1

Introduction

1.1 Municipal Solid Waste Incineration (MSWI) Process and Optimal Control

1.1.1 Description of MSWI Process

Currently, the global annual growth rate of municipal solid waste (MSW) has surged from 8% to 10% [1]. MSW incineration (MSWI) technology plays a crucial role as a waste-to-energy (WTE) method, providing an effective solution to the environmental sustainability challenges associated with waste management [2]. As a typical industrial process [3], MSWI achieves WTE through a series of stages, including fermentation, combustion, heat exchange, and gas cleaning [4]. In addition to meeting its own energy requirements, the MSWI process can generate various forms of energy, including electricity and heat [5]. Moreover, it helps mitigate the risk of environmental pollution emissions. Studies have shown that the MSWI process achieves significant results, with a mass reduction of up to 70%, a volume reduction of 90%, and energy recovery reaching 19% [6,7]. Both developed and developing countries worldwide have recognized the considerable economic and environmental benefits of this process [8,9].

After half a century of development, the MSWI control system has undergone a transformative shift toward large-scale, integrated, and intelligent operations. This evolution is driven by the integration of automation, computer technology, and artificial intelligence (AI) within complex industrial processes. Currently, most MSWI plants utilize grate furnace incinerators, high-parameter boiler power generation equipment, and advanced cumulative flue gas cleaning systems. The primary goal is to support the low-carbon transformation of enterprises, thereby enhancing economic efficiency and competitiveness [10]. However, the

A Hardware-in-Loop Digital Twin Approach for Intelligent Optimization of Municipal Solid Waste Incineration: AI and Its Application to Complex Industrial Processes, First Edition. Jian Tang, Wen Yu, and Junfei Qiao.

composition and generation of MSW are influenced by various uncertainties and regional factors, including societal, economic, and environmental considerations [11]. The deployment of large-scale operational equipment further complicates the achievement of efficient and stable control over the MSWI process [12,13]. Figure 1.1 illustrates the process flow of the grate-type MSWI system in Beijing.

Figure 1.1 illustrates the MSWI process, which consists of six distinct stages: solid waste fermentation, solid waste combustion, heat exchange, steam power generation, flue gas cleaning, and flue gas emission. The main functions of each stage are outlined as follows.

1) Solid waste fermentation stage: The original MSW undergoes biological fermentation for 3–7 days in the MSW deposit pool to reduce its moisture content, which would otherwise hinder combustion [14]. After fermentation, the MSW reaches incineration readiness and is transferred to the hopper, from where it is pushed into the incinerator. This process is facilitated by the feeder, marking the beginning of the solid waste combustion stage.
2) Solid waste combustion stage: The MSW is converted into high-temperature flue gas and solid residues through the complex interactions of multiple phases—solid, gas, and liquid—and various fields such as heat, force, and energy. This stage is further subdivided into three key sub-stages such as drying, combustion, and burnout. Details are as follows.
   a) Drying sub-stage: The total moisture content of MSW on the dry grate, which includes both surface and internal moisture, significantly affects its ignition. As the furnace temperature (FT) increases, surface moisture gradually evaporates, reaching complete evaporation at 100°C. Simultaneously, internal moisture is released and absorbs additional heat as the temperature continues to rise. As a result, the total moisture content of the MSW is closely linked to its calorific value, which in turn has a significant impact on the combustion process and the overall operational conditions of the system.
   b) Burning sub-stage: From the ignition of MSW to the intense luminescent heating, and finally the completion of the oxidation reaction, the process involves a series of complex reactions, including oxidation, pyrolysis, and atomic group collisions. The oxidation reaction represents the comprehensive interaction of the combustible components with oxygen. At the same time, pyrolysis occurs under anaerobic or near-anaerobic conditions, where thermal radiation energy breaks or reorganizes the chemical bonds in carbon-containing polymer compounds, leading to the release of volatiles, which are later oxidized. The atomic group collision reaction involves the electronic energy transitions of atomic groups, accompanied by molecular rotation and vibration, which produce infrared radiation, visible light, and

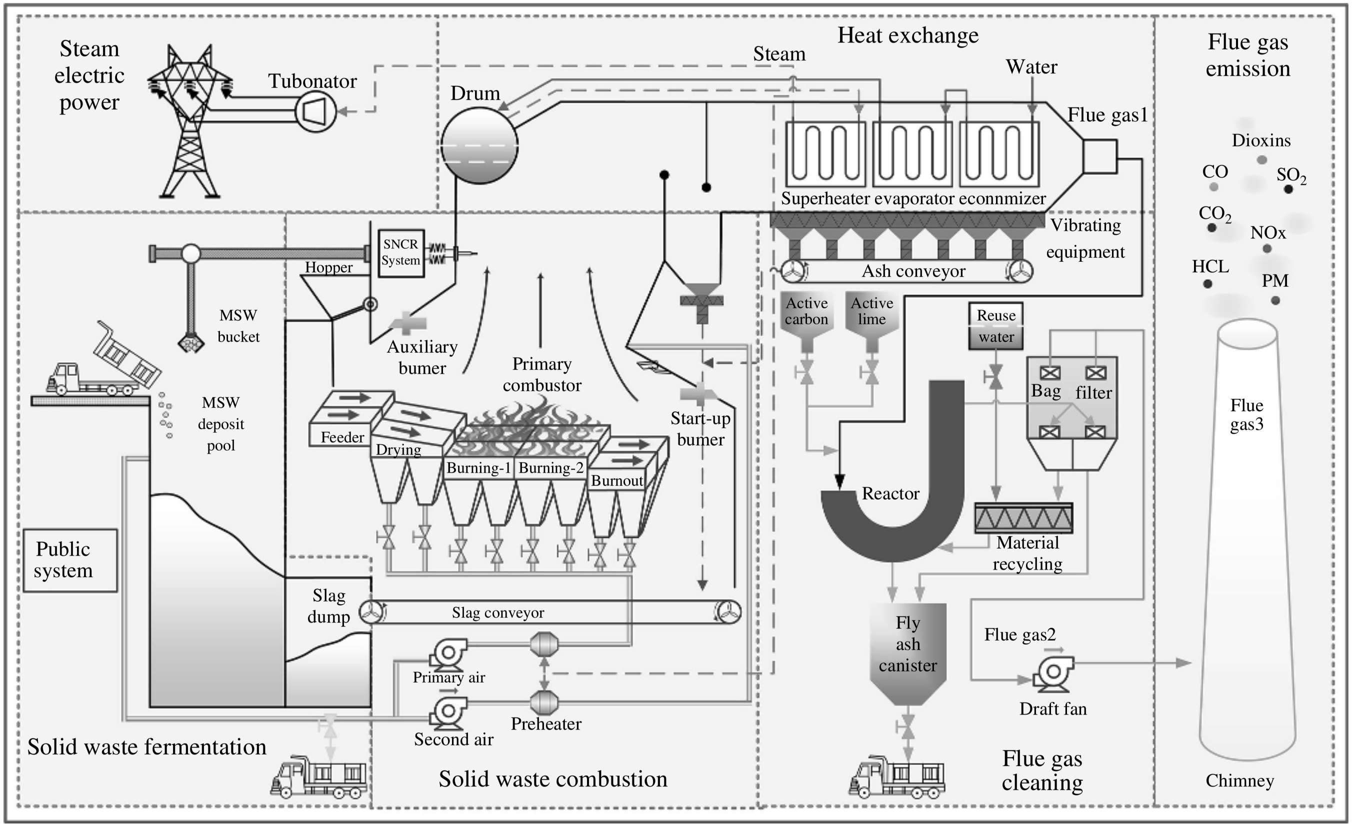

Figure 1.1 Process flow of a grate-type MSWI plant in Beijing

ultraviolet light. These intricate reactions ultimately form the flame. Thus, the combustion process is highly complex and variable, with strong coupling between reactions and the simultaneous operation of multiple processes.

c) Burnout sub-stage: After combustion, the remaining combustible components in MSW primarily consist of coke. At high temperatures and in the presence of primary air, coke undergoes oxidation with O_2, as well as gasification reactions with CO_2, water vapor, and other substances. Inert materials, including gases like CO, H_2O, and ash, gradually accumulate as the MSW on the grate is fully converted into ash. The combustion process weakens progressively until it ceases entirely [15]. As a result, this stage is characterized by low flammability, an increasing concentration of inert substances, a relatively high oxidant content, and a lower reaction zone temperature. Extending the burnout phase is often effective in improving the thermal ignition reduction rate of MSW and enhancing the level of reduction.

To ensure the complete decomposition and combustion of harmful substances in the flue gas, the “3T+E” principle is commonly applied [16]. This principle stipulates that the FT should exceed 850°C, the flue gas residence time must be greater than two seconds, and the intensity of flue gas turbulence along with the excess air coefficient should be maintained within optimal ranges.

3) Heat exchange stage: First, the high-temperature flue gas undergoes initial cooling via the water wall. Next, heat is transferred to the boiler through a combination of radiation and convection, involving key components such as the superheater, evaporator, and economizer. In the boiler, water is transformed into high-pressure superheated steam, which then enters the steam power generation phase. Finally, the flue gas temperature at the boiler outlet is rapidly reduced to 200°C. Controlling the cooling rate during this stage is critical for dioxins (DXN) generation concentration.
4) Flue gas cleaning stage: First, the selective non-catalytic reduction (SNCR) system begins the removal of NO_x at temperatures between 850°C and 1100°C. Next, the semi-dry deacidification process effectively neutralizes acidic gases, including HCl, HF, SO_2, and heavy metals, through the injection of lime and water. Following this, activated carbon plays a key role in adsorbing DXN and heavy metals present in the flue gas. Finally, the purification process is completed as particulate matter, neutralizing agents, and adsorbed substances on activated carbon are removed by the bag filter.
5) Flue gas emission stage: In the flue gas emission stage, the discharged flue gas complies with the national emission standards of various countries and is released into the atmosphere through the chimney, assisted by the induced draft fan. Currently, key environmental indicators of concern include pollutants such as particulate matter, NO_x, SO_2, HCl, and CO.

1.1.2 Control Mode in Developed and Developing Countries

The MSWI process achieves WTE through several stages, including fermentation, combustion, heat exchange, power generation, and gas cleaning. The fermentation stage involves a range of uncertain biological reactions, while the combustion stage is characterized by high-temperature chemical reactions and complex, often unclear interactions between solid, gas, and liquid phases, as well as heat flow fields. In the heat exchange and power generation stage, thermal energy is converted into mechanical and electrical energy. Gas cleaning stage employs physical and chemical principles to remove toxic and harmful substances from the flue gas. Therefore, the MSWI process is characterized by multiple stages, factors, and complex mechanisms.

The "3T+E" principle ensures the effective decomposition and combustion of harmful substances during the combustion stage. This principle involves maintaining FTs above 850°C, ensuring flue gas residence times of over two seconds, achieving sufficient turbulence intensity, and optimizing the excess air coefficient. Building on this principle, developed countries have identified key manipulated variables (MVs), such as the feed rate, grate speed, and air flow volume, along with controlled variables (CVs) like combustion line length, FT, flue gas oxygen content (FGOC), and steam flow. These countries have also developed automatic combustion control (ACC) systems customized to their specific MSW characteristics and management policies. However, the stable operation of these systems relies on the consistent components and calorific value of the MSW. Therefore, analyzing the differences in MSW components between developed and developing countries is essential.

The proportions of MSW components in different countries/regions are presented in Figure 1.2, based on the latest statistical data [17,18,19]. Beijing is used as an example of MSW components in developing countries like China.

Figure 1.2 shows that the proportion of food waste in MSW is significantly higher in developing countries compared to Japan, Europe, and North America, based on long-term average statistical data. One reason for this is that the aforementioned developed countries/regions began implementing MSW classification in the mid-20th century, leading to a higher level of environmental awareness among the public.

In contrast, developing countries like China are still refining their MSW classification policies and management systems, leading to greater uncertainty, lower calorific values, and higher component volatility in collected MSW. Therefore, the calorific value and stability of MSW in developing countries/regions are much lower than those in developed countries/regions. That is to say, the calorific value of MSW in the latter can be controlled to fluctuate within a smaller range. Therefore, the developed ACC system is difficult to be effectively applied to developing countries such as China. This leads to the manual control mode that is widely used in China. The overview is shown in Figure 1.3.

The manual control mode, as shown in Figure 1.3, adopted by domain experts in China, incorporates the principles of ACC systems. This approach addresses the specific challenges posed by numerous uncertain factors and varied operational demands in the MSWI processes of developing countries, thus forming an empirical model. In practice, operators of mechanical grab buckets rely on their

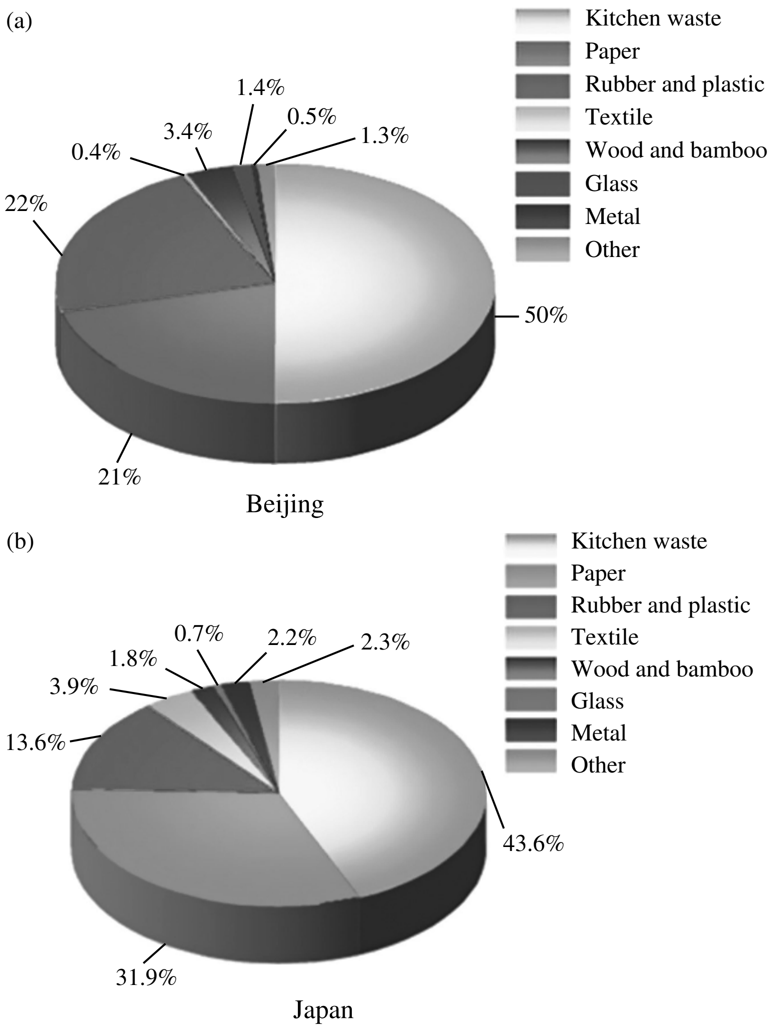

Figure 1.2 MSW components ratios of different countries/regions

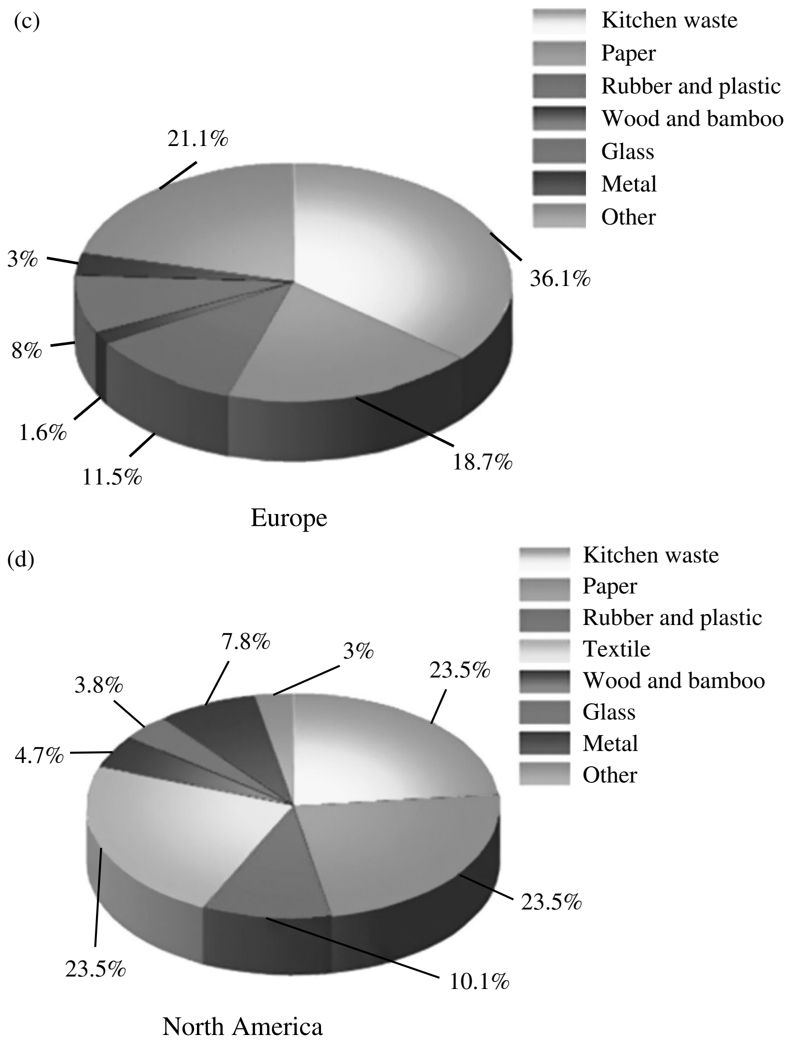

Figure 1.2 (Continued)

experience to manage MSW deposit pool partitioning. By mixing and preparing the MSW, they ensure that fermentation cycles meet standards and that the calorific value of MSW entering the furnace remains stable. Feeding frequencies are adjusted based on combustion flame video monitoring. Additionally, by predicting future trends in CVs, such as combustion state, combustion line position,

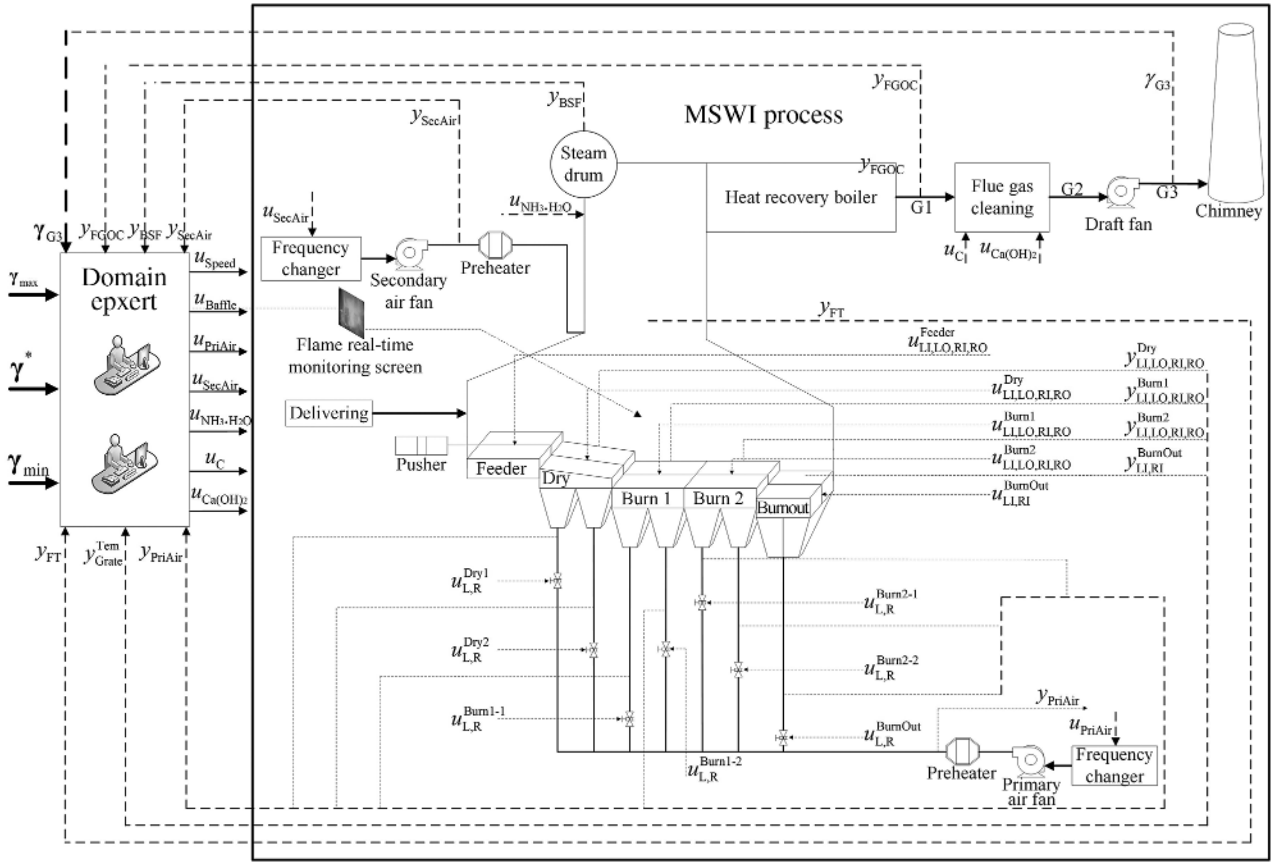

Figure 1.3 Schematic diagram of manual control mode in the MSWI process in China

FT distribution, and flue gas oxygen values, the operators of the programmable logic controller (PLC)/distribute control system (DCS) set MVs for various stages, including solid waste combustion, waste heat exchange, and flue gas cleaning, drawing on their accumulated historical experience.

