustrates the system-level impact of advanced modeling approaches on emission prediction and control.

Table 8 shows that the TR-LRDT model achieves higher prediction accuracy for NOx and CO_2 than CART, RF, and BPNN models. This model demonstrated a much stronger ability to capture the nonlinear and multivariable characteristics of the MSWI process. Better modeling accuracy allows more precise estimation of pollutant emissions, which is essential for determining optimal operating conditions, especially furnace temperature control. As a result, the system stayed closer to optimal setpoints, and showed reduced fluctuations, minimized energy losses, and improved combustion stability. Accurate emission prediction also supports more effective optimization algorithms and control strategies, lowering NOx and CO_2 emissions and improving environmental performance. Integrating a high-accuracy, data-driven model such as TR-LRDT strengthened the intelligent control framework, boosting operational efficiency, reducing emissions, and ensuring more reliable plant performance in waste-to-energy systems (Wang et al., 2024b).

Table 7. Performance comparison of TR-LRDT model with conventional methods for key variables in MSWI process

Variable	Metric	TR-LRDT (Proposed)	vs CART Improve (%)	vs RF Improve (%)	vs BPNN Improve (%)
FT	RMSE	12.202	↑ 24.9%	↑ 21.2%	↑ 19.7%
FT	MAE	8.976	↑ 20.4%	↑ 26.6%	↑ 22.3%
BSF	RMSE	1.113	↑ 26.9%	↑ 14.6%	↑ 10.5%
BSF	MAE	0.875	↑ 19.9%	↑ 11.3%	↑ 14.0%
FGOC	RMSE	0.564	↑ 13.1%	↑ 16.6%	↑ 1.6%
FGOC	MAE	0.394	↑ 10.7%	↑ 14.2%	↑ 12.1%
NOx	RMSE	22.021	↑ 12.3%	↑ 8.4%	↑ 0.5%
NOx	MAE	16.674	↑ 11.4%	↑ 11.5%	↑ 6.8%
CO	RMSE	3.264	↑ 24.8%	↑ 6.0%	↑ 4.6%
CO	MAE	2.069	↑ 7.3%	↑ -0.4%	↑ 8.5%
CO_2	RMSE	1.787	↑ 36.2%	↑ 6.9%	↑ 41.7%
CO_2	MAE	1.284	↑ 39.0%	↑ 8.9%	↑ 41.3%

Note: Improvement (%) = (Baseline − TR-LRDT) / Baseline × 100. Values based on Testing Set RMSE and MAE. Positive (↑) values indicate TR-LRDT outperforms the baseline algorithm. TR-LRDT is the proposed model in Wang et al. (2024b).

Table 8. Comparison of indicator modeling performance for NOx and CO_2 in MSWI process

Model	NOx Prediction Accuracy	CO_2 Prediction Accuracy	Overall Performance
TR-LRDT	Highest accuracy	Highest accuracy	⭐ Best
CART	Moderate	Moderate	Fair
RF	Moderate to High	Moderate	Good
BPNN	Moderate	Moderate to High	Good

Note: Based on RMSE and MAE, lower values indicated higher accuracy. TR-LRDT showed the best performance, enabling more accurate emission prediction and improved efficiency in MSWI operation (Wang et al., 2024b).

3.2 Performance enhancement of waste-to-energy power plants through waste heat recovery strategies

Integration of absorption heat pump (AHP) into municipal waste power plants is discussed in this section. The purpose of the municipal solid waste incineration power plant is to recover and upgrade waste heat for efficient use. The recovered heat can be used in several processes, including heating the garbage pit, sludge drying, and preheating condensate water and combustion air before entering the furnace. As a result, the garbage's moisture content is reduced, the net lower heating value (LHV) is increased, and the combustion process becomes more stable. This approach is therefore a highly promising method to increase the overall efficiency of waste-to-energy plants without increasing fuel consumption. The AHP system is shown in Figure 8 (Chen et al., 2024).

Based on Figure 9, the proposed integrated system (PR) was developed to address the decline in winter power generation capacity (WT) caused by lower waste pit temperatures, higher accumulated humidity, and a significant decrease in waste lower heating value (LHV). To explain the reasons for this reduction, the impact elements were separated into the non-preheating (NH) condition, reflecting the effects of moisture and slower fermentation, and the indirect distillation (IH) sludge-drying condition, reflecting the effects of steam extraction from the turbine. After that, the PR system was implemented with integration of efficiency measures such as waste pit heating (DH), secondary air heating (SP), condensate water heating (WP), and sludge drying with a heat pump (SH), thereby reducing waste moisture content. Steam use for drying was reduced, and heat is efficiently recovered and returned to the system. This implementation restored power generation capacity to 12,048 kW, which was close to the RE condition, and effectively reduced fluctuations in the calorific value of waste (Chen et al., 2024).

3.3. Hybrid energy integration strategies for performance enhancement in waste-to-energy systems

Hybrid energy integration is essential to improving the performance and stability of waste-to-energy (WtE) systems. A grid-connected hybrid setup combines photovoltaic (PV) generation with WtE plants. This arrangement enables flexible energy dispatch. It boosts the system's capacity to respond to load demand and changes in renewable generation. WtE plants adjust their output to balance PV generation variability. This reduces grid dependency, minimizes power fluctuations, and increases reliability and energy security. Figure 10 shows such an integrated system configuration (Majeed et al., 2024).