It is evident that the manual control mode relies on multimodal data – ranging from structured process data to unstructured images, operation records text, and even voice communications – to assess scene demands and adjust MVs accordingly. This approach is grounded in a deep understanding of MSWI mechanisms and accumulated historical experience. However, the model faces challenges such as resource constraints among domain experts and disparities in domain experience. As a result, subjective decision-making can hinder the sustained stability of MSWI power plants, potentially compromising the efficiency of pollution control and carbon reduction efforts in the MSWI process.

To overcome the limitations of the existing manual control mode in China, it is crucial to develop an intelligent optimal control strategy based on mechanistic knowledge and empirical data to focus on minimizing pollutant emissions and improving combustion efficiency. A systematic analysis of the challenges in implementing and applying optimal control strategies is necessary to address these issues.

1.1.3 Difficulties in the Implementation of Optimal Control and Application

1.1.3.1 Description of Optimal Control for Complex Industrial Process

1.1.3.1.1 Levels and Steps Description of the Industrial Operational Optimization

With the widespread adoption of large-scale industrial production and advancements in automation and computer technology, many complex process industrial plants have implemented PLC/DCSs, enterprise resource planning (ERP) systems, and manufacturing execution systems (MESs). These technologies have significantly improved management efficiency, increased production capacity, and enhanced market competitiveness. In actual operations, enterprise managers, production managers, operation management and process engineers, operators, inspectors, and other domain experts leverage their respective domain knowledge to optimize complex process industrial operations through a human–machine cooperation mode [20], as illustrated in Figure 1.4.

As shown in Figure 1.4, the levels and steps of the complex process industrial operational optimization are as follows:

1) Enterprise managers utilize ERP to access internal resources such as staffs, finances, materials, organizational structures, and knowledge, as well as external resources like industry trends, market conditions, and policies. With this

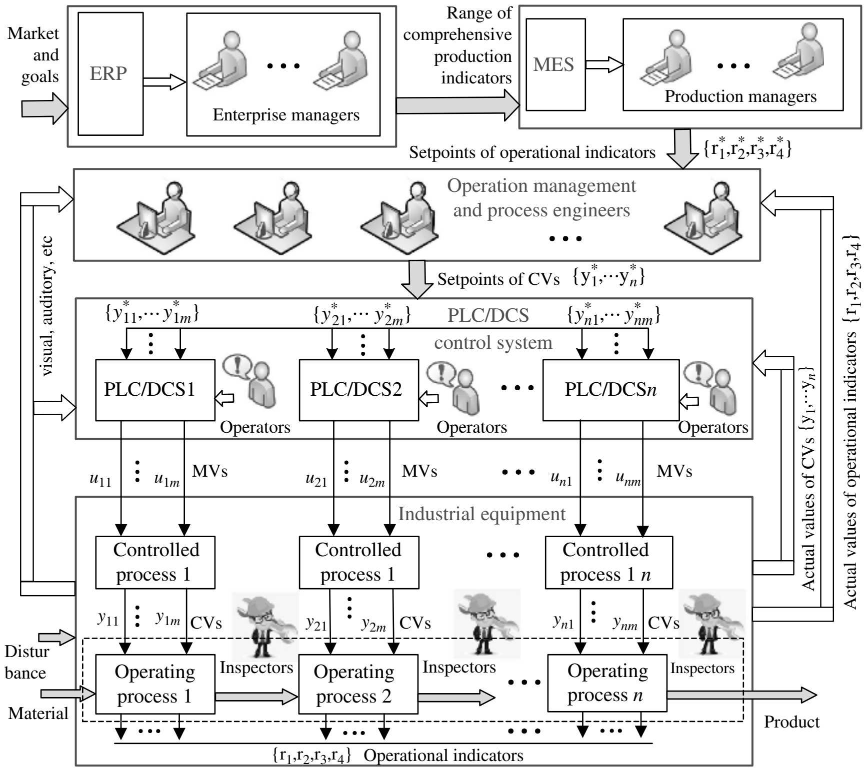

Figure 1.4 Schematic diagram of operation optimization process in complex process industries

information, they make informed decisions on comprehensive production indicators based on their experience.

2) Production manager accesses manufacturing data, production planning, scheduling, inventory, quality, cost, and other production-related information through MES. Based on their experience, they determine the setpoint values and acceptable fluctuation ranges for operational indicators $\{\mathbf{r}_1^*, \mathbf{r}_2^*, \mathbf{r}_3^*, \mathbf{r}_4^*\}$, such as quality, efficiency, consumption, and environmental factors. Additionally, using the setpoints of operational indicators provided by operation management and process engineers, the actual values $\{\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3, \mathbf{r}_4\}$ obtained through laboratory analysis or online statistics, along with multimodal production data gathered through visual, auditory, and tactile inputs (such as video monitoring and inspection feedback), the setpoint values for CVs $\{\mathbf{y}_1^*, ..., \mathbf{y}_n^*\}$ in PLC/DCSs are determined at various stages of the process. This is supported by process mechanisms and experiential knowledge.

3) Based on the error between the CV setpoint vector and the actual CV vector, the PLC/DCS operates in either automatic or manual control mode, with operator involvement. This ensures that the CV setpoints are followed and generates the corresponding MVs. For example, in PLC/DCS, the setpoints and actual values of CVs, as well as the output values of MVs, are denoted as $\{y_{n1}^{*}, ..., y_{nm}^{*}\}$, $\{y_{n1}, ..., y_{nm}\}$, and $\{u_{n1}, ..., u_{nm}\}$, respectively.
4) Finally, by applying different MVs to various controlled processes, different CVs are obtained, thereby regulating the operational indicators $\{\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3, \mathbf{r}_4\}$ – such as quality, efficiency, consumption, and environmental factors – within the setpoint range for the complex industrial process.

1.1.3.1.2 Formal Description of the Industrial Operational Optimization

According to Figure 1.4, the goal of complex process industrial operation is to maintain various operational indicators within the ranges while ensuring production safety. This can be denoted as follows:

$$r_j^{\min} \leq r_j(t) \leq r_j^{\max}, \ j = 1, 2, 3, 4 \tag{1.1}$$

In detail, the goals include maximizing product quality $r_1(t)$ and efficiency indicators $r_2(t)$ while minimizing consumption indicators $r_3(t)$ and pollutant emission concentrations $r_4(t)$.

To develop effective operational optimization control algorithms for achieving these objectives, it is essential first to construct a comprehensive process model of the complex industrial system, encompassing both the controlled and operational processes. Taking the mth controlled variable of the nth controlled process as an example, its dynamic model $f_{nm}^{\text{Controlled}}(\cdot)$ can be represented as,

$$\dot{y}_{nm}(t) = f_{nm}^{\text{Controlled}}\left(y_{nm}(t), u_{nm}(t), d_{nm}^{\text{y}}(t)\right) \tag{1.2}$$

where d_{nm}^{y} is the unknown disturbance of the dynamic model.

Furthermore, the dynamic model of complex industrial controlled processes $f^{\text{Controlled}}(\cdot)$ can be represented as,

$$\{\dot{\mathbf{y}}_1(t), \cdots \dot{\mathbf{y}}_n(t)\} = f^{\text{Controlled}}\left(\{\mathbf{y}_1(t), \cdots, \mathbf{y}_n(t)\}, \{\mathbf{u}_1(t), \cdots, \mathbf{u}_n(t)\}, \mathbf{d}_{nm}^{\text{y}}(t)\right) \tag{1.3}$$

Similarly, the dynamic model of operational indicators $f^{\text{Operational}}(\cdot)$ can be represented as,

$$\begin{aligned}\{\dot{\mathbf{r}}_1(t), \dot{\mathbf{r}}_2(t), \dot{\mathbf{r}}_3(t), \dot{\mathbf{r}}_4(t)\} = f^{\text{Operational}}(&\{\mathbf{r}_1(t), \mathbf{r}_2(t), \mathbf{r}_3(t), \mathbf{r}_4(t)\}, \\ &\{\mathbf{y}_1(t), \cdots, \mathbf{y}_n(t)\}, \mathbf{d}^{\text{r}}(t))\end{aligned} \tag{1.4}$$

where $\mathbf{d}^{\text{r}}(t)$ is the bounded unknown disturbances such as fluctuations in material composition and equipment wear.

Typically, the PLC/DCS incorporates an embedded proportional-integral-derivative (PID) module for loop control. For specific single-loop control, the primary challenge is tracking the setpoint of the CV. When the input and output of the controller, along with their corresponding change rates, are within a limited range, minimizing the tracking error of the CV in the controlled process can be formulated as the following optimization problem:

$$\min J_1(k) = \frac{1}{k}\sum_{t=0}^{k}\left(y_{nm}(t) - y_{nm}^{*}(t)\right)^2$$
$$s.t.\begin{cases} y_{nm}^{\min} \leq y_{nm}(t) \leq y_{nm}^{\max} \\ \Delta y_{nm}^{\min} \leq |y_{nm}(t) - y_{nm}(t-1)| \leq \Delta y_{nm}^{\max} \\ u_{nm}^{\min} \leq u_{nm}(t) \leq u_{nm}^{\max} \\ \Delta u_{nm}^{\min} \leq |u_{nm}(t) - u_{nm}(t-1)| \leq \Delta u_{nm}^{\max} \end{cases} \tag{1.5}$$

For complex industrial processes with intricate and unclear mechanisms, experienced operators can manually provide MV values instead of relying on PID controller outputs, effectively using manual control mode. These operators possess rich experience, strong perception, and cognitive intelligence. Replicating and even surpassing these capabilities is undoubtedly the most effective and feasible approach to achieving AI empowerment. However, the limited computing resources and closed nature of PLC/DCSs make it challenging to support this research. Therefore, this must be conducted on a higher layer with more powerful computing resources, requiring support from edge-side servers. Additionally, undisturbed data acquisition and reverse transmission must be carefully considered to ensure the safe operation of existing control systems.

Furthermore, while ensuring the safe and stable operation of complex industrial processes, operation management and process engineers aim to maximize economic benefits by considering multimodal information, actual operating indicators, production plans, and other factors. This can be expressed as follows:

$$J_2(t) = f_2(\max(r_1(t), r_2(t));\ \min(r_3(t), r_4(t))) \tag{1.6}$$

This requires operation management and process engineers to have a strong understanding of the mechanism knowledge and extensive practical experience to effectively meet the goals set by production managers, particularly in the face of dynamic changes and significant delays in multiple conflicting operational indicators. Clearly, the manual control mode is inadequate for meeting long-term operational optimization needs due to varying levels of experience and response delays. Therefore, leveraging the powerful computing capabilities of cloud-side servers is crucial to addressing these challenges using AI optimization algorithms.

The research on AI optimization algorithms that replicate the comprehensive production and operational indicators established by experts in ERP and MES integration levels for enterprise and production managers is not covered in this book and will not be discussed further here.

1.1.3.2 Requirements of the MSWI Process in Academic Research and Industrial Applications

From the perspective of control disciplines, both in academic research and industrial application, Figure 1.5 illustrates the requirements and relationships among the MSWI process control object, AI-based modeling and monitoring, AI-based control and optimization, and AI algorithm validation using a hardware-in-loop simulation platform.

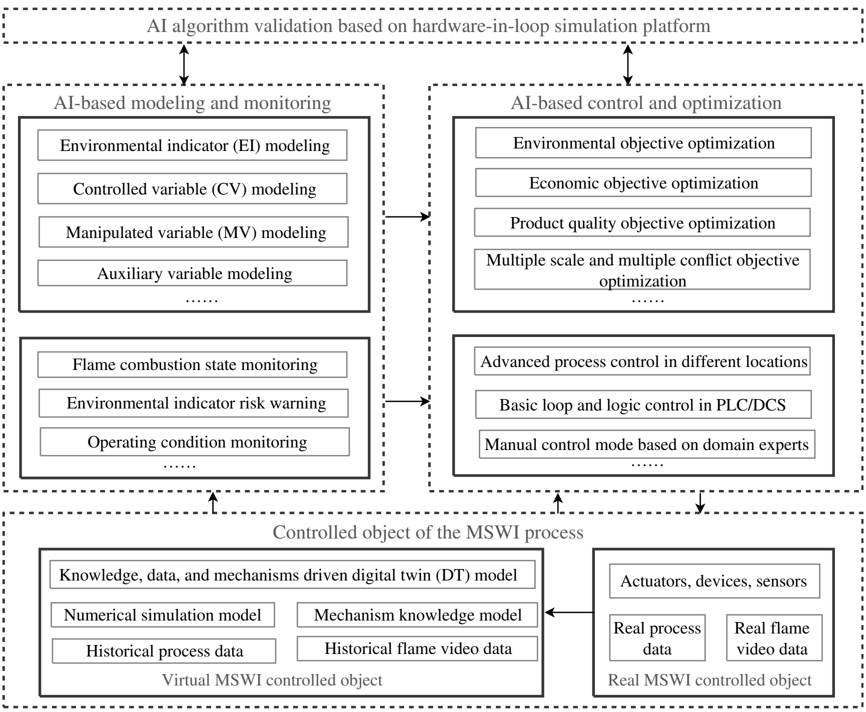

Figure 1.5 Requirements and relationships in academic research and industrial applications

The descriptions of the different parts in Figure 1.5 are as follows:

1) The MSWI controlled object is central to AI algorithm research and practical applications, encompassing both real and virtual MSWI controlled objects. The former uses actual actuators, devices, and sensors to validate AI algorithms, while the latter involves constructing mechanism knowledge models, numerical simulation models, and a hybrid-driven digital twin (DT) model that integrates knowledge, data, and mechanisms based on historical data by the former.
2) AI-based modeling and monitoring consists of two main components: modeling and monitoring. The modeling component involves research on environmental indicators (EIs), CVs, MVs, and auxiliary variables (AVs), while the monitoring component focuses on flame combustion state recognition, environmental indicator risk warnings, and operational status monitoring.
3) AI-based control and optimization consists of two main components: optimization and control. The optimization component, supported by AI-based modeling and monitoring, aims to optimize multiscale, multi-objective tasks, such as environmental protection, economic efficiency, and product quality. The control component leverages AI-based modeling, monitoring, and optimization to achieve closed-loop control of MSWI controlled objects through advanced process control at various locations, basic loop and logic control in PLC/DCSs, and manual control based on domain expert input.
4) AI algorithm validation using a hardware-in-loop simulation platform enables offline research and verification of AI algorithms before their practical application in the actual MSWI process.
5) Therefore, meeting the MSWI process requirements that simultaneously align with both academic research and industrial applications is challenging to achieve in the short term. This is a problem that demands continuous and in-depth research to address.

1.1.3.3 Difficulties of AI Algorithm Research and Validation for MSWI Processes

Implementing intelligent optimization control of MSWI processes based on AI algorithms to accommodate the regional characteristics of developing countries is a challenging task. The key challenges that need to be addressed in both academia and industry are as follows:

1) Controlled object modeling of the combustion process. The precise construction of the controlled object model is typically the foundation for research on industrial process intelligent control. Key elements in establishing a combustion process controlled object model include an accurate description of the combustion mechanism, a clear understanding of the fluctuation range

of combustion boundary conditions, and complete data on the combustion process under multiple conditions. However, the complexity of the combustion mechanism and the varying levels of expertise among field professionals lead to complex and diverse operating conditions in real-world processes, making it difficult to construct accurate mechanistic models or comprehensive data-driven models.

2) Self-organized intelligent control of the combustion process. The core challenge lies in ensuring stable combustion through effective "air distribution and material distribution" operation with the primary CVs being FGOC, FT, steam flow rate, and combustion line. In addition to the variability of MSW components and the uncertainty of calorific value, which act as significant interference factors, long-term uninterrupted operation, equipment wear, and periodic maintenance also contribute to these disturbances. Furthermore, the combustion line, as a key CV, can only be estimated based on the experience of domain experts, which greatly limits the intelligence control of combustion stage. The strong coupling relationships and long time delays among MVs, CVs, and between MVs and CVs require the controller to have self-organizing structures and adaptive parameter capabilities to suppress these interferences.
3) Operational indicators real-time monitoring. The relevant indicators include EIs such as pollutant and greenhouse gas emission concentrations, product indicators like fly ash production, slag thermal reduction rate, combustion efficiency, and organic matter removal rate, as well as economic indicators such as MSW treatment fees and grid-connected power generation. While conventional pollutants and greenhouse gases can be detected online in real-time using continuous emission monitoring systems (CEMSs), other operational indicators remain difficult to measure online due to technical or cost constraints. The long time delays associated with offline laboratory testing hinder the optimization of overall process operation. Moreover, constructing soft sensing models with these data faces challenges, including sparse labeled samples, imbalanced modeling samples, and unknown expected distributions.
4) Operation status perception and abnormal monitoring. Currently, abnormal monitoring based on domain experts' cognitive experience is inefficient and prone to false positives and false negatives, making it challenging to identify the underlying factors causing abnormalities. In addition to the difficulty in extracting and quantifying knowledge from process data, especially with frequent changes in operating conditions, domain experts also struggle to model the knowledge extraction mechanism related to combustion flames. The variability of feed components, uncertainty in calorific value fluctuations, and dynamic time-varying factors due to equipment wear, irregular maintenance, and other influences make it difficult to achieve intelligent perception and abnormal monitoring of MSWI process operation status, even for experienced domain experts.

5) Whole-process collaborative optimization operation. The optimization goal of the MSWI process is “reduction, low emissions, and revenue generation,” which involves increasing the MSW reduction ratio (reduction), lowering the emission concentration of pollutants (low emissions), and enhancing the economic benefits of WTE (revenue generation). These operational indicators not only conflict and constrain each other but also exhibit dynamic time-varying characteristics and span multiple temporal and spatial scales. They are linked to several relatively independent processes, such as fermentation, combustion, and cleaning. Furthermore, the diversity of raw material sources, the complexity of their components, and the variability and frequency of operating conditions during the incineration process all contribute to the challenge of achieving collaborative optimization across the whole system.
6) AI algorithm verification simulation platform. Algorithms developed for intelligent optimization control in the process industry must undergo rigorous validation and testing before being applied in actual engineering. This requires the use of high-reliability evaluation techniques to assess both the expected outcomes and the potential risks of implementation. The inherent characteristics of the MSWI process—such as multiple variables, strong coupling, high nonlinearity, and uncertainty—along with the need for operational safety, information confidentiality, and economic efficiency at industrial sites, make it challenging to debug and test newly developed AI technologies in real-world processes. The primary challenge is to develop a modular simulation verification platform that can collect a wide range of physical quantities, time scales, data sources, and multimodal data. This platform should allow for safe isolation between different components and simulate the real MSWI process effectively.

To address the research challenges, it is essential to first examine the current state of academic research and industrial applications of AI algorithms for operational optimization in the MSWI process.

1.1.4 Development of Optimal Control Research Based on Artificial Intelligence (AI)

Recently, AI has become the primary catalyst for intelligent manufacturing, with widespread integration across various industries, including metallurgy, petrochemicals, and energy [21, 22, 23]. The evolution from the third industrial revolution, characterized by automation, is now progressing into the fourth industrial revolution, commonly referred to as Industry 4.0 [24,25]. This new phase is marked by the seamless integration of AI technologies. In response to the demands of industrialization and automation, industrial sites deploy numerous sensors to collect diverse process data [26]. At the same time, advancements in the Internet of Things (IoT), cloud computing, and big data analytics significantly enhance the potential for integrating AI into industrial processes [27,28].

These AI algorithms application in MSWI process include neural networks (NNs), support vector machines (SVMs), principal component analysis (PCA), tree-based models, fuzzy logic (FL), particle swarm optimization (PSO), and deep learning.