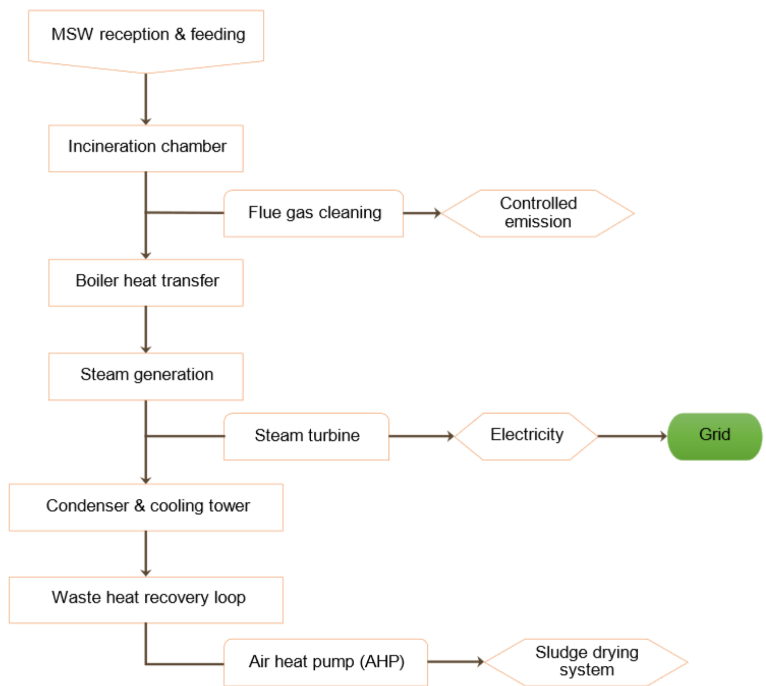


Figure 8. Integrated waste-to-energy power generation system incorporating waste heat recovery through an air heat pump (AHP) to enhance overall energy efficiency

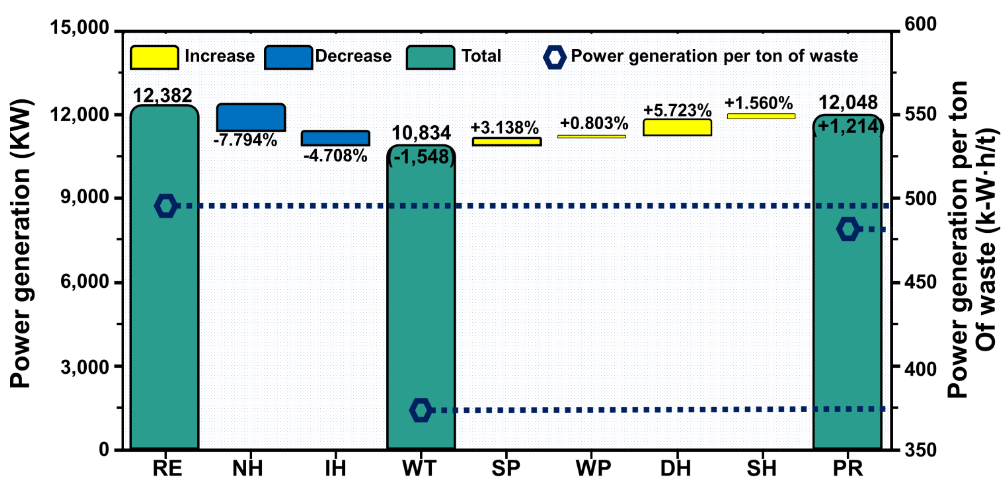


Figure 9. Power generation under different reference conditions and integrated improvement measures, with a breakdown of individual contributions associated with thermal and moisture-related effects

Figure 10 shows the integration of the power system comprising a waste-to-energy (WTE) plant, a solar PV generation system, and a power grid. The system included an inverter that converted direct current (DC) from solar panels into alternating current (AC) to supply community loads. Meanwhile, waste-to-energy plants can continue to generate electricity and adjust their capacity to compensate for fluctuations in PV power generation, resulting in a more stable overall system production capacity. As a result, this integration reduces dependence on the power grid, minimized power supply fluctuations, and effectively enhanced the reliability and energy security of the power system in practical applications (Majeed et al., 2024). Table 9 presents a comparative analysis of system performance under different load conditions for both base-case and hybrid configurations.

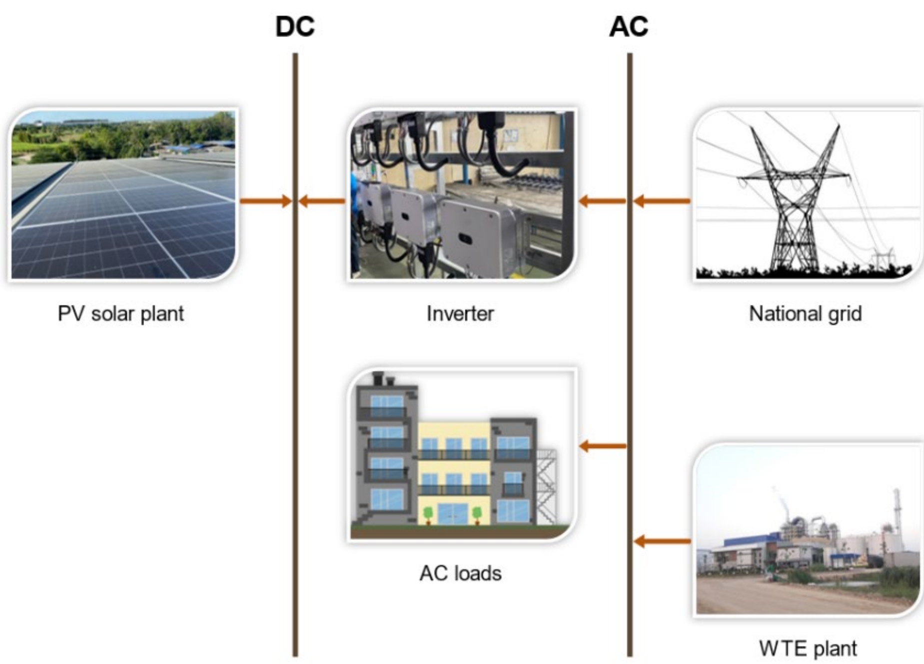


Figure 10. Hybrid grid-connected configuration integrating a photovoltaic (PV) system and a waste-to-energy (WtE) power plant to enhance power generation stability

Table 9 compares system performance under low, medium, and peak loads for both the base case and a hybrid system that integrates photovoltaic (PV) and waste-to-energy (WtE) generation. Key metrics included grid power import, grid dependency ratio, renewable energy penetration, and minimum bus voltage (in per unit, p.u.). The hybrid system reduced grid power import by about half across all load conditions. It lowers the average grid dependency from 1.00 to approximately 0.50-0.51. Renewable energy penetration remains stable at 49-50%, which reflected a consistent contribution from clean energy sources. The minimum bus voltage was also higher in the hybrid system, especially under peak load. It increased from 0.918 p.u. to 0.973 p.u. This indicated that the combination of WtE and PV improved voltage support and reduced the impact of load variations (Majeed et al., 2024). Table 10 summarizes the overall system-level improvements achieved through hybrid integration.