NN-based methods are the most popular due to their robust learning capabilities, which make them applicable to various tasks such as modeling, monitoring, control, and optimization. Additionally, the flexible structure of NN allows for adjustments based on specific operational requirements and conditions. While tree-based models and SVM methods were proposed earlier, their application to the MSWI process began only in 2017. Furthermore, PCA is used for feature extraction in modeling and concept drift detection in monitoring, although its practical applications remain relatively limited.

FL-based methods are well-known for their effectiveness in modeling and controlling complex industrial processes. As a result, FL has been applied in the MSWI process since 1989. Between 2003 and 2005, it became one of the most popular control methods and was later expanded to maintenance and modeling within the MSWI process. However, research on FL has gradually declined in recent years, likely due to the rise of NN and other methods. In response to this trend, researchers have introduced the fuzzy neural network (FNN) method, which seamlessly combines FL and NN.

PSO is an evolutionary algorithm categorized under metaheuristic methods. These methods are effective in searching for optimal parameters for models and controllers in the MSWI process. However, the application of metaheuristic methods is limited by factors such as randomness and time costs. Deep learning (DL) is relatively new compared to other methods. Its application in the MSWI process gained momentum in 2021 and 2022 and is expected to see rapid growth in future studies.

These AI algorithms for the MSWI process can be categorized into AI-based modeling and monitoring and AI-based control and optimization. The details are presented in the following subsections.

1.2 AI-Based Modeling and Monitoring

1.2.1 Numerical Simulation Modeling

1.2.1.1 Brief Description of Numerical Simulation for MSWI Processes

Operating under optimized conditions for extended periods is challenging for the MSWI process due to the uncertainty in MSW composition and frequent fluctuations in operational conditions. A customized numerical simulation model can be used to account for these varying conditions, ensuring the safe operation of actual MSWI power plants.

Early attempts to simulate the incinerator date back to the 1970s, aimed at exploring the combustion process. The combustion area inside the incinerator was divided [29], followed by a numerical simulation of a fixed combustion bed [30]. In [15], the physical and chemical changes of the MSW during bed combustion were analyzed. The study established the mass, momentum, and heat transfer control equations and developed the fluid dynamic incinerator code (FLIC) software.

Furthermore, computational fluid dynamics (CFD) techniques have been used to simulate the influence of secondary air and incinerator structure on the MSWI process [31]. The combustion area is divided into the solid-phase MSW area on the grate and the gas component area in the combustion chamber [32]. The solid-phase combustion model on the grate allows for the study of MSW characteristics, operating parameters, and other design factors. The discrete element method (DEM) has recently been employed to simulate the solid-phase MSW combustion [33], while Fluent is used to simulate the combustion of gas components. However, these studies focus solely on simulating the process within the incinerator.

Another commercial software, Aspen Plus, can facilitate simulations based on mass and energy conservation principles in terms of a macro perspective. Numerous investigations have been conducted to simulate various industrial processes from both micro and macro perspectives. In the petrochemical industry, Fluent and Aspen Plus were used to simulate the convection section of the ethylene cracking furnace and perform regional coupling [34]. The parameters of the C2 hydrogenation reactor model were adjusted using actual operating data to align the numerical simulation with real-world conditions. In the discrete industry, a workshop management and control system from the perspectives of system function, architecture, and simulation analysis was designed [35], and a framework for spacecraft system engineering based on DTs was proposed [36]. However, similar research has not been reported for the MSWI process in grate-type furnaces. Therefore, creating a customized numerical simulation that closely matches actual operating conditions is crucial. This would enable real-time simulation of the combustion process in the furnace and validate the optimized control algorithms developed offline, ensuring both the safety and optimal performance of the MSWI process.

Several reviews have been conducted on numerical simulations in fields with similar backgrounds. The numerical simulations of falling film evaporation outside horizontal tubes using CFD were summarized [37]. Other numerical simulation applications include sewage treatment [38], flight safety [9], ship–ice interaction [40], and pneumatic conveying [41]. Additionally, recent reviews have focused on combustion simulations in circulating fluidized bed reactors and rotating packed beds using CFD [42,43]. Many reviews of the MSWI process have concentrated on topics such as fly ash, heavy metals, and dioxins [44–50]. Based on the research achievements in these fields, we classify the numerical simulation of the MSWI process into two categories: those based on commercial software and those utilizing self-developed software. The details are provided in the following subsections.

1.2.1.2 Based on Commercial Software

1.2.1.2.1 Based on Fluent Software

The combustion stage can be divided into two parts: the combustion of solid-phase MSW on the grate and the combustion of gas components in the combustion chamber. Fluent is primarily used for simulating flue gas flow and heat transfer in the latter part. There are four modes in Fluent software to complete the numerical simulation of MSW combustion.

Based on Fluent Software and Actual Measured Value This method uses experimentally measured values, such as gas velocity, temperature, and composition on the surface of the grate, as inputs for Fluent in simulating gas component combustion. Experimental research and numerical simulations of a grate incinerator were conducted [51], and the data on the grate were obtained through actual measurements. These values serve as boundary conditions for gas component combustion. Additionally, gas composition distribution data from [52] were used to simulate combustion in the incinerator. Furthermore, [53,54] all adopt this method. The advantages of this approach include that the simulation results are closely aligned with actual operating conditions. However, the drawbacks are that experimental measurements are expensive, and the data are specific to certain incineration conditions, limiting the application range.

Based on Fluent Software and its User-defined Functions (UDFs) This method treats the solid-phase MSW on the grate as particulate matters (PMs) with uniform physical properties [55]. When the flame heat is transferred to the grate, the MSW undergoes various types of reactions. Each sub-reaction is compiled in a UDF and imported into Fluent. Additionally, the combustion of biomass is simulated by considering fuel drying, pyrolysis, and char oxidation processes, which are calculated in the UDF [56]. However, the gas composition produced from the solid-phase combustion on the grate is assumed to be independent of temperature [57], and the PMs are is treated as homogeneous, with temperature gradients being neglected [58].

Based on Fluent Software with Continuum Model The continuum model assumes that the solid-phase MSW on the grate consists of uniform PMs. These PMs, regardless of their different shapes and sizes, are all treated as spherical particles. As a result, temperature, gas composition, and solid composition are described as continuous spatial functions. This approach is simple to use, captures the basic information of radiant heat flux, and does not require precise boundary conditions. However, it overlooks the temperature and elemental concentration gradients within the particles, as well as the interactions among parameters in the horizontal direction. Additionally, this model is not suitable for describing hot and thick PMs with large temperature gradients.

In the FLIC software, the solid-phase MSW is treated as a continuum model. Using the obtained temperature, velocity, and concentration of each component, FLIC and Fluent are coupled. The temperature, velocity, and gas concentration calculated by FLIC serve as the inlet boundary conditions for simulating the gas flow field in Fluent. Conversely, the simulation results from Fluent are used to calculate the radiation flux incident on the waste bed model. A cycle of the coupled simulation is completed by modeling the MSW combustion on the grate and the combustion of gas components in the combustion chamber. This process is repeated until the radiant heat flux distribution in the combustion chamber stabilizes, indicating convergence between the two models. This method has been widely used to study the MSWI process and its related parameters [31, 35, 59, 60, 61, 62, 63, 64, 65, 66, 67].

Coupling Fluent Software with Discrete Element Method (DEM) The use of the DEM to simulate MSW combustion on the grate has been proposed [68]. This approach approximates the MSW on the grate as spherical particles. Additionally, the method of coupling Fluent with DEM is employed to simulate the entire incineration process [168]. Each PM on the grate is assumed to undergo various changes, such as drying, devolatilization, and carbon burnout. As a result, this method can handle hot and thick particles and capture the dynamic characteristics of a single PM. However, the number of PMs on the grate is very large, leading to excessively long computation times for the simulation. Furthermore, the PMs have various shapes and sizes, which complicates the simulation. This obviously necessitates more in-depth research and more powerful computing resources to support such numerical simulations.

1.2.1.2.2 Based on Aspen Plus Software

Based on the simulation objectives, numerical simulation model using Aspen Plus can be categorized into four main areas: optimizing the MSWI process flow, improving power generation efficiency, enhancing economic benefits, and analyzing optimized parameters. The details are as follows:

1) Optimizing the MSWI process flow: A numerical simulation model for air incineration and O_2/CO_2 incineration technologies was established using the block modeling method [170]. However, the incineration process is simplified into two subprocesses: pyrolysis and pyrolysis product combustion. Additionally, the impact of PM size on combustion is neglected. A simulation of the flue gas deacidification process in a pure oxygen melting system showed that the efficiency of HCl and SO_2 removal approaches 100%, with denitrification efficiency reaching 93% [69]. A simplified method for simulating combustion operation and flue gas treatment has also been proposed [70].
2) Improving power generation efficiency: Electrical energy generation simulations indicate that reducing moisture content can enhance power generation efficiency [71]. Furthermore, simulations exploring power generation efficiency improvements using strategies such as air heater rearrangement, reheater introduction, flue gas condensation, and comprehensive gasification have been conducted [72]. Four different flue gas cleaning processes were simulated to compare their impact on power generation efficiency [73].
3) Enhancing economic benefits: Different strategies were simulated to evaluate the efficiency of MSWI power plants [74], demonstrating that a combination strategy of waste gasification, gas boilers, and flue gas condensation yields the highest efficiency.
4) Analyzing optimized parameters: Simulations examining the effect of temperature and moisture content on carbon conversion and cooling efficiency revealed that increased moisture content leads to a decrease in the concentration of combustible components and gasification efficiency [75]. A numerical simulation model for an MSW fixed-bed gasifier was developed to analyze gasification process performance under various operating parameters [76].

Although simulation model based on Aspen Plus offers fast simulation speeds, it has several drawbacks, including limited visualization capabilities and difficulty in accurately simulating solid-phase combustion processes. Additionally, these studies face challenges in effectively supporting research on pollution reduction and operational optimization for real MSWI power plants.

1.2.1.2.3 Based on Other Software

The non-mainstream approaches using other software have also garnered increasing attention. For instance, DEM and ANSYS CFX are combined to simulate both solid-phase and gas-phase combustion [77]. A simulation model of a moving grate is developed using Phoenics software [78], which focuses solely on simulating the solid-phase combustion on the grate.

Therefore, numerical simulation methods based on commercial software have gained widespread use. However, the types of models embedded in different software are often limited. For example, most Fluent-based simulations primarily focus on gas-phase combustion. To simulate solid-phase combustion on the grate, techniques like UDF or FLIC must be employed. Simulations based on Aspen Plus encompass the entire MSWI process and are mainly used during the design phase of MSWI plants. However, they cannot analyze the effects of key operating variables such as grate speed. Consequently, the reliability and stability of other software tools need to be gradually verified.

1.2.1.3 Based on Self-developed Software

To simulate the solid-phase MSW combustion on the grate, a two-dimensional steady-state model is proposed [79], which is solved using the finite element analysis method after discretizing the partial differential equations. A specific equation is employed to solve the pressure–velocity coupling and to adapt to the shrinking cell height.

Overall, numerical simulations based on self-developed software can avoid certain limitations, such as the restricted types of embedded models. However, their range of application is often narrow, and their reliability requires extended periods of verification. Consequently, self-developed software can be useful in enhancing commercial software over the long term. The development of specialized numerical simulation software for the MSWI process is also essential.

1.2.1.4 Difficulties of Numerical Simulation Modeling

1.2.1.4.1 Mechanism Analysis Combined with Numerical Simulation

The MSWI process involves complex physical and chemical reactions, with fluctuating and uncertain component properties, as well as the mutual influence of multiple MVs and CVs. As a result, establishing precise mathematical models is challenging. Therefore, combining different numerical simulation models is essential for facilitating mechanism analysis.

Mechanism analysis based on numerical simulation has been successfully applied in various related fields. For instance, a numerical simulation of the ethylene glycol production process was established using Aspen Plus [80], which examined the dynamic response of the desorption tower based on changes in feed, feed components, and reboiler heating value. Similarly, Aspen Plus has been used to analyze pollution emissions and alternative fuel utilization [81]. In biomass combustion, numerical simulations established by Aspen Plus have been used to analyze NO_x emissions [82]. Additionally, the numerical simulation model of the hydrogenation reactor, developed with HYSYS, combines process mechanisms to assist in industrial process modeling. The three-dimensional pressure field in the pressure energy exchanger, based on Fluent, provides effective support for studying the end-surface liquid film model [83]. Similarly, Fluent-based simulations have been used to analyze factors affecting the heat absorption of furnace tubes and the location of the reflux zone [34].

These approaches can contribute to the research on the combustion mechanism analysis of the MSWI process. However, performing an effective numerical simulation that can support the mechanism analysis of the actual MSWI process remains an open challenge.

1.2.1.4.2 Numerical Simulation for the Whole MSWI Process

The MSWI process encompasses fermentation, combustion, heat exchange, and gas cleaning. Establishing a numerical simulation for the entire complex industrial process, tailored to specific user needs, using a single commercial software package is challenging [84]. However, by combining the strengths of different software tools, a comprehensive numerical simulation of the entire process can be achieved with customized interface functions.

The approach of building numerical simulations using multiple software tools has been successfully applied in other related fields. For example, Aspen Plus and CFD are coupled to simulate the pyrolysis process of biomass [85], where CFD simulations are performed by selectively importing Aspen Plus results as inputs. Similarly, a coupled model based on Fluent, Modefrontier, and MATLAB has been constructed [86]. CFD and Aspen Plus have been used together to simulate the exchange esterification process [87]. Aspen Plus and MATLAB have been combined for the organic solvent nanofiltration process [88]. Additionally, MATLAB and HYSYS have been integrated to optimize industrial processes [89].

Establishing a numerical simulation for the entire MSWI process by combining multiple software tools, while incorporating the MSWI mechanism, remains an ongoing challenge.

1.2.1.4.3 Matching the Numerical Simulation Results with the Actual Process Data

The variables used in the numerical simulation, such as MVs, are significantly fewer than those in the actual MSWI process. Although numerical simulation models are constructed based on the physical parameters and operational data of actual MSW processes, these models often fail to effectively reflect the real-time status of the MSWI process. Moreover, many of the numerical simulation parameters are based on default values or assumptions. Therefore, combining the numerical simulation parameters with actual MSWI parameters and enabling dynamic, real-time interaction remains an unresolved challenge. Further research is needed to integrate machine learning, AI, incineration mechanisms, and domain expert knowledge to address these issues.

Studies on aligning the results of numerical simulations with actual industrial process data have been proposed in various related fields. For example, an integrated process model has been developed using Aspen Plus, incorporating empirical knowledge, optimization algorithms, and mechanism modeling [90]. This ensures consistency between simulation results and real-world operations. Additionally, the kinetic parameters of the C2 hydrogenation reaction are calibrated using a least squares algorithm with industrial process data, facilitating real-time communication between HYSYS and MATLAB [91]. In other cases, numerical simulation models have been calibrated using actual industrial data, with reaction kinetics and inactivation models being fitted with industrial data using a genetic algorithm [92].

These studies indicate that there are few efforts to calibrate MSWI simulations based on actual process data. However, the methodologies discussed above can provide valuable insights for aligning numerical simulations with actual data in the MSWI process.

1.2.1.5 Digital Twin (DT) Model Construction for MSWI

The DT model can provide valuable support for the intelligent optimization and control of complex industrial processes [93]. However, studies on the DT model for the MSWI process are currently lacking.

Several issues must be addressed when applying DT to MSWI, such as real-time interaction methods, operation of numerical simulation models, input/output management of the DT model, authenticity evaluation, and feedback calibration. Most successful DT-based studies have focused on discrete manufacturing industries. For example, DT-based system software, which includes the design and implementation of system functions, system architecture, and simulation analysis, is developed with consideration for workshop production processes [35]. An overall model and application framework for spacecraft system engineering based on DT is proposed [36]. Additionally, a DT model of the cutting process is introduced [94], providing details on its concept, components, functions, and operational flow to support optimization, decision-making, and tool usage precision.

The modeling methods for creating virtual models are discussed in [95], and the mechanism for connecting the physical production system at the workshop level to its mirrored virtual model is described. A DT modeling method based on the principles of bionics has been recently proposed for the manufacturing process of aviation parts [96]. Furthermore, a digital and physical spaces framework has been proposed [97], which accounts for updates when the performance of the model degrades. Other application scenarios for the DT model include manufacturing processes [98,99], smart cities [100], complex equipment [101], and healthcare [102].

Studies on the application of DT models to the MSWI process are increasingly available. Both offline and online modes should be used for constructing the DT model. The offline mode can be developed by coupling multiple numerical simulation models, utilizing existing commercial software and high-performance computational hardware. Software tools such as DEM, FLIC, Fluent, and Aspen Plus can be coupled to facilitate offline modeling. However, a fast and low-energy-consuming online DT model is necessary for interaction with the actual MSWI process. This online model can be created by building an agent-based model from the offline mode using machine learning algorithms.

Existing data security isolation and acquisition technologies can support the implementation of such models, considering the actual data acquisition and pre-processing needs due to the closed nature of the DCS and the safety requirements of the MSWI process. These technologies can also aid in feedback calibration, enabling effective interaction between the DT model and the MSWI process.

However, before applying the DT model to the real MSWI process, a hardware-in-loop platform should be developed to simulate the actual MSWI process. As a result, significant research has been conducted on the application of DT models to the actual MSWI process.

Figure 1.6 illustrates the relationship among the incineration mechanism, the actual MSWI process, human brain cognitive theory, the challenges in numerical simulation, and DT model construction.

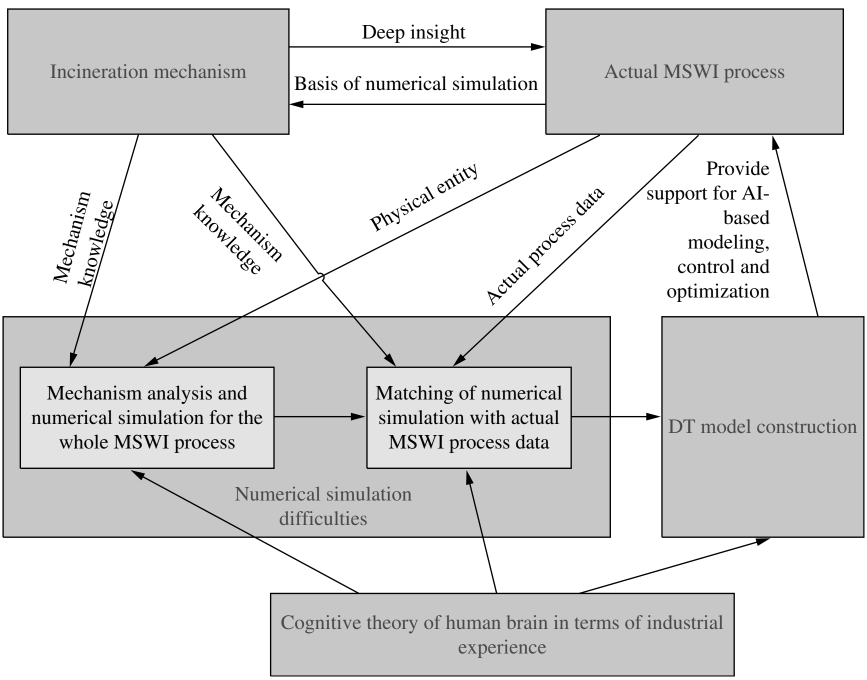

Figure 1.6 Relationship between the incineration mechanism, the actual MSWI process, human brain cognitive theory, numerical simulation challenges, and DT model construction. [103] / John Wiley & Sons / CC BY 4.0

Therefore, it is essential to integrate human brain cognition theory and AI algorithms with the mechanisms of the actual industrial process to construct a DT model of the MSWI process [103].

1.2.2 Combustion Process Modeling

Typically, complex industrial processes use historical data to construct models of controlled objects for validating intelligent control algorithms [104, 105, 106, 107]. This subsection is further divided into two parts: key CVs and AVs.

1.2.2.1 Key Controlled Variables (CVs) Modeling

Key CVs in the combustion process include furnace temperature (FT), flue gas oxygen content (FGOC), boiler steam flow (BSF), and combustion line position [108]. These models can be classified into two types: multi-input single-output (MISO) and multi-input multi-output (MIMO).

For FT, it is typically measured using a thermocouple, serving as a critical parameter to characterize the stability of the combustion process and directly influencing pollutant emission concentrations [109,110]. Developing a controlled FT model is a crucial prerequisite for achieving stable control and validating algorithms [111,112]. Existing studies on data-driven models include multi-model intelligent combinations [113], FNN, and least squares support vector regression (LS-SVR) [114]. However, these studies primarily focus on a single operating condition within a narrow range, highlighting the need for improved adaptability.