Table 9. Comparative performance of base case and hybrid system under different load periods

Load period	Scenario	Avg. Grid Power (kW)	Grid Dependency Ratio	Renewable Share (PV + WtE)	Minimum Bus Voltage (p.u.)
Low load	Base case	3,82 x 10^3	1.00	0.00	0.953
	Hybrid system	1,90 x 10^3	0.50	0.50	0.997
Medium load	Base case	5,43 x 10^3	1.00	0.00	0.933
	Hybrid system	2,86 x 10^3	0.50	0.50	0.987
Peak load	Base case	7,25 x 10^3	1.00	0.00	0.918
	Hybrid system	3,69 x 10^3	0.51	0.49	0.973

Note: Grid dependency ratio represents the ratio of grid-imported power to total power demand. Renewable share indicates the combined contribution of photovoltaic (PV) and waste-to-energy (WtE) generation. Values are period-averaged for each load condition.

Table 10 indicates that implementing a hybrid system configuration (PV–WtE–Grid) substantially improved overall power system performance, particularly in energy utilization and power quality. The average grid import power decreased from approximately 5.47×10^3 kW to 2.76×10^3 kW, representing a 50% reduction. This reduction aligns with a decrease in grid dependency from 1.00 to approximately 0.50, reflecting a significant increase in reliance on on-site generation. At the same time, the minimum system voltage rises from 0.918 p.u. to 0.973 p.u., improving voltage quality by 0.055 p.u. These results showed that adding a stable generation source, such as waste-to-energy (WtE), to a variable one, such as photovoltaic (PV) power, reduced demand on the main grid. This setup also strengthened voltage support and operational stability. As a result, the hybrid configuration gave the system greater flexibility and resilience to load changes in practical use (Majeed et al., 2024).

Table 10. Overall system improvement achieved by the hybrid configuration

Indicator	Base Case	Hybrid System	Improvement
Average grid power (kW)	≈ 5.47×10^3	≈ 2.76×10^3	↓ ~50%
Minimum voltage (p.u.)	0.918	0.973	+0.055
Grid dependency	1.00	≈ 0.50	↓ ~50%

Note: Average grid power was obtained from the mean of hourly data. Grid dependency denotes the share of grid-imported power in total demand. Approximate values (~) reflect average operating conditions.

The analyses in Tables 9 and 10 show that integrating waste-to-energy plants with photovoltaic systems reduces grid load, improves voltage stability, and increases system reliability, enhancing resilience to load and solar fluctuations (Majeed et al., 2024). Table 11 compares different thermal integration configurations between MSW and natural gas subsystems.

Table 11 provides a technical comparison of three operational modes for integrating a municipal solid waste (MSW) incineration power plant with a natural gas (NG) power plant. The separate mode served as the reference case, where no thermal energy exchange occurred between the two systems. In the first configuration, partial thermal integration was achieved using an air preheated heat exchanger (AHPH), which enables thermal energy from the NG system to support the MSW plant. However, a portion of the thermal load continued to be managed by the MSW superheater (SH) and economizer (ECO), limiting the overall reduction in thermal duty. The second configuration demonstrated a higher level of thermal integration, as the SH and ECO units of the MSW plant are eliminated and the NG reheater became the primary component for steam conditioning. This arrangement reduced redundant internal heat-transfer losses in the combined cycle, resulting in the most significant improvements in operational stability and overall system performance among the evaluated configurations (Sabagh et al., 2023). Table 12 further evaluates the impact of these configurations on net power output and WtE efficiency.

Table 11. Comparison of operating modes and their impact on the performance of the waste-to-energy and natural gas hybrid power generation system

Operating mode	**Key System Characteristics**	**Heat / Steam Path**	**Role of SH / ECO**	**System-Level Impact (non-efficiency results)**	**Technical Remarks**
Separate mode	No shared heat or steam exchange between systems	No shared heat or steam exchange between systems	SH and ECO operate independently; no thermal coupling	Serves as the baseline operating condition of the system	No thermal synergy between MSW and NG units
First configuration	The MSW boiler receives partial thermal support from the NG unit via the air reheater (APHP)	Condensate and steam extraction from NG → APHP → MSW superheater	NG SH/ECO remain in operation; partial heat transfer occurs through APHP	Reduced firing duty in the MSW boiler; limited thermal gain achieved	Thermal losses persist due to SH/ECO remaining on the MSW side
Second configuration	MSW SH and ECO are removed; the NG reheater operates in conjunction with APHP	Condensate → MSW evaporator → APHP → NG reheater → IP turbine	SH and ECO of the MSW boiler are eliminated; NG reheater assumes the heat recovery function	Reduced internal thermal losses and simplified heat exchange pathways	Enhanced thermal coupling achieved; internal irreversibility is reduced

Note: SH denotes superheater, ECO denotes economizer, APHP denotes air preheater, MSW refers to municipal solid waste, and NG refers to natural gas.

Table 12. Impact of integration configurations on net power output and waste-to-energy (WtE) performance

Operating Mode	Total Net Power Output (MW)	Δ vs. Separate Mode (MW)	Net MSW Power Output (MW)	WtE Efficiency (%)	Technical Remarks
Separate mode	331.2	-	8.3	21.4	No energy coupling between MSW and NG systems; no thermal synergy is realized
First configuration	331.5	+0.3	8.6	22.24	Reduced steam extraction from the NG unit; however, duty losses persist as MSW SH/ECO remain partially loaded
Second configuration	334.1	+2.9	11.2	28.8	Full thermal coupling achieved; elimination of MSW SH/ECO significantly reduces internal thermal losses

Note: Δ indicates the change in total net power output relative to the separate operating mode. WtE efficiency is defined as the net electrical output from the MSW unit divided by the corresponding MSW thermal input. MSW refers to municipal solid waste, and NG refers to natural gas.