For FGOC, it refers to the coefficient of excess air, which can help characterize the combustion status to some extent. Measurement points for FGOC are typically located at the outlet of the waste heat boiler (Flue Gas1) and the chimney (Flue Gas3). A weighted PCA and an improved long short-term memory (LSTM) network strategy is used to construct a prediction model for the Flue Gas3 location [115]. However, further improvements are needed in terms of modeling accuracy.

For BSF, it determines the recovery efficiency of the waste heat boiler and the power generation of the steam turbine [116]. Studies on prediction models for BSF include adopting a radial basis function (RBF) NN with adaptive Kalman filter parameter updating [111], using RBF based on the average influence value algorithm for feature selection [117], and employing the LSTM algorithm [118].

The aforementioned studies primarily rely on data-driven methods to construct MISO soft sensing or prediction models, which are not control-oriented models for controlled objects. As a result, these models face challenges in supporting the development of optimal control algorithms.

As a typical MIMO system, the coupling between MVs and CVs in the combustion process is significant. For FGOC and BSF, an auto-regressive with extra Inputs (ARX) model has been constructed [119]. Additionally, Ding et al. [120] developed a T-S FNN model for FT, FGOC, and BSF. While these studies contribute to the research on optimal control, they face challenges such as poor modeling accuracy and unresolved issues regarding the model's adaptability under various operating conditions.

Based on existing studies of other industrial processes [121,122], the nonlinear and strong coupling characteristics of the combustion process necessitate in-depth research on the MIMO-controlled object model of the MSWI process. Moreover, future research should focus on its adaptability to complex operating conditions.

1.2.2.2 Auxiliary Variables (AVs) Modeling

The stability of the combustion process is influenced by numerous AVs. However, this study specifically focuses on the calorific value of MSW and the thickness of the MSW layer.

The calorific value of MSW directly influences the selection of manipulation strategies, including decisions regarding the addition of auxiliary fuel and its quantity. It also impacts the operation, maintenance, management, and economic benefits of enterprises [123,124]. Due to the difficulty of direct detection, heat balance mechanisms are employed [125,126]. To overcome the unclear mechanisms, a soft sensing model based on process data is constructed [127]. Subsequently, various data-driven models have been proposed, such as the backpropagation neural network (BPNN) [128, 129, 130], L-M BPNN [131], RBF [128], adaptive network-based fuzzy inference system (ANFIS) [128], and FNN [132]. Non-NN soft sensing models, such as SVM [133], LS-SVM [134], and random forest (RF) [133], are also used to build soft sensor models. A comparison study of artificial neural networks (ANNs), ANFIS, SVM, and RF showed that ANFIS exhibited the best performance, followed by RF, while ANN was less effective [133]. Recently, a real-time soft sensing model based on deep learning and image recognition has been proposed [135]. However, the true samples used to construct such a soft sensing model present challenges, including high acquisition costs, sparse samples, and a limited range of operating conditions. Enhancing generalization performance by combining modeling data characteristics remains an open issue.

The thickness of the MSW layer changes dynamically during the combustion process and is closely related to the calorific value of MSW. It is also considered a CV in some control strategies. While nuclear instruments can be used for direct detection, they present challenges such as high costs, complicated maintenance, and limited practicality. Similar to the calorific value of MSW, obtaining the true value of the MSW layer's thickness is difficult. Therefore, soft sensing models for its detection primarily rely on indirect calculations using data such as air pressure, air volume, negative pressure, and grate area, taking into account physical properties [136]. As a result, further research is needed to develop more accurate and economical real-time detection methods in the future.

1.2.3 Operational Indicators Modeling

1.2.3.1 Environmental Indicators (EIs) Modeling

The EIs can be divided into two types. The first type consists of those that can be detected online using CEMS, such as particulate matter, NO_x, SO_2, HCl, HF, and CO_2. The second type includes those that are difficult to measure, such as the emission concentrations of toxic heavy metals and organic pollutants like DXN and volatile organic compounds (VOCs). The emission concentrations of these difficult-to-measure indicators are primarily determined through offline laboratory analysis [137]. Therefore, this subsection is divided into two categories: the prediction models for easily detectable indices and the soft sensing models for difficult-to-detect indices.

1.2.3.1.1 Prediction Model for Easily Detectable EIs

Considering the reliability of the CEMS and the need for intelligent optimal control, it is crucial to develop a prediction model for easily detectable indices.

For NO_x emissions, a system identification model was initially developed in [138] and used its output as a feedback signal to control the amount of NH_3 injected. Additionally, a multi-transfer model of NO_x emissions, with FGOC and secondary air volume as inputs, was established using continuous-time system identification [139]. Subsequently, prediction models were built using BPNN [140], RBF [141], and LSTM [142] algorithms. However, practical verification of these models in actual MSWI plants has yet to be conducted.

Carbon monoxide (CO) is a toxic gas that must be strictly controlled [143]. Additionally, CO concentration is directly related to DXN emissions [144], with the latter exhibiting a noticeable spike phenomenon in its half-hour average. Zhang et al. [145] proposed a CO emission prediction method based on reduced-depth features and an LSTM optimization strategy, which includes particle design, fitness function design, and optimization through PSO. The results show that the aforementioned prediction models can effectively predict EIs in specific scenarios.

Unfortunately, prediction models for particulate matter and acidic gases, such as HCl and HF, have not yet been reported [146]. Most existing studies have employed software tools, such as CFD, for numerical simulations [147,148], which have then supported process design optimization and mechanism analysis. Notably, studies on carbon emissions in the MSWI process remain unreported.

1.2.3.1.2 Soft Sensing Model for Difficult-to-Detect EIs

Considering that some EIs cannot be detected online, this study focuses exclusively on DXN, which is the primary contributor to the "Not In My Back Yard" (NIMBY) phenomenon in MSWI plants [149]. From a generation mechanism perspective, the formation, decomposition, resynthesis, and adsorption phases of DXN are interrelated with the entire MSWI process. Additionally, a “memory effect” exists that has not been sufficiently explained [150]. DXN emission concentration is typically determined through laboratory tests, which are costly and time-consuming. Therefore, establishing a soft sensing model for DXN emission concentration offers a promising approach to guide research on its optimal control.

A mapping relationship between flue gas temperature, CO, and DXN concentration was established [144]. Subsequently, a multiple linear regression analysis model was developed [151], which indicates a linear mapping relationship exists between DXN concentration, combustion chamber temperature, and CO concentration with 7% FGOC. Additionally, a linear model for DXN concentration with FGOC, the proportion of primary air volume, and total air volume as inputs was constructed [152]. However, these models fail to accurately describe the nonlinear relationship between the input features and DXN emission concentration. To address this, BPNN and genetic programming were employed to construct a DXN model [153], and a method combining BPNN with genetic algorithm to optimize learning parameters was proposed [154]. Given the small sample size, feature selection based on the underlying mechanism and the SVR algorithm were utilized [155]. Despite these efforts, the feature learning ability of these models requires further enhancement.

Currently, existing studies primarily focus on constructing the DXN emission concentration model at the G3 flue gas (chimney) position. However, this approach does not effectively support DXN reduction control at the generation source. Furthermore, the mechanistic characteristics of the entire DXN process should be examined.

1.2.3.2 Product Indicators (PIs) Modeling

The PIs of the MSWI process differ from those of traditional industrial processes, such as mineral processing and petrochemical processes [156]. In this study, we define fly ash yield, heat reduction rate, and combustion efficiency as the PIs of the MSWI process.

1.2.3.2.1 Fly Ash Yield

Fly ash consists of particulate matter generated after the combustion of MSW and the removal of acidic gases, as well as activated carbon resulting from the adsorption of DXN and heavy metals [157,158]. It poses a potential threat to the sustainable development of the ecological environment [159]. Research on fly ash yield primarily focuses on its harmless treatment [160,161] and resource utilization [162,163]. However, the modeling, prediction, and intelligent optimal control of fly ash yield in the MSWI process remain largely unaddressed.

1.2.3.2.2 Heat Reduction Rate

The heat reduction rate is defined as the percentage reduction in slag quality after combustion compared to its original state. It is used to assess combustion effectiveness and capacity reduction rate [164]. In China, the upper limit is 5%. Currently, it is detected using an offline laboratory method, which involves steps such as on-site sampling, transportation, sample delivery, weighing, drying, burning, cooling, and laboratory analysis [165]. Although an online detection device has been developed [166], the harsh working environment makes it difficult for the device to maintain stable operation. Sun et al. [167] proposed associating the appearance characteristics of slag with the heat reduction rate; however, a mapping model was not constructed.

1.2.3.2.3 Combustion Efficiency

Combustion efficiency is defined as the ratio of heat produced during fuel combustion to the low calorific value released by complete fuel combustion under adiabatic conditions. Currently, there is no existing research specifically on the combustion efficiency of the MSWI process. According to the Chinese standard for pollutant control in hazardous waste incineration (GB 18484–2020), combustion efficiency is defined as the percentage of CO_2 concentration in the flue gas relative to the total concentration of CO_2 and CO. Studies on coal combustion and co-combustion [168,169] have shown that combustion efficiency serves as a quantitative measure of combustion status. Generally, higher combustion efficiency is considered favorable; however, it may conflict with the carbon reduction objective. Therefore, this presents a multi-objective optimization problem that remains to be solved.

As a result, there are currently no relevant reports on PIs, which hinders the multi-objective optimal control research of the MSWI process.

1.2.3.3 Economic Indicators Modeling

The economic income of an MSWI plant is primarily driven by MSW processing fees and on-site power generation quality. Since the main goal of the MSWI process is environmental protection, it is crucial to maintain the rated capacity and turbine power generation quality at their upper limits to ensure maximum returns. Typically, the power generation of an MSWI plant ranges from 0.3 to 0.7 MWh/t. Currently, there are no documented studies on modeling and predicting economic indicators for MSWI plants.

1.2.4 Flame Status Monitoring

Flame characteristics, such as area, height, brightness, and combustion line position, play a pivotal role in evaluating the flame status during the combustion process. These features directly influence abnormal phenomena, including partial burning, local burning through, coking, ash deposition, and corrosion [170]. Various approaches for recognizing combustion status based on combustion line position and other flame characteristics have been proposed. For instance, a combustion status recognition model integrating multiscale color moment features with the RF algorithm has been used [171], and hybrid enhancement with generative adversarial networks (GANs) was applied for combustion status recognition [172].

Additionally, a semi-supervised strategy was used to construct a recognition model for unknown flame combustion status [173]. The Newton iteration method and Hottel emissivity model were combined to establish a relationship between multispectral flame images and temperature [174]. In other studies [175,176], spectrometers were employed to detect flames and construct mapping models between flame features and the concentration of alkaline metals emitted. Using Monte Carlo simulations and multi-imaging angles, three-dimensional visualization modeling of flame temperature was conducted [177]. Notably, most of these studies did not consider how to recognize combustion status based on multimodal data. In summary, further research should focus on flame status monitoring.

1.2.5 Operational Abnormal Monitoring

Since the 1990s, computer and AI technologies have been applied to diagnose abnormalities in the MSWI process, assisting domain experts in decision-making. A fuzzy expert fault reasoning system for the incineration and boiler system was developed [178], enabling symptom analysis, early warnings, abnormal alarms, and both internal and external analysis within the DCS limits. Subsequently, online diagnosis of abnormal exhaust emissions and steam flow was conducted using cluster analysis, NNs, and Monte Carlo statistics [179]. A fault tree based on process analysis and historical experience was constructed [180], employing a rule-based expert system for abnormal detection and achieving an experimentally validated accuracy rate of 90%. A BPNN modeling strategy was used for diagnostic purposes [181], and a BPNN-based model was also developed to recognize combustion status. However, challenges such as overfitting and high requirements for training samples remain unresolved. For diagnosing issues like superheater and economizer leakage, ash deposition, slagging in horizontal flues, coking, and poor slag discharge in the furnace, a case-based reasoning (CBR) model based on random weight neural network (RWNN) similarity retrieval was built [182], delivering satisfactory performance. Despite these advances, these studies primarily focus on constructing classifier models, lacking quantification or localization of abnormal status.

Multivariate statistical process monitoring (MSPM) technology, which leverages industrial data for quantitative abnormal monitoring, has gained significant attention in recent years [183, 184, 185]. After constructing a latent structure model using normal operating condition data, statistical indices such as squared prediction error (SPE) and Hotelling's T^2 are employed to detect abnormalities. By reconstructing data, the location of abnormalities can also be identified. Zhao et al. used PCA and rule-based reasoning for monitoring incinerator faults [186], resulting in a significant reduction in the false-positive rate. Similarly, a comparative analysis between PCA-based and partial least squares (PLS)-based fault diagnosis approaches was conducted [187]. However, it is noteworthy that existing research on abnormal monitoring in MSWI processes is still limited and predominantly relies on linear methods like PCA/PLS. The dynamic, nonlinear, multiscale, and multimodal characteristics inherent in the MSWI process call for further research from both theoretical and applied perspectives.

1.3 Control and Optimization Based on AI and DT

The effective control of multiple variables, strong coupling, and the nonlinear nature of the combustion process present a significant challenge for both industrial applications and academic research. Given the research gap between industrial applications and academic studies in many complex industrial processes [188], we provide an overview of AI-based control in terms of both on-site and off-site control strategies. AI-based optimization efforts have primarily focused on pollution reduction research.

1.3.1 Control in On-site

Although the ACC system can manage the combustion process to maintain a stable calorific value of MSW under normal operating conditions [189], various abnormal situations can arise. These include fluctuations in the composition and calorific value of MSW, steam flow falling below or exceeding the rated value, and issues related to the maintenance of incineration equipment. To address these challenges, research has been conducted on-site in the industry to enhance the ACC system.

1.3.1.1 Research of Automatic Combustion Control (ACC) System

An infrared thermal imager is employed to detect FT and its fluctuations [190], enhancing the rapid response during the fine-tuning process. An NN is used to construct a combustion status recognition model [191], with its output serving as feedback for the ACC system, resulting in a significant reduction in CO concentration. Infrared image analysis is employed to detect the temperature information of MSW, flue gas, and flame [192], which aids in combustion control. To address fluctuations in furnace negative pressure caused by grate turnover, a control scheme based on a filtering algorithm was implemented to ensure FT stability [193]. For optimal combustion, a closed-loop control strategy for steam flow was designed to adapt to changes in MSW calorific value [194], ensuring prolonged stable operation.

1.3.1.2 Research of Non-ACC System

Fuzzy rule control was applied to FT in an MSWI plant in Japan [195]. After summarizing expert knowledge into fuzzy control rules, this system was implemented in an MSWI plant in Shenzhen, China [196]. A combustion control system based on expert rules was also developed for an MSWI plant in Spain [197]. However, rule-based control systems struggle to maintain stable operation under frequent fluctuating conditions.

Although the ACC system has been introduced in developing countries for many years, actual control remains largely manual, relying on domain experts. Therefore, AI-based control for on-site applications remains an unresolved challenge.

1.3.2 Control in Off-site

The academic community has conducted numerous studies on AI-based control, which are categorized into intelligent control of key CVs in terms of single-input single-output (SISO) and MIMO.

1.3.2.1 Single Input Single Output (SISO) Control

For FT, the MSW water content estimation model was used to compensate for feeder control based on fuzzy rules [189], and a fuzzy rule controller with a self-tuning factor was developed [198], demonstrating control stability. A fuzzy rule controller with an adaptive weighted factor was designed [199], highlighting its effective control. A hierarchical fuzzy rule control strategy, featuring an optimized quantization factor and a self-tuning scaling factor, was proposed to address real-time requirements and computational memory consumption issues [200], with the correction factor selectable based on operating conditions.

To enhance the system's anti-interference ability, flexibility, and adaptability, a fuzzy adaptive PID controller was introduced using traditional PID control [201]. An RBF-based PID parameter dynamic adjustment strategy was also proposed to suppress disturbances [202]. Additionally, the human-simulated intelligent controller (HSIC) was employed to simulate the cognitive mechanism and operational behavior of domain experts [203,204]. Building on this, a PSO-based HSIC temperature controller was proposed [205].

For FGOC, an RBF-based model predictive controller was introduced, and its effectiveness was verified through simulation [206]. To control steam flow, a fuzzy rule controller with grate speed as the MV was implemented [207], demonstrating a significant reduction in fluctuations caused by abnormal operating conditions. A feedback control strategy with a fixed time window was adopted to achieve stability control. Furthermore, a stable closed-loop control system based on a linear quadratic regulator was introduced and verified through simulation experiments [208].

These studies have yielded satisfactory results in simulation experiments. However, AI-based SISO control is insufficient to address the strong coupling characteristics inherent in the MSWI process.

1.3.2.2 Mutiple Input Multiple Output (MIMO) Control

For the control of steam flow and FGOC, a linear model predictive control (LMPC) strategy was proposed [209], demonstrating that the errors in both the MVs and CVs were lower than those in traditional control systems. However, the LMPC strategy faces challenges when dealing with strong nonlinearities. To address this, a nonlinear model predictive control (NMPC) strategy was presented to estimate the optimal air distribution and material distribution across the rolling time domain [210].

Additionally, a PID control strategy that integrates two loops was introduced [211], showing significant improvement in tracking performance. Further, a self-organizing FNN controller was proposed and validated [212]. For the concurrent control of FT, steam flow, and FGOC, a multi-loop PID controller utilizing a quasi-diagonal recurrent neural network (RNN) was introduced [213], demonstrating the ability to dynamically adjust its parameters in response to error signals. Moreover, a single-neuron adaptive PID controller was presented [214], and its accuracy and effectiveness were validated using industrial process data.

However, most of these studies are limited to specific operational conditions. In other words, the universality of these AI-based control methods needs to be further enhanced.

These studies highlight the divergence between industrial applications and academic research. Clearly, the application of AI-based control to the MSWI process addresses the fluctuations in operating conditions associated with manual control methods. Additionally, it contributes to cost reduction, improved energy efficiency, and reduced pollution emissions. As a result, AI-based control is poised to become the dominant approach in future research. However, the current AI algorithms face significant challenges in their direct application to industrial plants. Therefore, the development of a hardware-in-loop simulation platform is essential for testing and validating AI algorithms in scenarios that closely resemble industrial environments [188].

The challenge of conducting in-depth academic research with industrial applications, and improving the universality of AI algorithms for real-world industries, remains a key issue that requires further exploration.

1.3.3 Optimization of Pollution Emission

Optimizing the setpoints of key CVs to achieve a trade-off among various operational indices has received limited attention in existing research. Most studies primarily focus on the output values of MVs related to "air distribution and material distribution." AI-based optimization of the MSWI process requires the simultaneous minimization of exhaust emissions, material consumption, and maximization of combustion efficiency, while also optimizing other relevant PIs. This must be done within the constraints of various equality and inequality conditions. Therefore, intelligent optimization algorithms are essential to address these multi-objective conflicts.

For the "air distribution" optimization problem, the secondary air volume was intelligently adjusted using a CBR-based intelligent setting, leveraging expert experience reuse [215]. However, this approach is limited by the scope of known cases and faces challenges in finding the true optimal setpoints. Recently, a multi-objective PSO algorithm [216] and a multi-condition operational optimization with an adaptive knowledge transfer algorithm [217] were used to optimize the primary and secondary air volumes, with validation from industrial data. For the "material distribution" optimization problem, a multi-objective evolutionary algorithm was employed to maximize the feed rate while minimizing ash carbon content [218]. These studies have shown promising results, but further research is needed to improve adaptability under varying operating conditions, address multiple objectives, and integrate multimodal data effectively.

Studies addressing the optimization of setpoint values for CVs are very limited. The multi-objective competitive swarm optimization algorithm was employed to determine the setpoint values for FT and FGOC [219], with the goal of optimizing the multiple conflict objectives by minimizing NO_x emission concentration and maximizing combustion efficiency. However, this study focused solely on providing setpoints and did not consider the implementation of controllers for these CVs. Therefore, further exploration is needed in this area of research.

Therefore, AI-based optimization in the MSWI process still faces numerous challenging issues that need to be addressed. For example, how to determine the optimal setpoints for multiple CVs under conflicting objectives, and how to optimize the entire MSWI process's operational indices using multimodal data.

1.4 Hardware-in-Loop DT for MSWI Processes

1.4.1 Brief Description of Simulation Platform for Industrial Process

Complex process industries, such as those similar to MSWI processes, often involve unclear mechanisms, as well as controlled systems with multiple physical and chemical reactions, making it difficult to describe them using precise mathematical models [20,220]. Additionally, the production process generates and decomposes toxic and harmful substances [221,222], further complicating the construction of a physical platform for these complex industrial processes in a laboratory environment [223]. To address this, Kocaeli University introduced the concept of distributed object linking and embedding (OLE) for process control (distributed OPC [DOPC]), utilizing simulation models to build experimental platforms [224]; Northeastern University proposed an intelligent decoupling simulation platform for powder production systems [225], consisting of a management optimization layer, a control layer, and a controlled object layer, which includes both real controllers and virtual controlled objects; Yanshan University developed a simplified simulation platform for computer control using Q8 cards connected to resistance furnaces [226]; and Shanghai University proposed using software simulation to build a platform for optimizing control in intermittent production processes [227].

In addition, relevant companies have also conducted research on simulation platforms. For example, Beijing Lingsi Chuangqi Technology Co., Ltd. proposed the development of a multifunctional industrial process control experimental device that integrates both virtual and real elements. This device is notable for its ability to replace simulation models and covers various experimental components, such as liquid level control, temperature control, and virtual instrument monitoring. It is designed to meet the needs of laboratory environments while also being suitable for harsh environments with wide temperature variations and vibration characteristics. Dafeng Technology developed the SimuWorks large-scale scientific computing and simulation support platform, which includes simulation engines, graphical modeling tools, module resource managers, module resource libraries, and other simulation software. This platform can be used for large-scale scientific computing, dynamic characteristic modeling research, simulation system development, optimization design, and verification, among other applications.

The aforementioned platforms do not meet the needs for researching AI modeling, control, and optimization algorithms based on multimodal data-driven approaches, especially when high operational safety and strong on-site similarity are required. Additionally, different industrial sites present varied challenges in parameter detection, key parameter prediction, intelligent autonomous control, and operational index optimization. Therefore, there is a need to study a hardware-in-loop simulation platform with modular combination functions, suitable for both laboratory research and industrial application verification. Obviously, the AI algorithms developed through offline laboratory research should gain recognition from industry domain experts in some form before they can be fully implemented and applied.

1.4.2 Simulation Platform in Terms of Real/Virtual Perspective

From a control perspective, industrial systems can be broadly divided into two main components: the control system and the controlled object [228]. Based on the attributes of these components in the simulation platform, this book categorizes them into four types: "real control system and real controlled object" (Real–Real), "real control system and virtual controlled object" (Real–Virtual), "virtual control system and real controlled object" (Virtual–Real), and "virtual control system and virtual controlled object" (Virtual–Virtual). The following sections will provide a detailed overview of each category.

1.4.2.1 "Real–Real" Simulation Platform

A scaled-down physical device was established for the chemical water treatment process flow [229], utilizing software systems that include hardware configuration, logic configuration, and human–machine interface. This setup was used to verify the effectiveness of the "Real–Real" platform in addressing valve failure issues. The structure of the system is shown in Figure 1.7.

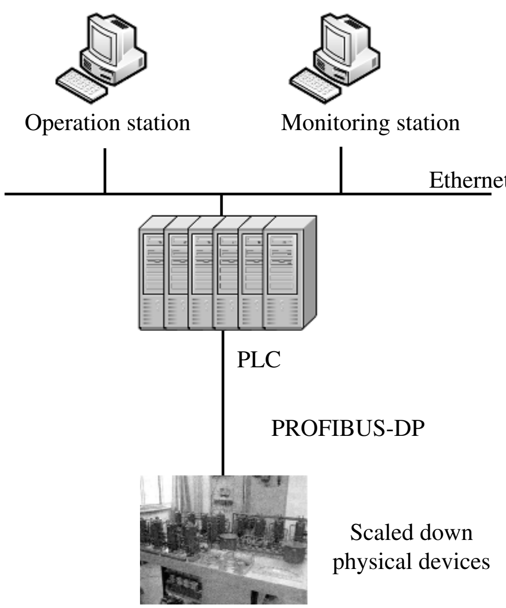

Figure 1.7 Structure of "Real–Real" simulation platform

As shown in Figure 1.7, the operation station and monitoring station communicate with the PLC via industrial Ethernet, running WinCC and Step7, respectively, to operate and monitor the control system. The S7–300 PLC acts as the controller, managing actual physical processes through PROFIBUS-DP fieldbus.

However, the "Real–Real" platform described above is limited in its ability to simulate only simple processes. Establishing physical objects in laboratory environments for typical process industries, such as MSWI, is particularly challenging due to the complexity of these processes, the intensity of reactions, the diverse types of materials involved, emission pollution, and the high toxicity of certain components.

1.4.2.2 "Real–Virtual" Simulation Platform

The "Real–Virtual" platform, based on the optimization and monitoring layer, loop control layer, and virtual object layer, was proposed [225,230]. It consists of an object model computer, a virtual device for instruments and actuators, a PLC, a monitoring computer, and an optimization computer, as shown in Figure 1.8.

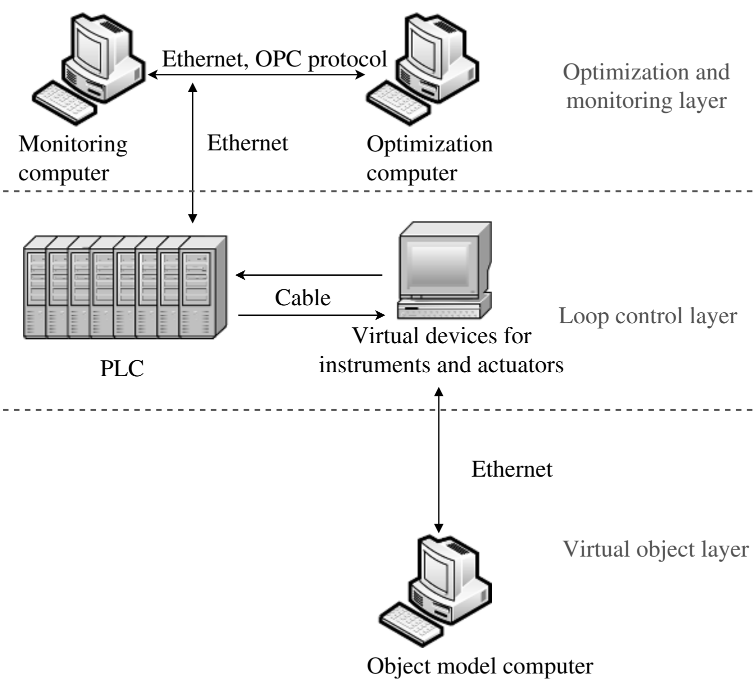

Figure 1.8 Structure of "Real–Virtual" simulation platform

From Figure 1.8, it can be observed that:

1) The optimization and monitoring layer uses Ethernet to enable data exchange between the monitoring computer and the optimization computer through OLE for process control (OPC).
2) The loop control layer comprises a real PLC, virtual instruments, and actuators, which transmit standard 4–20 mA industrial signals via cables and I/O boards.
3) The object model computer in the virtual object layer utilizes MATLAB to construct a plant model for simulating laminar cooling objects and employs configuration software to create a frontend interface for setting the characteristic parameters of the virtual controlled object model.

In this "Real–Virtual" platform, the control system is simulated using real PLC/DCS, while the actuator and instrument devices are simulated through a combination of software and hardware. The controlled object is modeled using AI algorithms. This structure not only ensures the portability of testing and validation for intelligent control and optimization algorithms in laboratory environments but also guarantees the safety of the controlled object during the simulation process. However, the platform falls short in fully characterizing the inherent complexities of industrial processes, such as MSWI, which involve multimodal data like traditional process variables, combustion flame videos, and on-site operator audio. Additionally, the platform lacks the capability for undisturbed forward data acquisition and secure backward transmission for industrial PLC/DCSs, making modular portability difficult to achieve.

1.4.2.3 "Virtual–Real" Simulation Platform

A "Virtual–Real" type platform was proposed in [231], which utilizes MATLAB to build a virtual controller and connects it to a real electric heating water tank through interface devices. The structure is shown in Figure 1.9.

In Figure 1.9, the virtual control computer uses a PID algorithm to control the temperature of the real electric heating water tank, with the advantage of being

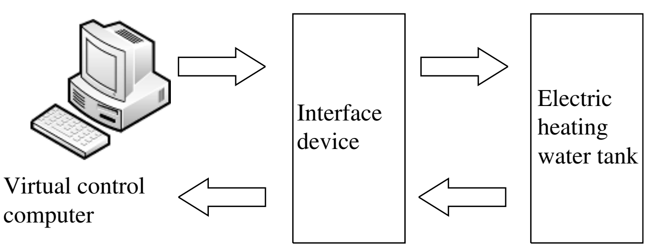

Figure 1.9 Structure of "Virtual–Real" simulation platform

able to optimize PID parameters online and incorporate other AI control algorithms. Similarly, reference [232] connects real experimental devices, such as wind turbines, to a virtual control computer through interface devices, establishing a "Virtual–Real" simulation platform.

The "Virtual–Real" platforms are limited to simulating simpler processes, and controllers simulated using MATLAB software are challenging to directly transfer to actual PLC/DCSs. In comparison to the "Real–Virtual" platform, this type of platform builds the controlled object model using real physical devices, making it suitable only for simulating simple and safe controlled object models. It is difficult to replicate the complexities of industrial processes, such as the MSWI process, within this framework.

1.4.2.4 "Virtual–Virtual" Simulation Platform

A "Virtual–Virtual" simulation platform for optimizing control of intermittent production processes was established [227], consisting of computers and servers, and utilizing OPC technology. The structure is shown in Figure 1.10.

As shown in Figure 1.10, the optimization control computer uses MATLAB and various algorithms to control the virtual object model, with data transmission between the two facilitated through Ethernet and OPC technology.

As observed, the shortcomings of the "Virtual–Virtual" platform are more apparent compared to the other three types of platforms. It is primarily suited for testing AI algorithms, lacks modularity and portability, offers limited guidance for real industrial processes, and struggles to achieve algorithm verification that closely resembles real-world scenarios.

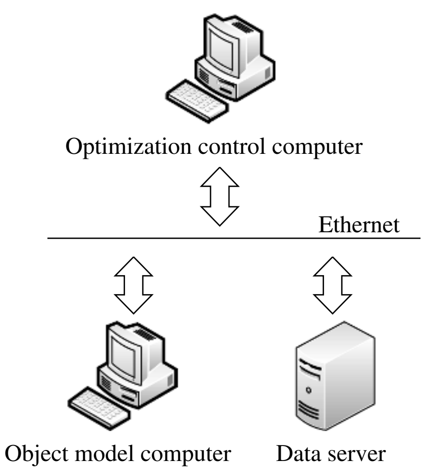

Figure 1.10 Structure of "Virtual–Virtual" simulation platform

1.4.3 Difficulties of Simulation Platform for MSWI Process

As described earlier, the "Real–Virtual" platform structure is currently the optimal solution for typical process industry simulation in laboratory environments. However, there have been no reports on research regarding a modular hardware-in-loop simulation platform for AI algorithm validation that considers the applicability of multimodal data, the security of data transmission, the effectiveness of multi-loop control, and the functional requirements of modular architecture and portability for MSWI processes.

To develop a modular hardware-in-loop simulation platform for AI algorithm testing and validation, which can be used in both laboratory and industrial settings for complex industrial processes such as MSWI, several challenges currently exist.

1) An AI algorithm testing and validation platform that simulates domain experts using multimodal data for perception, cognition, decision-making, and control, driven by synchronized multimodal historical data, is essential. In the actual MSWI process, domain experts make intelligent and autonomous decisions based on multimodal information such as process data, flame videos, production records, and inspection voice reports. These decisions lead to safe, stable, and efficient operation of the production process. However, existing simulation platforms often rely on simple structured process data for AI algorithm research, overlooking the comprehensive representation and application of multimodal data in real-world production scenarios. Moreover, due to differences in data collection methods and time scales, significant effort is required to synchronize and ensure the accuracy of intelligent models before using multimodal data for algorithm research. A major challenge in hardware-in-loop simulation platform development is achieving near real-time re-driving of offline multimodal historical data to simulate industrial environments, along with effective engineering testing and verification of multimodal data-driven intelligent algorithms.
2) A testing and validation platform with a bidirectional safety isolation mechanism, capable of interfacing with actual industrial sites, is crucial for overcoming the challenges of real-time data collection and online verification of AI algorithms. The stringent safety requirements of industrial sites and the closed nature of PLC/DCSs make direct connection of external devices difficult, resulting in a lack of real-time, effective data support for AI algorithm research. This creates challenges when attempting to transplant offline-developed intelligent algorithms to industrial environments for online testing and verification. The primary challenge facing hardware-in-loop simulation platforms is achieving real-time collection of multimodal data and conducting online verification of AI algorithms without interfering with the safe and stable operation of the

industrial process. A key concern is ensuring the safe and effective transmission of process parameters derived from offline AI algorithms – such as difficult-to-measure key parameter values, CV setpoint values, controller parameters, and MV output values – while ensuring that on-site domain experts gradually gain an understanding of the algorithms to ensure operational safety.

3) A modular and easily portable hardware-in-loop simulation platform is essential for facilitating offline research and development of AI algorithms and industrial software, enabling their seamless transfer to actual industrial sites. Existing simulation platforms often fail to incorporate a modular and portable design, leading to excessive coupling of various components that are difficult to separate. While this may appear to reduce equipment costs, it ultimately limits the platform's use to laboratory environments, making it unsuitable for industrial on-site applications without requiring secondary development and verification. This, in turn, hampers the development of industrial software with independent intellectual property rights. The key challenge in the research of simulation platforms is making modular design and portable application, which is critical for the rapid implementation and deployment of AI algorithms in real-world industrial settings.

1.5 Book's Structure

The book's structure is shown in Figure 1.11.

Figure 1.11 shows that the book consists of three principal parts:

- The first part relates to the modeling and monitoring based on AI (Chapters 2–7).
- The second part deals with control and optimization based on AI and DT (Chapters 8–11).
- The third part makes the hardware-in-loop DT platform design and validation (Chapters 12–15).

PART I

Chapter 2: To address the complex and poorly understood mechanism of the MSWI process, and the challenges in effectively constructing mechanism models for specific practical MSWI plants, we propose a whole-process modeling approach combining integrated numerical simulation software coupling and virtual mechanism data-driven methods. First, a multi-software coupled whole-process numerical simulation model is developed under benchmark operating conditions to simulate the operation of a real MSWI plant proportionally. Next, virtual

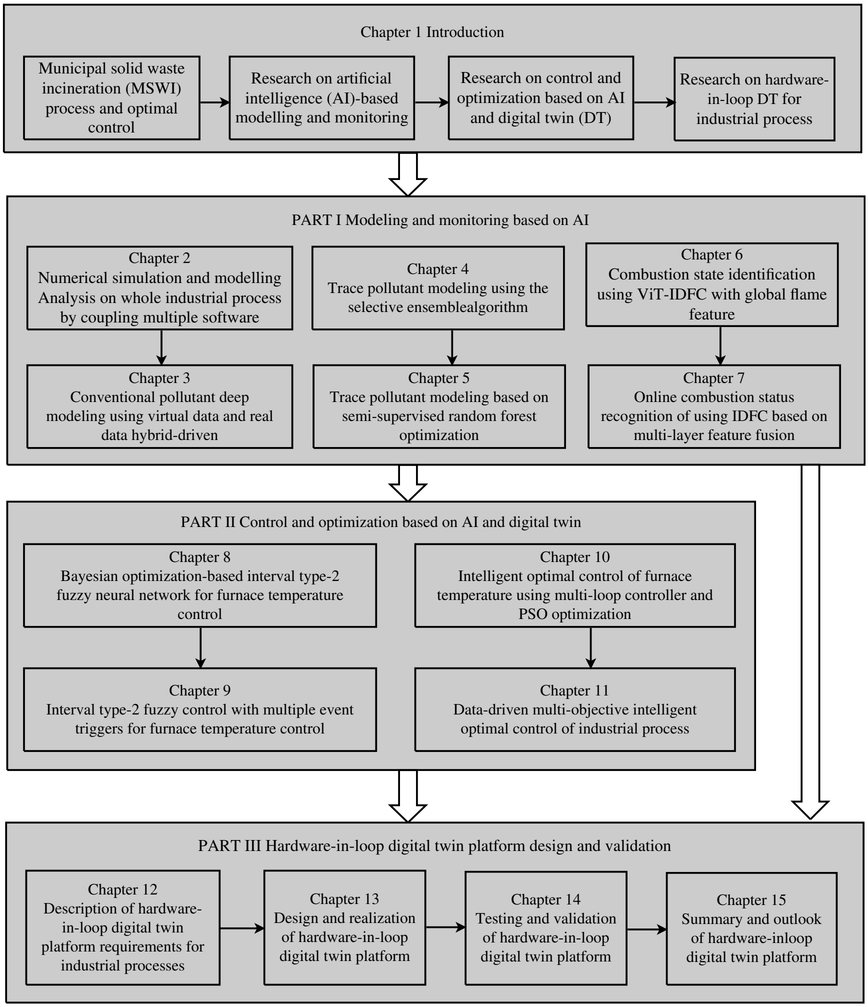

Figure 1.11 The book's structure

simulation data under various operating conditions are obtained through orthogonal experimental design, extending the scope of actual on-site operating conditions. Then, an interpretable linear regression decision tree (LRDT) algorithm is employed to construct a model for exhaust emissions pollutants, using "air distribution and material distribution" MVs as inputs. Finally, causal analysis is performed between MVs and pollutant concentrations based on single or double factor variations. The experimental results demonstrate that the whole-process mechanism model developed using this approach exhibits strong interpretability and representational performance.

Chapter 3: To address the issue that existing conventional pollutant prediction models, such as for CO, mainly rely on historical real data and overlook the effective integration of combustion process mechanism knowledge, we propose a hybrid-driven deep modeling approach that combines virtual and real data. First, a multi-condition mechanism model is developed by coupling numerical simulations of FLIC and Aspen Plus, with virtual mechanism data generated through orthogonal experiments. Next, a mechanism mapping model is constructed using the LRDT algorithm based on the aforementioned virtual mechanism data, while a real historical data-driven model is built using the LSTM NN algorithm. During the offline training and validation phase, the models are integrated by matching virtual and real samples representing various operating conditions through K-nearest neighbor (KNN) and applying an inequality-constrained RWNN. In the online testing and verification phase, CO emission concentration is predicted by combining the LRDT-based mechanism mapping model and the LSTM-based data-driven model. The effectiveness and rationality of this modeling strategy are validated through a case study of an MSWI power plant in Beijing.

Chapter 4: To address the limitations of traditional single models and ensemble models in predicting trace pollutant emission concentrations, we propose a method for constructing a selective ensemble model based on Bayesian inference and binary decision trees. First, Bagging sampling is employed to generate a subset of data with differences, from which candidate submodels based on binary decision trees are constructed. The prior information of the leaf nodes and predicted values of these candidate submodels are calculated, and Bayesian inference is then applied to compute the posterior information, reflecting the fitness of each submodel. Based on the posterior error, the best submodel is selected as part of the ensemble. This process is repeated to generate all the ensemble submodels along with their corresponding posterior information. Next, the fused weights are determined based on the posterior information of the integrated submodels, thereby constructing the selective ensemble. The effectiveness of the proposed method is validated using benchmark datasets as well as trace pollutant dataset in actual MSW power plant.

Chapter 5: To address the challenge of optimizing both hyperparameter selection and pseudo-labeled samples in existing semi-supervised RF algorithms, we propose a modeling method for trace pollutant emission concentration based on multi-objective optimization. First, we design an encoding scheme for the selection of hyperparameters and pseudo-labeled samples. Next, we initialize and decode particles for fitness evaluation, focusing on two objectives such as model generalization performance and the quantity of pseudo-labeled samples. The termination condition for the optimization process is then determined. If the condition is not met, the PSO parameters are updated. Once the termination condition is satisfied, the optimal solution is selected from the Pareto solution set. Finally, an RF model is constructed using the optimized mixed sample set. The effectiveness of the proposed method is validated through both benchmark and real MSWI power plant datasets.

Chapter 6: To address the challenge of characterizing the global complexity of flame images using traditional methods based on combustion line positions, we propose a flame combustion state recognition method based on a vision transformer (ViT) and improved deep forest classification (IDFC). This method is built on the MSWI flame image combustion state dataset, which is constructed using prior knowledge from on-site domain experts. First, we leverage the pre-trained ViT encoding layer to extract multi-layer visual transformation features from the flame images. Deep features are then selected based on domain expert experience. These selected visual transformation features, along with the original flame images, are used as input for a cascaded forest to construct the IDFC model. The model's effectiveness is validated using the constructed flame image dataset, which is based on combustion flame data from an MSWI power plant in Beijing. The results demonstrate that the proposed method effectively extracts deep features from flame images and achieves high monitoring accuracy.