Table 12 presents a comparison of the net electrical output of the integrated power generation system and the performance of the waste-to-energy (WtE) subsystem across three operating modes. In the separate mode, the WtE unit and the natural gas (NG) power plant functioned independently. The total net power output was 331.2 MW. The municipal solid waste (MSW)-based line contributed 8.3 MW, resulting in a WtE efficiency of 21.4%. In the first configuration, condensate and steam from the NG plant were used to support the MSW boiler. This arrangement increased the total net output marginally to 331.5 MW. The MSW power output rose to 8.6 MW, and the WtE efficiency improved to 22.24%. The second configuration eliminated the MSW superheater and economizer and used the NG reheater together with the air preheated heat exchanger (AHPH) for thermal conditioning. This configuration achieved the highest overall performance. The total net power output increased to 334.1 MW. The MSW power output rose to 11.2 MW, and the WtE efficiency improved significantly to 28.8%. These findings showed that the second configuration yielded the highest overall plant output and WtE performance. The gains resulted primarily from reduced internal thermal losses in the superheater and economizer units and more effective thermal integration between the MSW and NG subsystems (Sabagh et al., 2023). Table 13 summarizes key thermodynamic enhancement strategies applied in hybrid WtE systems.

Table 13 presents the principal strategies identified in the reviewed literature for improving the energy efficiency of waste-to-energy (WtE) systems integrated with coal-fired power plants. The heat regeneration scheme utilized flue gas and extracted steam to preheat feedwater, thereby increasing heat-exchange duty and reducing overall thermal losses. Air preheating for the WtE boiler, achieved through flue gas utilization, reduces stack losses and improved combustion efficiency. In the heat recovery steam generator (HRSG) integration approach, coordinated operation of the superheater (SH), evaporator (EVA), and economizer (ECO) improved heat recovery, reduced local logarithmic mean temperature differences (LMTD), and minimized system irreversibility. Furthermore, integrating carbon capture and storage (CCS) via a monoethanolamine (MEA) process lowered CO_2 emission intensity, though it incurred an energy penalty from solvent regeneration and increased auxiliary power consumption. Collectively, these four measures mitigate thermal losses, optimize the utilization of secondary energy, and promote more balanced thermal management in WtE systems operating in conjunction with coal-fired power plants (Wang et al., 2023). Table 14 presents the performance improvement achieved through integrated hybrid configurations.

Table 13. Summary of energy efficiency enhancement measures for waste-to-energy power systems through thermal integration and carbon capture

System / Measure	Key Features Applied in This Study	Reported Overall Performance Indicators
Heat Regeneration scheme	Utilization of flue gas and steam extraction for feedwater heating	Improvement in overall heat recovery effectiveness of the system
Air preheating for WtE boiler	Use of flue gas heat to preheat combustion air	Reduction in stack heat losses
HRSG integration	Integration of SH, ECO, and EVA sections to increase total heat duty	Increased overall heat exchange duty, with localized reduction in LMTD to mitigate irreversibility
CCS integration (MEA)	CO_2 capture from flue gas using monoethanolamine (MEA)	Reduction in CO_2 intensity accompanied by additional energy demand (energy penalty)

Note: SH denotes superheater, ECO denotes economizer, EVA denotes evaporator, HRSG denotes heat recovery steam generator, and CCS refers to carbon capture and storage. LMTD denotes the logarithmic mean temperature difference. MEA denotes monoethanolamine.

Table 14 presents the performance improvements resulting from integrating a waste-to-energy (WtE) plant with a coal-fired power plant (CFPP–WtE), comparing the conventional and integrated configurations. The total gross power output increased from 330.79 MW to 345.16 MW, a 4.35% improvement, while net power output rose from 309.50 MW to 323.86 MW, a 4.64% increase. These findings indicate that WtE system integration significantly enhanced net electricity exported to the grid without negatively impacting the core operational performance of the existing coal-fired plant. The net power generation from waste fuel increases from 8.27 MW to 22.63 MW, representing an improvement of over 170%, which aligns with the increase in net waste-to-electricity efficiency from 18.31%

to 50.13%. This demonstrated a substantial improvement in converting waste-derived thermal energy into electricity. However, the overall system energy efficiency increases only modestly from 37.71% to 39.46%. Therefore, the primary advantage of the proposed configuration was the enhanced contribution of waste-based power generation and increased net electrical output, rather than a fundamental change in the overall thermal efficiency of the main coal-fired power plant, whose performance remained stable (Wang et al., 2023). Table 15 outlines advanced integration pathways for enhancing WtE system performance.

Table 15 outlines an integrated framework designed to enhance the performance of waste-to-energy (WtE) systems. This framework couples WtE with an organic Rankine cycle (ORC), reverse osmosis (RO) desalination, a proton exchange membrane (PEM) electrolyzer, and hydrogen storage. Integrating WtE with steam systems improved combustion continuity and thermal stability. As a result, fluctuations in calorific value were reduced, and conversion stability was enhanced. ORC-based heat recovery captured residual heat from the flue gas and steam cycle. This increased cumulative electricity generation and minimized heat losses, leading to higher exergy recovery. Incorporating RO desalination enabled surplus thermal and electrical energy to be used productively for freshwater production. This improved overall resource utilization efficiency and reduced wastewater discharge. The PEM electrolyzer converts excess electricity into hydrogen and oxygen. This process mitigated energy losses during periods of low load and enabled energy storage in chemical form. The subsequent hydrogen and oxygen storage system further increased operational flexibility. It absorbed surplus power, alleviated peak loads, and supported grid stability. Together, these integrated technologies improved plant-level energy efficiency. They also enhanced system resilience, flexibility, and long-term energy management within the power grid (Khan et al., 2022). Table 16 analyzes the impact of key thermodynamic parameters on system performance.

Table 14. Performance improvement achieved by the proposed CFPP–WtE integration

Performance Indicator	Conventional Scheme	Proposed Scheme	Relative Change
Gross power output (MW)	330.79	345.16	+4.35%
Net total power output (MW)	309.50	323.86	+4.64%
Net MSW power contribution (MW)	8.27	22.63	+173.6%
Net waste-to-electricity efficiency (%)	18.31	50.13	+173.8%
Overall energy efficiency (%)	37.71	39.46	+4.64%

Note: Relative change was calculated with respect to the conventional scheme. Net MSW power contribution refers to the net electrical output attributed to the waste-to-energy unit. Overall energy efficiency represents the ratio of total net electrical output to the total thermal energy input of the integrated system.

Table 15. Summary of integration pathways for enhancing the performance of waste-to-energy systems with ORC, RO, PEM electrolysis, and hydrogen storage

Integration Pathway	Primary Technological Objective	System-level Outcomes
WtE-Steam integration	Enhance combustion continuity and stabilize steam generation	Reduction in LHV fluctuations and improved conversion stability
ORC heat recovery	Recover low-grade waste heat from flue gas and steam cycles to increase net power output	Increased electricity generation, reduced heat losses, and enhanced exergy recovery
RO desalination coupling	Utilize available thermal energy for freshwater production from seawater	Reduced thermal discharge and improved resource utilization efficiency
PEM electrolyzer (H_2 splitting)	Convert surplus electricity into hydrogen and oxygen via water electrolysis	Mitigation of power curtailment through energy storage in the form of H_2/O_2
H_2 / O_2 storage	Store energy for flexible use and system support	Peak load reduction and improved grid stability

Note: ORC denotes organic Rankine cycle, RO denotes reverse osmosis, and PEM denotes proton exchange membrane. LHV refers to the lower heating value of municipal solid waste. Exergy recovery represents the effective utilization of available thermal energy within the integrated system.

Table 16 shows how key thermodynamic parameters affect waste-to-energy (WtE) systems, focusing on thermal efficiency, exergy efficiency, sustainability, and net power output. The results demonstrated that maintaining turbine inlet steam temperature and pressure within optimal ranges enhanced the energy conversion efficiency of the steam cycle. This improvement resulted in higher net electricity generation and greater turbine load stability, while also reducing internal energy losses and irreversibilities. Conversely, an excessive steam extraction ratio negatively impacts performance, as high extraction levels decreased the energy available to the turbine. This reduction led to lower net power output, diminished exergy efficiency, and a decrease in the sustainability index (SI). These findings underscore the trade-off between allocating extracted steam for auxiliary or downstream applications and retaining sufficient energy for power generation. Therefore, precise regulation of these thermodynamic parameters is essential for maintaining high energy efficiency, economic viability, and stable electricity production in waste-to-energy power plants (Khan et al., 2022). Table 17 compares conventional and advanced hybrid WtE systems in terms of overall performance.

Table 16. Effects of key operating parameters on power generation performance and sustainability indicators of a waste-to-energy power plant

Varied Parameter	Investi-gated Range	Impact On Process Energy Efficiency	Impact On System Exergy Efficiency	Impact On MSW Power Plant Performance	Economic Implications (cost & sustainability index, SI)
Turbine inlet temperature	650-800 K	Higher inlet temperature improves energy efficiency by reducing internal heat losses	Exergy efficiency increases due to reduced irreversibility at higher operating temperatures	Improved thermal and exergy performance enhances combustion quality and overall energy utilization	SI increases as exergy-related losses decrease, contributing to more stable and cost-effective operation
Turbine inlet pressure	3000-8000 kPa	Higher pressure increases net power output by improving steam expansion potential	Exergy efficiency improves as system irreversibility and exergy destruction are reduced	Enhanced thermal and exergy performance of the MSW plant leads to more effective heat recovery	SI increases as lower exergy destruction reduces operational costs and improves system sustainability
Extracted steam flow rate	0.5-3.0 kg/s	Energy efficiency decreases due to steam diversion from the power generation process	Exergy efficiency decreases as useful energy potential is removed from the main cycle	Reduced thermal and exergy performance negatively affects heat transfer effectiveness and energy quality	SI decreases because higher exergy losses and energy penalties make continuous operation less economical

Note: Energy efficiency refers to the ratio of useful electrical output to thermal input. Exergy efficiency reflects the effective utilization of available energy considering irreversibility. SI denotes the sustainability index, representing combined economic and thermodynamic performance. MSW refers to municipal solid waste.

Table 17 indicates that the proposed solar-assisted waste-to-energy system offers substantial improvements in overall performance relative to conventional methods. Specifically, the integration of a cascaded sCO_2 Brayton cycle, an Organic Rankine Cycle, and a PEM electrolyzer increased energy utilization by enabling effective recovery of both high- and low-grade heat. Consequently, this configuration led to higher energy and exergy efficiencies and facilitated hydrogen production as an additional output. Unlike previous studies that addressed only single improvements, such as waste heat recovery or hybrid integration, the proposed system achieves a more comprehensive enhancement by combining multi-generation capability with multi-objective optimization. As a result, the system demonstrated reduced energy losses, improved sustainability, and greater overall efficiency in waste-to-energy operations (Zhou et al., 2025). Following this analysis, Table 18 provides a techno-economic comparison of waste-to-energy, solar photovoltaic, and hybrid systems.

Table 18 compares the techno-economic performance of waste-to-energy (WtE), solar photovoltaic (PV), and hybrid WtE–solar systems using net present value (NPV), internal rate of return (IRR), and payback period. Solar PV offered the highest economic return, reflected by strong profitability and a short payback period. The WtE-only system showed moderate performance, with a focus on waste management. The hybrid WtE–solar system combined the strengths of both options, resulting in strong economic viability and sustainability. Although its profitability was slightly lower than solar PV alone, the hybrid improved resource use, supports waste reduction, and ensured more stable long-term performance. Thus, hybrid integration effectively delivers economic and environmental benefits in waste-to-energy applications (Asante et al., 2023).

Integrating solar thermal with waste-to-energy processes increased heat supply stability and enabled more consistent power generation. This hybrid setup enhanced combustion, expanded fuel flexibility, and improved heat recovery by using both solar and waste-derived energy. This resulted in higher energy utilization and more efficient electricity generation than conventional systems. In addition, utilizing solar energy reduced carbon emissions, lowered environmental impact, and promoted waste valorization. Overall, the hybrid system increased stability, minimized losses, and advanced system sustainability (Yangchongthuochuaya & Chaiyat, 2023).