Chapter 7: To address the limitation of existing research, which primarily relies on offline image datasets for model training and accuracy verification, and lacks dynamic recognition capabilities for real-time or near real-time videos in practical applications, we propose a method for online recognition of flame combustion status. This method combines convolutional multi-layer feature fusion with deep forest classifier (DFC), focusing on image global information partitioning. First, flame images collected on-site are used to train the LeNet-5 network to extract deep features from the images. Then, using a multi-layer feature adaptive selection fusion method, the fused deep features are chosen to represent the flame combustion state. These deep fusion features are subsequently input into the DFC to construct an offline recognition model for flame combustion states. Finally, the offline recognition algorithm is integrated into the developed MSWI process data monitoring system to enable online recognition of flame videos. Experimental results based on the historical flame video of an MSWI power plant demonstrate that the proposed method achieves a high recognition rate for both left and right grate flame combustion states, meeting the requirements for real-time monitoring.

PART II

Chapter 8: Due to the many uncertainties of the MSWI process introduced by factors such as material composition, feeding mode, and equipment operation and maintenance, conventional control strategies struggle to effectively regulate the

FT. This temperature is closely linked to the stable operation and pollution reduction. To address this, we propose an interval type-2 fuzzy neural network (IT2FNN) control method based on Bayesian optimization for FT control. First, we analyze the FT control characteristics to identify the key control variables that influence it. Next, we design an IT2FNN controller. Finally, using Bayesian optimization, we select the appropriate learning rate for the controller to ensure effective parameter learning and stability analysis. Control experiments conducted with actual MSWI process data demonstrate the effectiveness of the proposed method.

Chapter 9: To address the issues of frequent adjustment of MV, mechanical wear, and increased energy consumption associated with traditional time-triggered FT control in the MSWI process, we propose an FT control strategy based on a multi-event trigger mechanism (METM) and interval type-2 fuzzy broad learning system (IT2FBLS). First, we analyze the control characteristics of FT and develop a controller based on IT2FBLS. Then, we design a dynamic static switching event triggering mechanism (DSSETM) to trigger the control law and reduce the frequency of MV updates. Next, we implement an event triggering mechanism for updating the controller structure, dynamically adjusting it to enhance performance by evaluating the enhanced node parameters. Finally, the stability of the proposed control strategy is demonstrated using Lyapunov's second method. The effectiveness of the method is verified through simulations based on numerical data and actual operating data from an MSWI power plant.

Chapter 10: To address the challenge of effectively obtaining the optimal FT setpoint vlaue, which is influenced by multiple MVs and directly affects pollutant emission concentrations in exhaust gas, we propose an FT optimization control method. This method combines multi-loop control with PSO to minimize pollutant emission concentrations. First, the Tikhonov regularized linear regression decision tree (TR-LRDT) algorithm is employed to establish a model for the FT control object. Then, leveraging domain expert knowledge, a multi-loop temperature controller is designed using an improved single neuron adaptive PID (ISNA-PID) algorithm. Further, NO_x and CO_2 indicator models are developed, and the PSO algorithm is applied to determine the FT setpoint value that minimizes pollutant emission concentrations. Finally, the intelligent optimization control framework is validated. Experimental results demonstrate that the optimal FT setpoint value can effectively reduce NO_x and CO_2 emission concentrations.

Chapter 11: To address the challenge of improving combustion efficiency and reducing the emission concentration of major pollutants, we propose a data-driven multi-objective optimization control method for the MSWI process, considering multiple CVs. First, based on an analysis of the factors influencing pollution reduction in the MSWI process, a multi-objective optimization model is developed. This model treats key CVs as decision variables, aiming to minimize the comprehensive pollutant emission concentration and maximize combustion efficiency. Corresponding multi-objective optimization control strategies are then proposed. Next, a complete process model for MSWI pollutant emissions is established, including controlled object models for FT, steam flow rate, and FGOC, as well as emission index models for CO, CO_2, and NO_x pollutants. A single neuron adaptive PID controller is used to design a MIMO loop controller for key CVs, ensuring stable combustion process control. Finally, leveraging domain expert knowledge, an adaptive solution for optimizing the setpoint values of these variables is achieved using an improved multi-objective PSO algorithm. Experimental validation using on-site data from an MSWI power plant in Beijing shows that the proposed method effectively optimizes the setpoint values of key CVs, leading to reduced pollutant emissions and improved combustion efficiency.

PART III

Chapter 12: This chapter outlines the requirements for a hardware-in-loop (HIL) DT platform designed for complex industrial processes, viewed from both laboratory research and industrial application perspectives. From a laboratory research standpoint, the requirements include alignment with the actual industrial control hierarchy and expert cognitive models, with a focus on the verifiability and scalability of multi-loop intelligent control for future development. Additionally, the platform should be capable of simulating isolated data exchange modes, ensuring both applicability and portability for real-world industrial settings. From an industrial application perspective, the requirements encompass secure data transmission isolation, qualitative identification of combustion states, quantitative detection of combustion line parameters, multi-step prediction of conventional pollutants, real-time detection of difficult-to-measure pollutants, and optimization of CV setpoints and MV outputs.

Chapter 13: To address the challenges of online validation for AI algorithms in offline research of MSWI processes – stemming from safety requirements and the closed nature of control systems – as well as the limitations of existing laboratory simulation platforms in simulating the perception, cognition, decision-making, and control of domain experts based on multimodal data in industrial practice, a modular HIL DT platform for AI algorithm verification is proposed. This platform consists of a multimodal historical data-driven system, a safety isolation and optimization control system, and a MIMO loop control system, which has been designed and implemented. First, we conduct a functional requirement analysis for both laboratory academic research and industrial applications. Next, we proceed with functional and structural design, followed by hardware construction and software development. Finally, the platform is implemented. The design and implementation of the AI algorithm verification platform were completed at the Beijing Laboratory of Intelligent Environmental Protection at Beijing University of Technology.

Chapter 14: To address the challenges of testing and porting academic AI algorithms and software for MSWI processes to industrial scenarios, a modular HIL DT platform for AI algorithm validation is developed. First, the effectiveness of the platform, which consists of a multimodal historical data-driven system, a safety isolation and optimization control system, and a MIMO loop control system, is tested and verified. Next, laboratory testing and validation are conducted for modeling, monitoring, control, and optimization algorithms separately. Following this, module porting and application are carried out in industrial scenarios, with existing issues and their corresponding solutions analyzed. Finally, potential follow-up research topics for further platform development are outlined.

Chapter 15: The future prospects of the MSWI process hardware-in-loop DT platform for AI algorithm research and validation were discussed, highlighting its potential for advancing AI safety. The overall structure, functional description, and development prospects of the future AI safety empowerment end-edge-cloud collaboration platform were also presented. Based on this platform, a vision for a future AI safety empowerment system, capable of being deployed at industrial sites, was proposed. This system aims to provide a development blueprint for pollution reduction and operation optimization research in the MSWI process.

References

1 A. Gómez-Sanabria, G. Kiesewetter, Z. Klimont, W. Schoepp, and H. Haberl, "Potential for future reductions of global GHG and air pollutants from circular waste management systems," *Nature Communications*, vol. 13, no. 1, 106, 2022.

2 R. Naveenkumar, J. Iyyappan, R. Pravin, S. Kadry, J. Han, R. Sindhu, M. K. Awasthi, S. L. Rokhum, and G. Baskar, "RETRACTED: A strategic review on sustainable approaches in municipal solid waste management and energy recovery: Role of artificial intelligence, economic stability and life cycle assessment," *Bioresource Technology*, vol. 379, p. 129044, 2023.

3 T. Walser, L. K. Limbach, R. Brogioli, E. Erismann, L. Flamigni, B. Hattendorf, M. Juchli, F. Krumeich, C. Ludwig, and K. Prikopsky, "Persistence of engineered nanoparticles in a municipal solid-waste incineration plant," *Nature Nanotechnology*, vol. 7, no. 8, pp. 520–4.

4 G. Vilardi and N. Verdone, "Exergy analysis of municipal solid waste pncineration processes: The use of O_2-enriched air and the oxy-combustion process," *Energy*, vol. 239, p. 122147, 2022.

5 W. He, Y. Zheng, B. Liu, and B. Zhang, "Effects of garbage classification on air pollutant emissions from garbage incineast indirect measurement of PCDD/F TEQ emission from municipal solid waste incinerationration," *China Environmental Science*, vol. 42, no. 5, pp. 2433–41, 2022.

6 A. Kumar and S. R. Samadder, "A review on technological options of waste to energy for effective management of municipal solid waste," *Waste Management*, vol. 69, pp. 407–22, 2017.

7 Y. Liu, W. Sun, and J. Liu, "Greenhouse gas emissions from different municipal solid waste management scenarios in China: Based on carbon and energy flow analysis," *Waste Management*, vol. 68, pp. 653–61, 2007.

8 B. Bajić, S. N. Ž. Dodić, D. G. Vučurović, J. M. Dodić, and J. A. Grahovac, "Waste-to-energy status in Serbia," *Renewable and Sustainable Energy Reviews*, vol. 50, pp. 1437–44, 2015.

9 K. A. Kalyani and K. K. Pandey, "Waste to energy status in India: A short review," *Renewable and Sustainable Energy Reviews*, vol. 31, pp. 113–20, 2014.

10 J. Long, H. Du, X. Zou, and J. Huang, "Systematic study on carbon emission reduction of municipal solid waste treatment," *Bulletin of Chinese Academy of Sciences*, vol. 37, no. 8, pp. 1143–53, 2022.

11 J. Wang, E. Nketiah, X. Cai, B. Obuobi, G. Adu-Gyamfi, and M. Adjei, "What establishes citizens' household intention and behavior regarding municipal solid waste separation? A case study in Jiangsu province," *Journal of Cleaner Production*, vol. 423, p. 138642, 2023.

12 H. Khandelwal, H. Dhar, A. K. Thalla, and S. Kumar, "Application of life cycle assessment in municipal solid waste management: A worldwide critical review," *Journal of Cleaner Production*, vol. 209, pp. 630–54, 2019.

13 K. Kolekar, T. Hazra, and S. Chakrabarty, "A review on prediction of municipal solid waste generation models," *Procedia Environmental Sciences*, vol. 35, pp. 238–44, 2016.

14 M. Y. Liu, H. J. Lu, Q. K. Deng, S. Ji, L. B. Qin, and Y. Wan, "Shear strength, water permeability and microstructure of modified municipal sludge based on industrial solid waste containing calcium used as landfill cover materials," *Waste Management*, vol. 145, pp. 20–8, 2022.

15 Y. Yang, Y. Goh, R. Zakaria, V. Nasserzadeh, and J. Swithenbank, "Mathematical modelling of MSW incineration on a travelling Bed," *Waste Management*, vol. 22, no. 4, pp. 369–80, 2002.

16 H Hunsinger, K Jay, and J Vehlow, "Formation and destruction of PCDD/F inside a grate furnace," *Chemosphere*, vol. 46, no. 9–10, pp. 1263–1272, 2002.

17 Silpa K, Lisa C Y, Perinaz B T, and Frank V W, "What a waste 2.0 : A global snapshot of solid waste management to 2050," Urban Development, Washington, 2018. available: https://openknowledge.worldbank.org/handle/10986/30317 License: CC BY 3.0 IGO.

18 L. Gu, K. He, and H. W. Liu. 2022. "In: *Proceedings of Environmental Engineering Technology Innovation and Appl*ication (3)." In *Study on waste heat value characteristics and its impact on waste incineration power generation project in China*, Editorial Department of Environmental Engineering, Environmental Engineering Branch of Chinese Society of Environmental Sciences.

19 T. Yamada, M. Asari, T. Miura, T. Niijima, J. Yano, and S. Sakai, "Municipal solid waste composition and food loss reduction in Kyoto City," *Journal of Material Cycles and Waste Management*, vol. 19, no. 4, pp. 1351–60, 2017.

20 T. Y. Chai, "Development directions of industrial artificial intelligence," *Acta Automatica Sinica*, vol. 46, no. 10, pp. 2005–12, 2020.

21 R. Cioffi, M. Travaglioni, G. Piscitelli, A. Petrillo, and F. De Felice, "Artificial intelligence and machine learning aApplications in smart production: progress, trends, and directions," *Sustainability*, vol. 12, no. 2, 2020.

22 T. Yang, Y. Xi, S. Lu, K. H. Johansson, and T. Y. Chai, "Intelligent manufacturing for the process industry driven by industrial artificial intelligence," *Engineering*, vol. 7, no. 9, pp. 1224–30, 2021.

23 C. Zhao, "Perspectives on nonstationary process monitoring in the era of industrial artificial intelligence," *Journal of Process Control*, vol. 116, pp. 255–72, 2022.

24 J. Lee, H. Davari, J. Singh, and V. Pandhare, "Industrial artificial intelligence for industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 18, pp. 20–3, 2018.

25 I. Ahmed, G. Jeon, and F. Piccialli, "From artificial intelligence to explainable artificial intelligence in industry 4.0 : A survey on what, how, and where," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 8, pp. 5031–42, 2022.

26 Z. Yang and Z. Ge, "On paradigm of industrial big data analytics: From evolution to revolution," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 12, pp. 8373–88, 2022.

27 S. . S. Gill, S. Tuli, M. Xu, I. Singh, K. V. Singh, D. Lindsay, S. Tuli, D. Smirnova, M. Singh, and U. Jain, "Transformative effects of IoT, blockchain and artificial intelligence on cloud computing: Evolution, vision, trends and open challenges," *Internet of Things*, vol. 8, p. 100118, 2019.

28 N. Misra, Y. Dixit, A. Al-Mallahi, M. S. Bhullar, R. Upadhyay, and A. Martynenko, "IoT, big data, and artificial intelligence in agriculture and food industry," *IEEE Internet of Things Journal*, vol. 9, no. 9, pp. 6305–24, 2020.

29 R. H. Essenhigh and T. J. Kuo. 1970. "Combustion and emission phenomena in incinerators: Development of physical and mathematical models of incinerators, part I: Statement of the problem." In *National Incinerator Conference*, ASME, New York, pp. 261–71.

30 Y. R. Goh, C. N. Lim, R. Zakaria, K. H. Chan, G. Reynolds, Y. B. Yang, R. G. Siddall, V. Nasserzadeh, and J. Swithenbank, "Mixing, modelling and measurements of incinerator bed combustion," *Process Safety and Environmental Protection*, vol. 78, pp. 21–32, 2000.

31 C. D. Goddard, Y. B. Yang, J. Goodfellow, V. N. Sharifi, J. Swithenbank, J. Chartier, D. Mouquet, R. Kirkman, D. Barlow, and S. Moseley, "Optimisation study of a large waste-to-energy plant using computational modelling and experimental measurements," *Journal of the Energy Institue*, vol. 78, pp. 106–16, 2016.

32 C. Ryu, D. Shin, and S. Choi, "Combined simulation of combustion and gas flow in a grate-type incinerator," *Journal of the Air & Waste Management Association*, vol. 52, pp. 189–97, 2002.

33 F. Wissing, S. Wirtz, and V. Scherer, "Simulating municipal solid waste incineration with a DEM/CFD method–influences of waste properties grate and furnace design," *Fuel*, vol. 206, pp. 638–56, 2017.

34 G. H. Hu, J. Long, and W. L. Du, "Numerical simulation of the convection section of an ethylene cracking furnace considering the effects of vaporization," *Journal of East China University of Science and Technology*, vol. 45, pp. 719–27, 2019.

35 L. Y. Liu, H. X. Du, H. F. Wang, and T. Y. Liu, "Construction and application of digital twin system in workshop production process," *Computer Integrated Manufacturing System*, vol. 25, pp. 1536–45, 2019.

36 J. J. Wang, Y. Q. Xiang, and W. W. He, "Spacecraft system engineering model and implementation based on digital twin," *Computer Integrated Manufacturing System*, vol. 25, pp. 1348–60, 2019.

37 Q. F. Wang, M. X. Li, W. J. Xu, L. Yao, X. T. Liu, D. D. Su, and P. Wang, "Review on liquid film flow and heat transfer characteristics outside horizontal tube falling film evaporator: CFD numerical simulation," *International Journal of Heat and Mass Transfer*, vol. 163, p. 120440, 2020.

38 A. Mohammadian, H. K. Gildeh, and I. Nistor, "CFD modeling of effluent discharges: A review of past numerical studies," *Water*, vol. 12, no. 3, p. 856, 2020.

39 Y. Cao and M. Xin, "Numerical simulation of supercooled large droplet icing phenomenon: A review," *Archives of Computational Methods in Engineering*, vol. 3, pp. 1231–65, 2019.

40 Y. Z. Xue, R. W. Liu, Z. Li, and D. F. Han, "A review for numerical simulation methods of ship–ice interaction," *Ocean Engineering*, vol. 215, p. 107853, 2020.

41 S. B. Kuang, M. M. Zhou, and A. B. Yu, "CFD-DEM modelling and simulation of pneumatic conveying: A review," *Powder Technology*, vol. 365, pp. 186–207, 2020.

42 Q. Y. Tu, H. G. Wang, and R. Ocone, "Application of three-dimensional full-loop CFD simulation in circulating fluidized bed combustion reactors – A review," *Powder Technology*, vol. vol. 399, p. 117181, 2022.

43 W. C. Chen, Y. W. Fan, L. L. Zhang, B. C. Sun, Y. Luo, H. K. Zou, G. W. Chu, and J. F. Chen, "Computational fluid dynamic simulation of gas–liquid flow in rotating packed bed: A review," *Chinese Journal of Chemical Engineering*, vol. 41, pp. 85–108, 2022.

44 X. Cao, S. Y. Lu, W. R. Stevens, H. D. Zhong, K. C. Wu, X. D. Li, and J. H. Yan, "Fast indirect measurement of PCDD/FTEQ emission from municipal solid waste incineration: A review," *Waste Dispos Sustain Energy*, vol. 1, pp. 39–51, 2019.

45 B H Cho, B H Nam, J An, H Youn, "Municipal solid waste incineration (MSWI) ashes as construction materials – A review," *Materials*, vol. 13(14), 3143 2020.

46 C. C. Fan, B. M. Wang, T. T. Zhang, and L. B. Kong, "Review on cement stabilization/solidification of municipal solid waste incineration fly ash," *Advances in Materials Science and Engineering*, vol. 2018, pp. 1–7, 2018.

47 H. W. Luo, Y. Cheng, D. Q. He, and E. H. Yang, "Review of leaching behavior of municipal solid waste incineration (MSWI) ash," *Science of the Total Environment*, vol. 668, pp. 90–103, 2019.

48 R. V. Silva, J. D. Brito, C. J. Lynn, and R. K. Dhir, "Environmental impacts of the use of bottom ashes from municipal solid waste incineration: A review," *Resources, Conservation and Recycling*, vol. 140, pp. 23–35, 2019.

49 J. J. Zhang, S. G. Zhang, and B. Liu, "Degradation technologies and mechanisms of dioxins in municipal solid waste incineration fly ash: A review," *Journal of Cleaner Production*, vol. 250, p. 119507, 2020.

50 Y. K. Zhang, Z. Y. Ma, Z. T. Fang, Y. D. Qian, P. C. Zhong, and J. H. Yan, "Review of harmless treatment of municipal solid waste incineration fly ash," *Waste Dispos Sustain Energy*, vol. 2, no. 1–25, pp. 1–25, 2020.

51 H. Frey, B. Peters, H. Hunsinger, and J. Vehlow, "Characterization of municipal solid waste combustion in a grate furnace," *Waste Management*, vol. 23, pp. 689–701, 2003.

52 H. Thunman, F. Niklasson, F. Johnsson, and B. Leckner, "Composition of volatile gases and thermochemical properties of wood for modeling of fixed or fluidized beds," *Energy & Fuel*, vol. 15, pp. 1488–97, 2001.

53 J. C. Cai and Z. C. Chen, "SNCR denitrification technology for a 600 t/d MSW incinerator," *Thermal Power Generation*, vol. 42, pp. 30–5, 2013.

54 E. Ranzi, M. Corbetta, F. Manenti, and S. Pierucci, "Kinetic modeling of the thermal degradation and combustion of biomass," *Chemical Engineering Science*, vol. 110, pp. 2–12, 2014.

55 J Collazo, J Porteiro, E D Patiño, Granada, "Numerical modeling of the combustion of densified wood under fixed-bed conditions," *Fuel*, vol. 93, pp. 149–159, 2012.

56 M A Gómez, A R Comesa, M A Feijoo, "Simulation of the effect of water temperature on domestic biomass boiler performance," *Energies*, vol. 5, pp. 1044–1061, 2012.

57 E. Girgis and W. L. H. Hallett, "Wood combustion in an overfeed packed bed, including detailed measurements within the bed," *Energy & Fuel*, vol. 24, pp. 1584–91, 2010.

58 C G Yin, S K Kær, L Rosendahl, S L Hvid, "Co-firing straw with coal in a swirl-stabilized dual-feed burner: Modelling and experimental validation," *Bioresource Technology*, vol. 101, pp. 4169–4178, 2010.

59 Z G Chen, Q X Huang, B Yang, M D Li, G G Huang, L Y Cao, "Optimization on SNCR denitration system in municipal waste incinerators," *Guangdong Electric Power*, vol. 29, pp. 12–17, 2016.

60 Z F Hu, E C Jiang, X Q Ma, "Numerical simulation on NOx emissions in a municipal solid waste incinerator," *Journal of Cleaner Production*, vol. 233, pp. 650–664, 2019.

61 Z. F. Hu, E. C. Jiang, and X. Q. Ma, "Numerical simulation on operating parameters of SNCR process in a municipal solid waste incinerator," *Fuel*, vol. 245, pp. 160–73, 2019.

62 J. Li, Z. H. Xia, T. T. Wu, C. X. Chen, and X. K. Zhang, "Effects of secondary air injection angle on combustion and SNCR performance in MSW incinerators," *Chinese Journal of Environmental, Engineering*, vol. 10, pp. 5907–13, 2016.

63 H. Lin, X. Q. Ma, and Z. S. Yu, "Numerical simulation of large-scale municipal solid waste incinerator," *Journal of Chinese Society of Power Engineering*, vol. 30, pp. 128–32, 2010.

64 R. M. Liu, Y. K. Liu, Z. H. Wang, Y. Z. Liu, L. H. Hu, Z. R. Shao, and K. F. Cen, "CFD simulation and optimization of secondary air distribution for waste incineration in grate furnace," *Journal of Zhejiang University(Engineering Science)*, vol. 51, pp. 500–7, 2017.

65 Z. Xia, J. Li, T. Wu, C. Chen, and X. Zhang, "CFD simulation of MSW combustion and SNCR in a comm ercial incinerator," *Waste Management*, vol. 34, pp. 1609–18, 2014.

66 J. C. Xu, Y. F. Liao, Z. S. Yu, Z. L. Cai, X. Q. Ma, M. Q. Dai, and S. W. Fang, "Co-combustion of paper sludge in a 750 t/d waste incinerator and effect of sludge moisture content: A simulation study," *Fuel*, vol. 217, pp. 617–25, 2018.

67 M. Yan, J. Y. W. Antoni, and E. K. DHantoko, "Numerical investigation of MSW combustion influenced by air preheating in a full-scale moving grate incinerator," *Fuel*, vol. 285, 119193, 2021.

68 E. Simsek, F. Sudbrock, S. Wirtz, and V. Scherer, "Influence of particle diameter and material properties on mixing of monodisperse spheres on a grate: Experiments and discrete element simulation," *Powder Technology*, vol. 221, pp. 144–54, 2012.

69 X. H. He, W. P. Yan, and Y. M. Zhao, "Numerical simulation of new oxygen-enriched waste incineration flue gas purification technology, *Electric Power*,", vol. 47, pp. 148–52, 2014.

70 E. Jannelli and M. Minutillo, "Simulation of the flue gas cleaning system of an RDF incineration power plant," *Waste Management*, vol. 27, pp. 684–90, 2007.

71 B. Lokahita, G. Samudro, H. S. Huboyo, M. Aziz, and F. Takahashi, "Energy recovery potential from excavating municipal solid waste dumpsite in Indonesia," *Energy Procedia*, vol. 158, pp. 243–8, 2019.

72 L. Zhu, L. Zhang, J. M. Fan, P. Jiang, and L. L. Li, "MSW to synthetic natural gas: System modeling and thermodynamics assessment," *Waste Management*, vol. 48, pp. 257–64, 2016.

73 E. Grieco and A. Poggio, "Simulation of the influence of flue gas cleaning system on the energetic efficiency of a waste-to-energy plant," *Applied Energy*, vol. 86, pp. 1517–23, 2009.

74 F. C. Eboh and T. R. BAndersson, "Economic evaluation of improvements in a waste-to-energy combined heat and power plant," *Waste Management*, vol. 100, pp. 75–83, 2019.

75 N. Deng, D. Y. Li, Q. Zhang, A. Zhang, R. C. Cai, and B. Zhang, "Simulation analysis of municipal solid waste pyrolysis and gasification based on Aspen plus," *Frontiers in Energy*, vol. 13, pp. 64–70, 2017.

76 S. Begum, M. G. Rasul, and D. A. Akbar, "A numerical investigation of municipal solid waste gasification using Aspen Plus," *Procedia Engineering*, vol. 90, pp. 710–7, 2014.

77 E Simsek, B Brosch, S Wirtz, V Scherer, F Krüll, "Numerical simulation of grate firing systems using a coupled CFD/discrete element method (DEM)," Powder Technology, vol. 193, pp. 266–73, 2009.

78 E. Magnanelli, O. L. Tranås, P. Carlsson, J. Mosby, and M. Becidan, "Dynamic modeling of municipal solid waste incineration," *Energy*, vol. 209, p. 118426, 2020.

79 A. Asthana, Y. Menard, P. Sessiecq, and F. Patisson, "Modeling on-grate MSW incineration with experimental validation in a batch incinerator," *Industrial & Engineering Chemistry Research*, vol. 49, pp. 7597–604, 2010.

80 F. Sun, N. Luo, W. M. Zhong, and F. Qian, "Dynamic simulation and optimization of ethylene glycol desorption and resorption process," *Computers and Applied Chemistry*, vol. 27, pp. 277–82, 2010.

81 Y. Zhang, S. X. Cao, S. Shao, Y. Chen, S. L. Liu, and S. S. Zhang, "Aspen Plus-based simulation of a cement calciner and optimization analysis of air pollutants emission," *Clean Technologies and Environmental Policy*, vol. 13, pp. 459–68, 2011.

82 X. N. Song, H. B. Xu, R. J. Fang, H. T. Wang, and J. Q. Gu, "Simulation of the NOx emissions during biomass combustion based on Aspen Plus," *Acta Scientiae Circumstantiate*, vol. 29, pp. 1696–700, 2009.

83 F. Zhao, S. Yang, J. Wu, C. J. Wu, and D. Z. Wu, "Analysis on support mechanism of the axial film in rotary pressure exchanger based on Fluent," *Journal of Zhejiang University (Engineering Science)*, vol. 48, pp. 1528–33, 2014.

84 B. Zhang, J. J. He, C. M. Hu, and W. Chen, "Experimental and numerical simulation study on co-incineration of solid and liquid wastes for green production of pesticides," *Processes*, vol. 7, 2019.

85 D. Y. Che, S. H. Li, W. G. Yang, J. Jia, and N. Zheng, "Application of numerical simulation on biomass gasification," *Energy Procedia*, vol. 17, pp. 49–54, 2012.
86 M. Costa, V. Indrizzi, N. Massarotti, and A. Mauro, "Modeling and optimization of an incinerator plant for the reduction of the environmental impact," *International Journal of Numerical Methods for Heat & Fluid Flow*, vol. 25, pp. 1463–87, 2015.
87 A, Selemani, "Thermal chemical enhancement and influence of fluid flow in transesterification of palm oil," *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 40, pp. 81–87, 2017.
88 D. Peshev and A. G. Livingston, "OSN Designer, a tool for predicting organic solvent nanofiltration technology performance using Aspen One, Matlab and CAPE OPEN," *Chemical Engineering Science*, vol. 104, pp. 975–87, 2013.
89 A. Kummer and T. Varga, "Process simulator assisted framework to support process safety analysis," *Journal of Loss Prevention in the Process Industries*, vol. 22-29, p. 58, 2019.
90 N. Luo, Y. Jiang, Z. C. Ye, W. L. Du, and F. Qian, "Simulation of ethylene glycol process based on integrated modeling method," *Journal of the Chemical Industry and Engineering Society of China*, vol. 60, pp. 151–6, 2009.
91 S. Evangelista, G. Giovinco, and S. Kocaman, "A multi-parameter calibration method for the numerical simulation of morphodynamic problems," *Journal Of Hydrology And Hydromechanics*, vol. 65, pp. 175–82, 2017.
92 X. W. Zeng, J. X. Peng, Z. H. Xi, L. Zhao, W. K. Yuan, C. H. Nie, and X. H. Zhao, "Simulation and optimization of the distillation process of methylchlorosilane," *The Chinese Journal of Process Engineering*, vol. 20, pp. 52–8, 2020.
93 R Rocca, P Rosa, C Sassanelli, L Fumagalli, S Terzi, "Integrating virtual reality and digital twin in circular economy practices: A laboratory application case," *Sustainability*, vol. 12(6), 2286 2020.
94 H. B. Sun, J. L. Pan, J. D. Zhang, and R. Mo, "Tool digital twin model for cutting process," *Computer Integrated Manufacturing System*, vol. 25, pp. 1474–80, 2019.
95 H. Jiang, S. Qin, J. Fu, J. Zhang, and G. Ding, "How to model and implement connections between physical and virtual models for digital twin application," *Journal of Manufacturing Systems*, vol. 58, pp. 36–51, 2021.
96 S. M. Liu, J. S. Bao, Y. Q. Lu, J. Li, S. Y. Lu, and X. M. Sun, "Digital twin modeling method based on biomimicry for machining aerospace components," *Journal of Manufacturing Systems*, vol. 58, pp. 180–95, 2021.
97 Y. L. Wei, T. L. Hu, T. T. Zhou, Y. G. Ye, and W. C. Luo, "Consistency retention method for CNC machine tool digital twin model," *Journal of Manufacturing Systems*, vol. 58, pp. 313–22, 2021.
98 I. M. Cavalcante, E. M. Frazzon, F. A. Forcellini, and D. Ivanov, "A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing," *International Journal of Information Management*, vol. 49, pp. 86–97, 2019.

99 F. Xiang, Z. Zhang, Y. Zuo, and F. Tao, “Digital twin driven green material optimal-selection towards sustainable manufacturing,” *Procedia CIRP*, vol. 81, pp. 1290–4, 2019.

100 M. Heidarinejad, M. Austin, P. Delgoshaei, and M. E. Coelho, “Architecting smart city digital twins: combined semantic model and machine learning approach,” *Journal of Management in Engineering*, vol. 36, no. 4, 04020026, 2020.

101 H. Laaki, Y. Miche, and K. Tammi, “Prototyping a digital twin for real time remote control over mobile networks: Application of remote surgery,” *IEEE Access*, vol. 7, pp. 20325–36, 2019.

102 R. He, G. M. Chen, C. Dong, S. F. Sun, and X. Y. Shen, “Data-driven digital twin technology for optimized control in process systems,” *ISA Transactions*, vol. 95, pp. 221–34, 2019.

103 Y. Y. Dong, J. Hou, N. Zhang, and M. C. Zhang, “Research on how human intelligence, consciousness, and cognitive computing affect the development of artificial intelligence,” *Complexity*, vol. 2020, p. 10, 2020.

104 S. Bardi and A. Astolfi, “Modeling and control of a waste-to-energy plant [applications of control],” *IEEE Control Systems Magazine*, vol. 30, no. 6, pp. 27–37, 2010.

105 C. Zhao, H. Han, P. Zhou, Y. Liu, and C. Shang, “Intelligent modeling and control methods and applications of complex industrial processes,” *Control Engineering of China*, vol. 29, no. 4, pp. 577–80, 2022.

106 B. Sun, B. Zhang, C. Yang, and W. H. Gui, “Discussion on modeling and optimal control of nonferrous metallurgical purification process,” *Acta Automatica Sinica*, vol. 43, no. 6, pp. 880–92, 2017.

107 Q. Liu and S. Qin, “Perspectives on big data modeling of process industries,” *Acta Automatica Sinica*, vol. 42, no. 2, pp. 161–71, 2016.

108 H. T. Guo, J. Tang, H. Xia, and J. F. Qiao, “Combustion line extreme abnormal flame image adversarial generation for municipal solid waste incineration processes,” *Proceedings of the CSEE*, vol. 44, no. 11, pp. 4376–86, 2024.

109 R. El Asri and D. Baxter, “Process control in municipal solid waste incinerators: Survey and assessment,” *Waste Management & Research*, vol. 22, no. 3, pp. 177–85, 2004.

110 S. Bunsan, W. Y. Chen, H. W. Chen, Y. H. Chuang, and N. Grisdanurak, “Modeling the dioxin emission of a municipal solid waste incinerator using neural networks,” *Chemosphere*, vol. 92, no. 3, pp. 258–64, 2013.

111 A. Giantomassi, G. Ippoliti, S. Longhi, I. Bertini, and S. Pizzuti, “On-line steam production prediction for a municipal solid waste incinerator by fully tuned minimal RBF neural networks,” *Journal of Process Control*, vol. 21, no. 1, pp. 164–72, 2011.

112 L. Hu, A. Tong, H. Liu, and X. Lin, "Modeling and control of combustion temperature system of circulating fluidized bed boiler," *Computer Simulation*, vol. 36, no. 1, pp. 112–6, 2019.

113 Z. Tang, B. Zhang, S. Cao, G. Wang, and B. Zhao, "Furnace temperature modeling based on multi-model intelligent combination algorithm," *CIESC Journal*, vol. 70, no. S2, pp. 301–10, 2019.

114 A. Yan and K. Hu, "Multi-objective optimization setting method for temperature control of municipal solid waste incinerator," *Control Theory & Applications*, vol. 40, no. 4, pp. 693–701, 2023.

115 J. Sun, X. Meng, and J. Qiao, "Prediction of oxygen content using weighted PCA and improved LSTM network in MSWI process," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–12, 2507512, 2021.

116 Q. Hu, J. Long, S. Wang, J. He, L. Bai, H. Du, and Q. Huang, "A novel time-span input neural network for accurate municipal solid waste incineration boiler steam temperature prediction," *Journal of Zhejiang University-Science A*, vol. 22, no. 10, pp. 777–91, 2021.

117 J. Sun, X. Meng, and J. Qiao, "Soft sensor method of main steam flow based on mean impact value and radial basis function neural network," *Control Engineering of China*, vol. 29, no. 10, pp. 1829–34, 2022.

118 B. Yang, J. Luo, X. Yao, Y. Zhang, and H. Liu, "Prediction of main steam parameters based on incineration MSWoperation parameters," *Nonferrous Metallurgical Equipment*, vol. 35, no. 1, pp. 15–9, 2021.

119 M. Leskens, L. Van Kessel, and P. Van den Hof, "MIMO closed-loop identification of an MSW incinerator," *Control Engineering Practice*, vol. 10, no. 3, pp. 315–26, 2002.

120 H. Ding, J. Tang, H. Xia, and J. Qiao, "Modeling of MIMO controlled object in municipal solid waste incineration process based on TS-FNN," *Control Theory & Applications*, vol. 39, no. 8, pp. 1529–40, 2022.

121 F. Qian, W. Du, W. Zhong, and Y. Tang, "Problems and challenges of smart optimization manufacturing in petrochemical industries," *Acta Automatica Sinica*, vol. 43, no. 6, pp. 893–901, 2017.

122 F. Qian, "Smart and optimal manufacturing: The key for the transformation and development of the process industry," *Engineering*, vol. 3, no. 2, pp. 51–8, 2017.

123 D. Wang, X. Li, and W. Yang, "Review of heating value estimating models for municipal solid waste," *Advances in New & Renewable Energy*, vol. 10, no. 1, pp. 69–79, 2022.

124 Y. F. Chang, C. J. Lin, J. Chyan, I. Chen, and J. E. Chang, "Multiple regression models for the lower heating value of municipal solid waste in Taiwan," *Journal of Environmental Management*, vol. 85, no. 4, pp. 891–9, 2007.

125 L. Chen, F. Guo, X. Li, R. Xu, and J. Liu, “Design and application of waste incinerator control scheme based on waste heat value calculation,” *Instrument Standardization & Metrology*, vol. 45, no. 6, pp. 26–7, 2017.

126 W. Zeng, S. Tian, Y. Yuan, and W. Chang, “Design and implementation of ACC system for waste incinerator,” *Thermal Power Generation*, vol. 48, no. 3, pp. 109–13, 2019.

127 L. Van Kessel, M. Leskens, and G. Brem, “On-line calorific value sensor and validation of dynamic models applied to municipal solid waste combustion,” *Process Safety and Environmental Protection*, vol. 80, no. 5, pp. 245–55, 2002.

128 L. Ding, W. Zhang, L. Zang, and J. Chen, “Prediction of household waste combustible component calorific value based on artificial neural network,” *Chinese Journal of Environmental Engineering*, vol. 10, no. 2, pp. 899–905, 2016.

129 C. Dong and B. Jin, “Prediction of the heating value of municipal solid waste (MSW) with the use of a neural network method,” *Journal of Engineering for Thermal Energy and Power*, vol. 17, no. 3, pp. 275–8, 2002.

130 C. Dong, B. Jin, and D. Li, “Predicting the heating value of MSW with a feed forward neural network,” *Waste Management*, vol. 23, no. 2, pp. 103–6, 2003.

131 E. Akkaya and A. Demir, “Predicting the heating value of municipal solid waste-based materials: An artificial neural network model,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 32, no. 19, pp. 1777–83, 2010.

132 C. Ding and A. Yan, “Characteristic variable selection method and predictive modeling for municipal solid waste heat value,” *Journal of Beijing University of Technology*, vol. 47, no. 8, pp. 874–85, 2021.

133 H. You, Z. Ma, Y. Tang, Y. Wang, J. Yan, M. Ni, K. Cen, and Q. Huang, “Comparison of ANN MLP, ANFIS, SVM, and RF Models for the online classification of heating value of burning municipal solid waste in circulating fluidized bed incinerators,” *Waste Management*, vol. 68, pp. 186–97, 2017.

134 A. Rostami and A. Baghban, “Application of a supervised learning machine for accurate prognostication of higher heating values of solid wastes,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 40, no. 5, pp. 558–64, 2018.

135 H. Xie, Q. Huang, X. Lin, X. Li, and J. Yan, “Study on the calorific value prediction of municipal solid wastes by image deep learning,” *CIESC Journal*, vol. 72, no. 5, pp. 2773–82, 2021.

136 Y. Feng, “Research on control method of waste incinerator based on automatic process,” *China Electrical Equipment Industry*, vol. 5, pp. 63–6, 2022.

137 Y. Ying, X. Lin, A. Wu, and X. Li, “Review and outlook on municipal solid waste smart incineration,” *CIESC Journal*, vol. 72, no. 2, pp. 886–900, 2021.

138 S. Matsumura, T. Iwahara, K. Ogata, S. Fujii, and M. Suzuki, “Improvement of De-NOx device control performance using a software sensor,” *Control Engineering Practice*, vol. 6, no. 10, pp. 267–1276, 1998.

139 E. Huselstein, H. Garnier, A. Richard, and P. Guernion, “Experimental modeling of NOx emissions in municipal solid waste incinerator,” *IFAC Proceedings*, vol. 35, no. 1, pp. 89–94, 2002.

140 D. Zhang, J. Yan, Y. Chi, and K. Cen, “Prediction of NOx emission in an MSW-fired fluidized bed with nonlinear theory,” *Power System Engineering*, vol. 20, no. 3, pp. 1–3, 2004.

141 X. Meng, J. Tang, and J. Qiao, “NOx emissions prediction with a brain-inspired modular neural network in municipal solid waste incineration processes,” *IEEE Transactions on Industrial Informatics*, vol. 18, no. 7, pp. 4622–31, 2021.

142 H. Duan, X. Meng, J. Tang, and J. Qiao, “Prediction of NOx concentration using modular long short-term memory neural network for municipal solid waste incineration,” *Chinese Journal of Chemical Engineering*, vol. 56, pp. 46–57, 2023.

143 B. Wang, P. Wang, L. H. Xie, R. B. Lin, J. Lv, J. R. Li, and B. Chen, “A stable zirconium based metal–organic framework for specific recognition of representative polychlorinated dibenzo-p-dioxin molecules,” *Nature Communications*, vol. 10, no. 1, 3861, 2019.

144 W. Hasberg, H. May, and I. Dorn, “Description of the residence-time behaviour and burnout of PCDD, PCDF and other higher chlorinated aromatic hydrocarbons in industrial waste incineration plants,” *Chemosphere*, vol. 19, no. 1–6, pp. 565–71, 1989.

145 R. Zhang, J. Tang, H. Xia, X. Pan, W. Yu, and J. Qiao, “CO emission predictions in municipal solid waste incineration based on reduced depth features and long short-term memory optimization,” *Neural Computing and Applications*, vol. 36, pp. 5473–98, 2024.

146 G. Antonioni, D. Guglielmi, V. Cozzani, C. Stramigioli, and D. Corrente, “Modelling and simulation of an existing MSWI flue gas two-stage dry treatment,” *Process Safety and Environmental Protection*, vol. 92, no. 3, pp. 242–50, 2014.