Table 17. Comparative performance of conventional and proposed waste-to-energy systems

Reference	Core Technological Objective	Key System-level Outcomes
Chen et al. (2020)	sCO_2 integration in WtE system	Improved power generation efficiency
Khan et al. (2023)	Solar-assisted WtE system	Enhanced energy and exergy efficiency
Carneiro & Gomes (2019)	Hybrid WtE with natural gas	Multi-output energy generation
Pan et al. (2022)	sCO_2–ORC waste heat recovery	Improved energy utilization efficiency
Proposed study (2025)	**Integrated solar-assisted WtE with sCO_2–ORC and hydrogen production**	**Highest overall performance and sustainability**

Note: The comparison was based on reported energy efficiency, exergy efficiency, and system integration level. Higher performance indicated improved energy utilization, reduced losses, and enhanced overall efficiency of the waste-to-energy system (Zhou et al., 2025).

Table 18. Techno-economic performance comparison of WtE, solar PV, and hybrid systems

Scenario	NPV	IRR	Payback Period	Performance Summary
WtE only	Moderate	Moderate	Long	Focus on waste treatment with limited economic return
Solar PV only	High	High	Short	Best economic performance
Hybrid WtE–Solar	High	Moderate–High	Medium	Improved overall performance with sustainability benefits

Note: The comparison was based on techno-economic indicators including NPV, IRR, and payback period. Hybrid integration improves overall system performance by combining the benefits of waste management and renewable energy, resulting in enhanced economic viability and sustainability (Asante et al., 2023).

The integration of advanced thermodynamic cycles, such as supercritical carbon dioxide (sCO_2) and organic Rankine cycle (ORC), further increase the efficiency of the hybrid system by enabling more effective conversion of thermal energy into useful power. In hybrid systems, these cycles leveraged both solar and waste heat sources, thereby enhancing performance under varying conditions. Incorporating multi-generation capabilities, including hydrogen and freshwater production, further increased overall system value and optimized resource utilization. Additionally, reducing exergy destruction in key system components improved thermodynamic performance and system sustainability. These findings demonstrate that hybrid energy integration not only increases energy efficiency but also offers a comprehensive approach for maximizing performance in waste-to-energy systems, particularly under variable operating conditions (Khan et al., 2022).

4. Discussion

Table 19 demonstrates that recent waste-to-energy (WtE) performance enhancement strategies fall into three principal categories: AI-based control, heat recovery strategies, and hybrid energy integration. Each category uniquely enhanced system performance and efficiency. AI-based control approaches stabilized combustion by minimizing thermal fluctuations and improving fuel property consistency. This resulted in more stable operations and reduced thermal losses. Heat recovery strategies boosted energy utilization by capturing both high- and low-grade waste heat. This increased power generation efficiency and reduced energy losses, especially under variable conditions. Hybrid energy integration provided the greatest overall improvement by merging multiple energy sources and technologies. This approach enabled multi-energy generation, greater system flexibility, and better sustainability. However, these advanced systems increased complexity and created integration challenges. They may impose energy penalties due to added subsystems. In addition to the representative studies summarized in Table 10, supporting works such as Falconi et al. (2020) and Di Maria et al. (2016) emphasized the importance of combustion stability and thermodynamic integration. More recent studies, including Syafrudin et al. (2025) and Gao et al. (2025), highlighted environmental sustainability and operational variability as key influences on system performance. These findings suggest that future research should focus on integrated intelligent frameworks that combine AI-based control, heat recovery, and hybrid energy systems. Such frameworks must ensure reliability, economic feasibility, and real-time adaptability under changing waste composition and operating conditions.

Table 19. Comparison of efficiency enhancement strategies for waste-to-energy power plants and their system-level impacts

Reference	Core Technological Objective	Key System-level Outcomes
Lee et al. (2024)	AI-based waste uniformity control	Reduced LHV fluctuations and mitigation of overshoot/ undershoot behavior, leading to improved combustion stability
Cui et al. (2023)	Multi-condition operational optimization with adaptive knowledge transfer (MCOO-TR)	Improved combustion efficiency and reduced NOx emissions through adaptive optimization under varying operating conditions, leading to enhanced operational stability in MSWI systems
Chen et al. (2022)	Deep learning-based modeling using CNN-BiLSTM with feature selection (LASSO)	Reduced prediction error by 82.5%, 71.3%, and 22.7% compared to CNN, LSSVM, and LSTM, improving modeling accuracy and combustion control in MSWI systems
Ding et al. (2021)	Fault detection using stochastic configuration networks combined with case-based reasoning (SCN-CBR)	Improved fault detection accuracy compared to BP, SVM, ED-CBR, and BP-CBR, leading to enhanced reliability and operational stability in MSWI systems
Ding et al. (2022)	MIMO-TSFNN modeling and QDRNN-PID control	Higher accuracy, lower error and overshoot, improved stability and efficiency in MSWI operation
Wang et al. (2024a)	TR-LRDT-based furnace temperature (FT) modeling combined with ISNA-PID multi-loop control and PSO-based setpoint optimization	Reduced NOx and CO_2 emission concentrations by 19.93% and 6.99% respectively, with improved FT tracking stability and reduced output oscillation in MSWI operation
Wang et al. (2024b)	Data-driven multi-objective optimal control using TR-LRDT modeling and adaptive PID-based control	Improved combustion efficiency and reduced comprehensive pollutant emissions, with enhanced control accuracy and operational stability in MSWI systems

Table 19. Comparison of efficiency enhancement strategies for waste-to-energy power plants and their system-level impacts (continued)

Reference	Core Technological Objective	Key System-level Outcomes
Chen et al. (2024)	Primary heat recovery (PR) integration	Alleviation of seasonal performance degradation, particularly under winter operating conditions, through enhanced heat utilization
Zhu & Zhang (2024)	Intelligent control and operational optimization	Increased overall plant efficiency, accompanied by reductions in auxiliary power consumption and operating costs
Majeed et al. (2024)	PV–WtE hybrid integration	Improved grid stability and voltage profile regulation, with enhanced resilience during peak load conditions
Sabagh et al. (2023)	Energy–exergy integrated evaluation and MSW–NG thermal coupling	Enhanced WtE efficiency through reduced irreversibility and improved heat recovery effectiveness
Wang et al. (2023)	Thermo-economic integration of WtE–CCS in coal-fired plants	Reduced CO_2 intensity and increased net power output from WtE, at the expense of additional energy penalty associated with CCS
Khan et al. (2022)	Solar-assisted multigeneration WtE configuration	Increased net electrical output and resource utilization efficiency, with synergistic benefits from solar energy integration
Zhou et al. (2025)	Solar-assisted WtE system integrating sCO_2 cycle, ORC, and PEM electrolyzer with multi-objective optimization	Improved energy and exergy efficiency with enhanced heat recovery and multi-generation capability, enabling hydrogen production and improving overall efficiency and sustainability in WtE systems

Table 19. Comparison of efficiency enhancement strategies for waste-to-energy power plants and their system-level impacts (continued)

Reference	Core Technological Objective	Key System-level Outcomes
Yangchongthuochuaya & Chaiyat (2023)	Integration of solar thermal system with waste-to-energy process including steam sterilization, drying, incineration, and ORC for hybrid power generation	Enhanced energy utilization through combined solar and waste heat sources, resulting in improved ORC performance and stable power generation. Achieved higher system efficiency (~6.67%) and reduced CO_2 emissions (~0.156 kg CO_2/kWh), leading to improved sustainability and operational stability in WtE systems
Asante et al. (2023)	Techno-economic comparison of WtE, solar PV, and hybrid systems	Solar PV shows highest economic return, WtE focuses on waste management, while hybrid provides balanced performance with improved sustainability

Note: The summarized studies represent diverse strategies for enhancing waste-to-energy performance, including AI-based control, optimization, hybrid energy integration, and thermo-economic analysis. Improvements were reflected in terms of increased efficiency, stability, emission reduction, and overall system performance, although trade-offs such as system complexity and integration challenges may occur.

5. Conclusions

The integrated review indicates that efficiency enhancement strategies for waste-to-energy (WtE) power plants produce distinct system-level impacts across three primary dimensions: improvements in fuel stability and thermal balance; energy recovery to reduce internal thermal losses and enhance power generation performance; and grid-level contributions that increase the quality and reliability of the electricity supply. Technologies focused on net power output enhancement, such as advanced thermal integration schemes and reduction of thermodynamic irreversibilities, offer substantial direct energy gains. In comparison, multi-energy integration approaches are more effective in improving operational stability and reducing grid stress, even when direct power output increases are modest. Additionally, strategies that address fuel variability and stabilize combustion processes are essential for maintaining flame continuity and minimizing heat losses, thereby indirectly increasing the thermal efficiency of the power generation cycle. Seasonal variations in waste composition significantly affect both energy conversion performance and process stability, underscoring the need for robust waste-fuel management and the systematic integration of secondary energy utilization to ensure the long-term sustainability of waste-to-energy power plants.

6. Authors' Contributions

Sooppasek Katruksa drafted and wrote the paper; Suchai Pongpakpian reviewed and revised the manuscript; and Patiphan Kerdlap reviewed and revised the manuscript.

7. Conflicts of Interest

The authors declare no conflict of interest.

References

Asante, K., Gyamfi, S., & Amo-Boateng, M. (2023). Techno-economic analysis of waste-to-energy with solar hybrid: A case study from Kumasi, Ghana. *Solar Compass*, *6*, Article 100041. https://doi.org/10.1016/j.solcom.2023.100041

Asian Development Bank. (2020). *Waste to energy in the age of the circular economy: Best practice handbook*. https://doi.org/10.22617/TIM200330-2

Carneiro, M. L. N. M., & Gomes, M. S. P. (2019). Energy, exergy, environmental and economic analysis of hybrid waste-to-energy plants. *Energy Conversion and Management, 179*, 397-417. https://doi.org/10.1016/j.enconman.2018.10.038

Chen, H., Guo, S., Song, X., & He, T. (2024). Design and evaluation of a municipal solid waste incineration power plant integrating with absorption heat pump. *Energy*, *294*, Article 131007. https://doi.org/10.1016/j.energy.2024.131007

Chen, H., Zhang, M., Wu, Y., Xu, G., Liu, W., & Liu, T. (2020). Design and performance evaluation of a new waste incineration power system integrated with a supercritical CO_2 power cycle and a coal-fired power plant. *Energy Conversion and Management, 210*, Article 112715. https://doi.org/10.1016/j.enconman.2020.112715

Chen, L., Wang, C., Zhong, R., Wang, J., & Zhao, Z. (2022). Intelligent modeling of the incineration process in waste incineration power plant based on deep learning. *Energies*, *15*(12), Article 4285. https://doi.org/10.3390/en15124285

Cui, Y., Meng, X., & Qiao, J. (2023). Multi-condition operational optimization with adaptive knowledge transfer for municipal solid waste incineration process. *Expert Systems with Applications*, *230*, Article 120571. https://doi.org/10.1016/j.eswa.2023.121783

Di Maria, F., Contini, S., Bidini, G., Boncompagni, A., Lasagni, M., & Sisani, F. (2016). Energetic efficiency of an existing waste to energy power plant. In *Proceedings of the 71st conference of the Italian thermal machines engineering association* (pp. 1175-1182). Elsevier. https://doi.org/10.1016/j.egypro.2016.11.159

Ding, C., & Yan, A. (2021). Fault detection in the MSW incineration process using stochastic configuration networks and case-based reasoning. *Sensors*, *21*(21), Article 7356. https://doi.org/10.3390/s21217356

Ding, H., Tang, J., & Qiao, J. (2022). MIMO modeling and multi-loop control based on neural network for municipal solid waste incineration. *Control Engineering Practice*, *127*, Article 105280. https://doi.org/10.1016/j.conengprac.2022.105280

Doka, G. (2003). *Life cycle inventories of waste treatment services. Ecoinvent report no. 13, Part II—waste incineration*. https://www.doka.ch/13_II_WasteIncineration.pdf

ESWET. (2017). *Everything you always wanted to know about Waste-to-energy*. https://www.eswet.eu/wp-content/uploads/2020/12/ESWET-Handbook_for-website.pdf