147 Z. Liang and X. Ma, “Mathematical modeling of MSW combustion and SNCR in a full-scale municipal incinerator and effects of grate speed and oxygen-enriched atmospheres on operating conditions,” *Waste Management*, vol. 30, no. 12, pp. 2520–9, 2010.

148 W. Ma, X. Liu, C. Ma, T. Gu, and G. Chen, “Basic: A comprehensive model for SOx formation mechanism and optimization in municipal solid waste (MSW) combustion,” *ACS Omega*, vol. 7, no. 5, pp. 3860–71, 2022.

149 Y. Ma, P. Wang, X. Lin, T. Chen, and X. Li, “Formation and inhibition of polychlorinated-ρ-dibenzodioxins and dibenzofurans from mechanical grate municipal solid waste incineration systems,” *Journal of Hazardous Materials*, vol. 403, p. 123812, 2021.

150 H. J. Zhang, Y. W. Ni, J. P. Chen, and Q. Zhang, “Influence of variation in the operating conditions on PCDD/F distribution in a full-scale MSW incinerator,” *Chemosphere*, vol. 70, no. 4, pp. 721–30.

151 N. B. Chang and S. H. Huang, "Statistical modelling for the prediction and control of PCDDs and PCDFs emissions from municipal solid waste incinerators," *Waste Management and Research*, vol. 13, no. 4, pp. 379–400, 1995.

152 R. Ishikawa, A. Buekens, H. Huang, and K. Watanabe, "Influence of combustion conditions on dioxin in an industrial-scale fluidized-bed incinerator: Experimental study and statistical modelling," *Chemosphere*, vol. 35, no. 3, pp. 465–77, 1997.

153 N. B. Chang and W. Chen, "Prediction of PCDDs/PCDFs emissions from municipal incinerators by genetic programming and neural network modeling," *Waste Management and Research*, vol. 18, no. 4, pp. 341–51, 2000.

154 H. Wang, Y. Zhang, and H. Wang, "A study of GA-BP based prediction model of dioxin emission from MSW incinerator," *Microcomputer Information*, vol. 24, no. 21, pp. 222–4, 2008.

155 X. Xiao, J. Lu, J. Hai, and L. Liao, "Prediction of dioxin emissions in flue gas from waste incineration based on support vector regression," *Renewable Energy Resources*, vol. 35, no. 8, pp. 1107–14, 2017.

156 T. Y. Chai, Q. Liu, J. Ding, S. Lu, Y. Song, and Y. Zhang, "Perspectives on industrial-internet-driven intelligent optimized manufacturing mode for process industries," *Scientia Sinica Technologica*, vol. 52, no. 1, pp. 14–25, 2022.

157 Z. Ghouleh and Y. Shao, "Turning municipal solid waste incineration into a cleaner cement production," *Journal of Cleaner Production*, vol. 95, pp. 268–79, 2018.

158 G. Li, Q. Wu, S. Wang, Z. Li, H. Liang, Y. Tang, M. Zhao, L. Chen, K. Liu, and F. Wang, "The influence of flue gas components and activated carbon injection on Mercury capture of municipal solid waste incineration in China," *Chemical Engineering Journal*, vol. 326, pp. 561–9, 2017.

159 W. Li, Y. Sun, Y. Huang, T. Shimaoka, H. Wang, Y. Wang, L. Ma, and D. Zhang, "Evaluation of chemical speciation and environmental risk levels of heavy metals during varied acid corrosion conditions for raw and solidified/stabilized MSWI fly ash," *Waste Management*, vol. 87, pp. 407–16, 2019.

160 S. Dontriros, S. Likitlersuang, and D. Janjaroen, "Mechanisms of chloride and sulfate removal from municipal-solid-waste-incineration fly ash (MSWI FA): Effect of acid–base solutions," *Waste Management*, vol. 101, pp. 44–53, 2020.

161 Z. Yang, S. Tian, R. Ji, L. Liu, X. Wang, and Z. Zhang, "Effect of water-washing on the co-removal of chlorine and heavy metals in air pollution control residue from MSW incineration," *Waste Management*, vol. 68, pp. 221–31, 2017.

162 A. M. Joseph, R. Snellings, P. Van den Heede, S. Matthys, and N. De Belie, "The use of municipal solid waste incineration ash in various building materials: A Belgian point of view," *Materials*, vol. 11, no. 1, p. 141, 2018.

163 M. J. Quina, E. Bontempi, A. Bogush, S. Schlumberger, G. Weibel, R. Braga, V. Funari, J. Hyks, E. Rasmussen, and J. Lederer, "Technologies for the management of MSW incineration ashes from gas cleaning: New perspectives on recovery of secondary raw materials and circular economy," *Science of the Total Environment*, vol. 635, pp. 526–42, 2018.

164 M. Margallo, M. B. M. Taddei, A. Hernández-Pellón, R. Aldaco, and Á. Irabien, "Environmental sustainability assessment of the management of municipal solid waste incineration residues: A review of the current situation," *Clean Technologies and Environmental Policy*, vol. 17, pp. 1333–53, 2015.

165 F. Huber, D. Blasenbauer, P. Aschenbrenner, and J. Fellner, "Complete determination of the material composition of municipal solid waste incineration bottom ash," *Waste Management*, vol. 102, pp. 677–85, 2020.

166 J. Luo, L. Zeng, and Y. Chen, "Development of automatic measuring instrument for the thermal reduction rate of incineration residue," *China Measurement and Test*, vol. 47, no. 9, pp. 169–74, 2021.

167 F. Sun, W. Li, H. Tan, C. Chen, D. Shen, and Y. Long, "Rapid evaluation method of domestic waste incineration effect based on slag image processing," *Acta Scientiae Circumstantiae*, vol. 42, no. 3, pp. 285–92, 2022.

168 S. R. Zhang, X. G. Jiang, G. J. Lv, B. X. Liu, Y. Q. Jin, and J. H. Yan, "SO_2, NOx, HF, HCl and PCDD/Fs emissions during co-combustion of bituminous coal and pickling sludge in a drop tube furnace," *Fuel*, vol. 186, pp. 91–9, 2016.

169 F. Guo and Z. Zhong, "Co-combustion of anthracite coal and wood pellets: Thermodynamic analysis, combustion efficiency, pollutant emissions and ash slagging," *Environmental Pollution*, vol. 239, pp. 21–9, 2018.

170 J Ballester, and T García-Armingol, "Diagnostic techniques for the monitoring and control of practical flames," *Progress in Energy and Combustion Science*, vol. 36, no. 4, pp. 375–411, 2010.

171 H. Duan, J. Tang, and J. Qiao. 2019. "Recognition of combustion condition in MSWI process based on multi-scale color moment features and random forest." In *2019 Chinese Automation Congress (CAC)*, IEEE, pp. 2542–7.

172 H. Guo, J. Tang, H. Ding, and J. Qiao, "Combustion states recognition method of MSWI process based on mixed data enhancement," *Acta Automatica Sinica*, vol. 50, no. 3, pp. 560–75, 2024.

173 Z. Han, J. Li, B. Zhang, M. M. Hossain, and C. Xu, "Prediction of combustion state through a semi-supervised learning model and flame imaging," *Fuel*, vol. 289, p. 119745, 2021.

174 S. Zheng, W. Cai, R. Sui, Z. Luo, and Q. Lu, "In-situ measurements of temperature and emissivity during MSW combustion using spectral analysis and multispectral imaging processing," *Fuel*, vol. 323, p. 124328, 2022.

175 W. Yan, C. Lou, Q. Cheng, P. Zhao, and X. Zhang, "In situ measurement of Alkali metals in an MSW incinerator using a spontaneous emission spectrum," *Applied Sciences*, vol. 7, no. 3, p. 263, 2017.

176 X. He, C. Lou, Y. Qiao, and M. Lim, “In-situ measurement of temperature and Alkali metal concentration in municipal solid waste incinerators using flame emission spectroscopy,” *Waste Management*, vol. 102, pp. 486–91, 2020.

177 H. C. Zhou, S. D. Han, F. Sheng, and C. G. Zheng, “Visualization of three-dimensional temperature distributions in a large-scale furnace via regularized reconstruction from radiative energy images: Numerical studies,” *Journal of Quantitative Spectroscopy and Radiative Transfer*, vol. 72, no. 4, pp. 361–83, 2002.

178 H. Ono, “Diagnosis system of abnormality in refuse incineration plant using fuzzy logic,” *JSME international journal. Ser. C, Dynamics, control, robotics, design and manufacturing*, vol. 37, no. 2, pp. 307–14, 1994.

179 J. C. Chen and K. Y. Lin, “Diagnosis for monitoring system of municipal solid waste incineration plant,” *Expert Systems with Applications*, vol. 34, no. 1, pp. 247–55, 2008.

180 H. Tao, W. Sun, J. Zhao, X. Chen, and Y. Yang, “Fault diagnosis using expert system for municipal solid waste incineration,” *Environmental Science & Technology*, vol. 31, no. 11, pp. 65–8, 2008.

181 H. Tao, W. Sun, J. Zhao, X. Chen, and Y. Yang, “Process control using BP neural networks for incineration of municipal solid waste,” *Computers and Applied Chemistry*, vol. 7, pp. 859–62, 2008.

182 C. Ding and A. Yan, “Fault detection in the MSW incineration process using stochastic configuration networks and case-based reasoning,” *Sensors*, vol. 21, no. 21, p. 7356, 2021.

183 S. J. Qin, “Survey on data-driven industrial process monitoring and diagnosis,” *Annual Reviews in Control*, vol. 36, no. 2, pp. 220–34, 2012.

184 Q. Liu, T. Y. Chai, S. J. Qin, and L. J. Zhao, “Progress of data-driven and knowledge-driven process monitoring and fault diagnosis for industry process,” *Control and Decision*, vol. 25, no. 6, pp. 801–7, 2010.

185 J. C. Fan, Y. Q. Wang, and S. J. Qin, “Combined indices for ICA and their applications to multivariate process fault diagnosis,” *Acta Automatica Sinica*, vol. 39, no. 5, pp. 494–501, 2013.

186 J. Zhao, J. Huang, and W. Sun, “On-line early fault detection and diagnosis of municipal solid waste incinerators,” *Waste Management*, vol. 28, no. 11, pp. 2406–14, 2008.

187 G. Tavares, Z. Zsigraiová, V. Semiao, and M. da Graca Carvalho, “Monitoring fault detection and operation prediction of MSW incinerators using multivariate statistical methods,” *Waste Management*, vol. 31, no. 7, pp. 1635–44, 2011.

188 T. Samad, M. Bauer, S. Bortoff, S. Di Cairano, L. Fagiano, P. F. Odgaard, R. R. Rhinehart, R. Sánchez-Peña, A. Serbezov, and F. Ankersen, “Industry engagement with control research: Perspective and messages,” *Annual Reviews in Control*, vol. 49, pp. 1–14, 2020.

189 D. Qian and Z. Sun, “A waste incineration intelligent control system,” *Information and Control*, vol. 22, no. 6, pp. 374–7, 1993.

190 F. Schuler, F. Rampp, J. Martin, and J. Wolfrum, “Taccos – A thermography-assisted combustion control system for waste incinerators,” *Combustion and Flame*, vol. 99, no. 2, pp. 431–9, 1994.

191 Y. Miyamoto, Y. Kurosaki, H. Fujiyama, and E. Nanbu, “Dynamic characteristic analysis and combustion control for a fluidized bed incinerator,” *Control Engineering Practice*, vol. 6, no. 9, pp. 1159–68, 1998.

192 S. Zipser, A. Gommlich, J. Matthes, and H. Keller, “Combustion plant monitoring and control using infrared and video cameras,” *IFAC Proceedings Volumes*, vol. 39, no. 7, pp. 249–54, 2006.

193 W. Zeng, X. Xue, and J. Xue, “Features of MSW incineration control in stocker-fired boiler,” *Thermal Power Generation*, vol. 33, no. 12, pp. 57–8, 2004.

194 R. Xu and J. Liu, “An automatic control strategy for combustion of grate-type waste incinerator,” *Instrument Standardization & Metrology*, vol. 5, pp. 28–30, 2017.

195 H. Ono, T. Ohnishi, and Y. Terada, “Combustion control of refuse incineration plant by fuzzy logic,” *Fuzzy Sets and Systems*, vol. 32, no. 2, pp. 193–206, 1989.

196 K. Shen, J. Lu, T. Dong, and P. Chang, “A fuzzy control system for stabilizing combustion of destructor,” *Electric Power*, vol. 36, no. 8, pp. 47–50, 2003.

197 F. Carrasco, X. Llauró, and M. Poch, “A methodological approach to knowledge-based control and its application to a municipal solid waste incineration plant,” *Combustion Science and Technology*, vol. 178, no. 4, pp. 685–705, 2006.

198 K. Shen, J. Lu, Z. Li, and G. Liu, “An adaptive fuzzy approach for the incineration temperature control process,” *Fuel*, vol. 84, no. 9, pp. 144–1150, 2005.

199 P. Chang, J. Lu, K. Shen, and Z. Li, “Research on weight factor adaptive control system of incinerator temperature,” *Boiler Technology*, vol. 35, no. 6, pp. 77–81, 2004.

200 Y. Wang, X. Ma, and Y. Liao, “Layered fuzzy control system of destructor,” *Industrial Furnace*, vol. 26, no. 6, pp. 29–34, 2004.

201 Q. Dai and J. Wang, “Fuzzy-PID control on garbage incineration temperature,” *Journal of Hefei University (Comprehensive ED)*, vol. 3, pp. 39–42, 2008.

202 H. He, X. Meng, J. Tang, and J. Qiao, “ET-RBF-PID-based control method for furnace temperature of municipal waste incineration process,” *Control Theory & Applications*, vol. 39, no. 12, pp. 2262–73, 2022.

203 Y. Ni and M. Li, “Garbage incineration and intelligent fusion strategy of secondary pollution control,” *Advanced Materials Research*, vol. 853, pp. 323–8, 2014.

204 Q. Xiao and H. Xu, “Algorithm for human-simulated intelligent temperature control of incinerator combustion process of urban household garbage,” *CAAI transactions on intelligent systems*, vol. 10, no. 6, pp. 881–5, 2015.

205 Q. Wu, "Application study of PSO improving based intelligent algorithm in incineration pollution control," *Journal of Chongqing University of Technology (Natural Science)*, vol. 12, pp. 133–8, 2018.
206 J. Sun, X. Meng, and J. Qiao, "Adaptive predictive control of oxygen content in flue gas for municipal solid waste incineration process," *Acta Automatica Sinica*, vol. 49, no. 11, pp. 2338–49, 2023.
207 X Yang, Y Soh, "Fuzzy logic control of batch-feeding refuse incineration process," *In 2000 26th Annual Conference of the IEEE Industrial Electronics Society," IECON 2000. 2000 IEEE International Conference on Industrial Electronics, Control and Instrumentation. Twenty-First Century Technologies*; IEEE, Vol. 4, pp. 2684–2689, 2000.
208 F. Falconi, H. Guillard, S. Capitaneanu, and T. Raissi, "Control strategy for the combustion optimization for waste-to-energy incineration plant," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 13167–72, 2020.
209 M. Leskens, L. B. M. van Kessel, and O. Bosgra, "Model predictive control as a tool for improving the process operation of MSW combustion plants," *Waste Management*, vol. 25, no. 8, pp. 788–98, 2005.
210 M. Leskens, L. Van Kessel, P. Van den Hof, and O. Bosgra, "Nonlinear model predictive control with moving horizon state and disturbance estimation–with application to MSW combustion," *IFAC Proceedings Volumes*, vol. 38, no. 1, pp. 291–6, 2005.
211 M. Leskens, P. Van't Veen, L. Van Kessel, O. Bosgra, and P. Van den Hof, "Improved economic operation of MSWC plants with a new model based PID control strategy," *IFAC Proceedings Volumes*, vol. 43, no. 5, pp. 655–60, 2010.
212 H. Ding, J. Tang, and J. Qiao, "Data-driven modeling and self-organizing control of municipal solid waste incineration process," *Acta Automatica Sinica*, vol. 49, no. 3, pp. 550–66, 2023.
213 H. Ding, J. Tang, and J. Qiao, "MIMO modeling and multi-loop control based on neural network for municipal solid waste incineration," *Control Engineering Practice*, vol. 127, p. 105280, 2022.
214 T. Wang, J. Tang, and H. Xia. 2023. "Multiple input mulitple output control method based on single neuron adaptive PID for municipal solid waste incineration process." In *2023 35th Chinese Control and Decision Conference (CCDC)*, *IEEE*, pp. 331–6.
215 C. Ding, A. Yan, and D. Wang, "Intelligent optimization setting method of secondary air volume in municipal solid waste incineration process," *Control and Decision*, vol. 39, no. 1, pp. 49–58, 2022.
216 Y. Y. Cui, X. Meng, and J. F. Qiao, "The intelligent optimization setting method of air flow for municipal solid wastes incineration process," *Control and Decision*, vol. 38, no. 2, pp. 318–26, 2023.

217 Y. Cui, X. Meng, and J. Qiao, "Multi-condition operational optimization with adaptive knowledge transfer for municipal solid waste incineration process," *Expert Systems with Applications*, vol. 238, 2024.

218 S. R. Anderson, V. Kadirkamanathan, A. Chipperfield, V. Sharifi, and J. Swithenbank, "Multi-objective optimization of operational variables in a waste incineration plant," *Computers & Chemical Engineering*, vol. 29, no. 5, pp. 1121–30, 2005.

219 W. Huang, H. Ding, and J. Qiao, "Large-scale and knowledge-based dynamic multi-objective optimization for MSWI process using adaptive competitive swarm optimization," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 54, no. 1, pp. 379–90, 2024.

220 P. Zhou, B. H. Gao, S. Wang, and T. Y. Chai, "Identification of abnormal conditions for fused magnesium melting process based on deep learning and multisource information fusion," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 3, pp. 3017–26, 2022.

221 H. Xia, J. Tang, L. Aljerf, C. L. Cui, B. Y. Gao, and U. Prince, "Dioxin emission modeling using feature selection and simplified DFR with residual error fitting for the grate-based MSWI process," *Waste Management*, vol. 168, pp. 256–71, 2023.

222 H. Xia, J. Tang, L. Aljerf, T. Z. Wang, B. Y. Gao, and Q. D. Xu, "Assessment of PCDD/Fs formation and emission characteristics at a municipal solid waste incinerator for one year," *Science of the Total Environment*, vol. 883, p. 163705, 2023.

223 T. Y. Chai, "Operational optimization and feedback control for complex industrial processes," *Acta Automatica Sinica*, vol. 39, no. 11, pp. 1744–57, 2013.

224 C. Sahin and E. D. Bolat, "Development of remote control and monitoring of web-based distributed OPC system," *Computer Standards & Interfaces*, vol. 31, no. 5, pp. 984–93, 2009.

225 L. F. Zhai, T. Y. Chai, Z. J. Gao, and H. Yue, "A distributed simulation platform for intelligent decoupling control of coal pulverizing systems," *Journal of System Simulation*, vol. 18, no. 07, pp. 1824–8, 2006.

226 J. Z. Xiao, H. R. Wei, H. R. Wang, and W. Zhang, "Hard-in-the-loop simulation of furnace temperature control system based on Q8 card," *Journal of System Simulation*, vol. 20, no. 05, pp. 1196–8, 2008.

227 L. Jia and K. Yuan, "Distributed simulation platform for optimization control of batch processes," *Journal of System Simulation*, vol. 23, no. 10, pp. 2254–7, 2011.

228 J. Tang, T. Y. Chai, J. X. Pian, and H. Yue, "A hard-in-the-loop simulation platform for optimized intelligent control of industrial process," *Journal of Northeastern University (Natural Science)*, vol. 30, no. 11, pp. 1530–3, 2009.

229 S. S. Zhao, Y. Bai, and C. Z. Huang, "Semi-physical simulation of chemical water treatment system," *Control and Instruments in Chemical Industry*, vol. 37, no. 01, pp. 79–84, 2010.

230 J. X. Pian, T. Y. Chai, S. J. Jia, and H. Yue, "Simulation platform for optimal control of laminar cooling system," *Journal of System Simulation*, vol. 19, no. 24, pp. 5667–71, 2007.

231 P. Ma, K. C. Wang, and Z. J. Li, "Design of temperature control system using semi-physical simulation platform," *Experiment Science and Technology*, vol. 15, no. 05, pp. 10–4, 2017.

232 N. Yan, G. F. Zhang, L. K. Man, S. H. Ma, and H. C. Zhao, "Research on primary frequency regulation experimental method of wind turbine based on RT-LAB semi-physical simulation platform," *Experimental Technology and Management*, vol. 37, no. 11, pp. 226–9, 2020.