Falconi, F., Guillard, H., Capitaneanu, S., & Raïssi, T. (2020). Control strategy for the combustion optimization for waste-to-energy incineration plant. In *Proceedings of the 21st IFAC world congress* (pp. 13167-13172). Elsevier. https://doi.org/10.1016/j.ifacol.2020.12.125

Gao, C., Bian, R., Li, P., Yin, C., Teng, X., Zhang, J., Gao, S., Niu, Y., Sun, Y., Wang, Y., & Wang, H. (2025). Analysis of carbon reduction potential from typical municipal solid waste incineration plants under MSW classification. *Journal of Environmental Management*, *373*, Article 123844. https://doi.org/10.1016/j.jenvman.2024.123844

GIZ. (2017). *Waste-to-energy options in municipal solid waste management: A guide for decision makers in developing and emerging countries*. https://www.giz.de/en/downloads/GIZ_WasteToEnergy_Guidelines_2017.pdf

IEA Bioenergy. (2014). *Waste to energy: Summary and conclusions from the IEA Bioenergy ExCo71 workshop*. https://www.ieabioenergy.com/wp-content/uploads/2014/03/ExCo71-Waste-to-Energy-Summary-and-Conclusions-28.03.14.pdf

Khan, M. S., Cui, J., Ni, Y., Yan, M., & Ali, M. (2023). Techno-economic and exergo-economic evaluation of a novel solar integrated waste-to-energy power plant. *Applied Thermal Engineering, 223*, Article 119929. https://doi.org/10.1016/j.applthermaleng.2023.119929

Khan, M. S., Huan, Q., Yan, M., Ali, M., Noor, O. U., & Abid, M. (2022). A novel configuration of solar integrated waste-to-energy incineration plant for multi-generational purpose: An effort for achieving maximum performance. *Renewable Energy*, *194*, 604-620. https://doi.org/10.1016/j.renene.2022.05.127

Lee, D.-S., Lee, S.-T., Chen, Y.-T., & Su, P.-Y. (2024). Artificial intelligence technique development for energy-efficient waste-to-energy: A case study of an incineration plant. *Case Studies in Thermal Engineering*, *61*, Article 105071. https://doi.org/10.1016/j.csite.2024.105071

Majeed, M. Q., Mahdi, A. J., Nawir, M. H., & Alkhafaji, M. H. (2024). Integrating a solar PV power plants and waste-to-energy facility for stable power generation. *Case Studies in Chemical and Environmental Engineering*, *10*, Article 100859. https://doi.org/10.1016/j.cscee.2024.100859

Maphuhla, N. G., & Oyedeji, O. O. (2025). From trash to treasure: Systematic evaluation of potential and efficiency of waste-to-energy incineration for electricity generation. *Waste*, *3*(1), Article 39. https://doi.org/10.3390/waste3040039

Pan, M., Chen, X., & Li, X. (2022). Multi-objective analysis and optimization of cascade supercritical CO_2 cycle and organic Rankine cycle systems for waste-to-energy power plant. *Applied Thermal Engineering, 214*, Article 118882. https://doi.org/10.1016/j.applthermaleng.2022.118882

Sabagh, F. A., Hossainpour, S., & Pourhemmati, S. (2023). Energy, exergy, and economic evaluation of integrated waste incineration facility with a thermal power plant. *Energy Conversion and Management: X*, *20*, Article 100434. https://doi.org/10.1016/j.ecmx.2023.100434

Syafrudin, Setyono, P., Raharjo, S., Chegenizadeh, A., Budihardjo, M. A., & Wati, H. R. (2025). Review on waste-to-energy towards circular economy using life cycle assessment. *Sustainable Futures*, *10*, Article 101164. https://doi.org/10.1016/j.sftr.2025.101164

Syam, D. J. (2023). *Electrical power generation: Methods and plants*. CRC Press.

UNEP. (2020). *CCET guideline series on intermediate municipal solid waste treatment technologies: Waste-to-energy incineration*. United Nations Environment Programme. https://wedocs.unep.org/20.500.11822/32795

Wang, T., Tang, J., Xia, H., Aljerf, L., Zhang, R., Tian, H., & Akele, M. L. (2024a). Intelligent optimal control of furnace temperature for the municipal solid waste incineration process using multi-loop controller and particle swarm optimization. *Expert Systems with Applications*, *257*, Article 125015. https://doi.org/10.1016/j.eswa.2024.125015

Wang, T., Tang, J., Xia, H., Yang, C., Yu, W., & Qiao, J. (2024b). Data-driven multi-objective intelligent optimal control of municipal solid waste incineration process. *Engineering Applications of Artificial Intelligence*, *137*, Article 109157. https://doi.org/10.1016/j.engappai.2024.109157

Wang, Y., Chen, H., Li, T., Pan, P., Zhai, R., Xu, G., Dong, Y., & Zhou, Z. (2023). Thermo-economic analysis of a waste-to-energy assisted carbon capture system for a coal-fired power plant. *Applied Thermal Engineering*, *229*, Article 120594. https://doi.org/10.1016/j.applthermaleng.2023.120594

World Energy Council. (2013). *World energy resources: Waste to energy*. https://www.worldenergy.org/assets/images/imported/2013/10/WER_2013_7b_Waste_to_Energy.pdf

Yangchongthuochuaya, K., & Chaiyat, N. (2023). A hybrid waste–solar power generation and waste disposal system in Luang Prabang, Lao People's Democratic Republic (Lao PDR). *Case Studies in Chemical and Environmental Engineering*, *7*, Article 100332. https://doi.org/10.1016/j.cscee.2023.100332

Zhou, S., Mao, Z., Khan, M. S., Jin, W., & Gao, Z. (2025). Solar-assisted waste-to-energy plant with cascaded energy systems for power and hydrogen production: 4E analysis and multi-objective optimization. *International Journal of Hydrogen Energy*, *189*, Article 152022. https://doi.org/10.1016/j.ijhydene.2025.152022

Zhu, M., & Zhang, Y. (2024). Intelligent control system and operational performance optimization of a municipal solid waste incineration power plant. *Fuel Processing Technology*, *266*, Article 108162. https://doi.org/10.1016/j.fuproc.2024.108162