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The Prediction and Assessment of Converting Municipal Solid Waste into Energy in Shenzhen by 2035

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Article

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ABSTRACT

Rapid urbanization has led to a large increase in municipal solid waste (MSW) and poses severe environmental challenges. From the perspective of circular economy, converting MSW into energy for recycling has become a hot topic in this field. In this paper, in order to accurately assess the potential of converting MSW into energy, a hybrid prediction model named GRA-BiLSTM was proposed. We mainly evaluates the MSW production in Shenzhen through the forecast model to 2035. Then, the heat generated by the incineration of urban domestic waste was estimated, and finally, the potential of converting it into energy was obtained. The experimental findings indicate that: (1) The combined GRA - BiLSTM model achieves a MAPE value of 3.5882%, demonstrating its strong applicability in predicting MSW generation in Shenzhen. (2) Under the MSW forecasting of three scenes, the MSW generation ranges from 15.08 million tons to 27.89 million tons in 2035. (3) The potential for converting MSW into energy is estimated by the MSW generation forecasting and the MSW structure in Shenzhen. The electricity generated from MSW incineration in Shenzhen will grow to about 24.90 TWh in 2035.

KEYWORDS

municipal solid waste, forecasting, potential assessment, GRA - BiLSTM

INTRODUCTION

Rapid urbanization in China over the past few decades, accompanied by an expanding urban population and sustained economic growth, has led to a significant increase in municipal solid waste (MSW) generation in cities [1]. This kind of waste is mainly defined as composed of various solid wastes generated by human activities [2]. These mainly include all kinds of food, biomass, metals, plastics and so on generated by life and production [3]. MSW is handled through three main methods: landfilling, composting and incineration [4].

Incineration of MSW is currently a popular strategy for MSW treatment [5]. It has been proved to be the most suitable way for the harmless treatment of municipal solid waste. As shown in Figure 1, the incineration rate of China's MSW increased fourfold from 2010 to 2020. In contrast, the landfill disposal rate has decreased. It dropped from 959.83 million tons in 2010 to 77.15 million tons in 2017, and accounted for only 33% of the total waste disposal volume in 2020. In the future, with the rapid growth of MSW in China, the demand for MSW disposal will then increase, and an underestimation of MSW generation may lead to a shortage of disposal capacity and consequently cause serious environmental degradation.[6]. With the continuous increase in the amount of MSW in China, accurately predicting the generation volume of waste has become crucial for effective management.

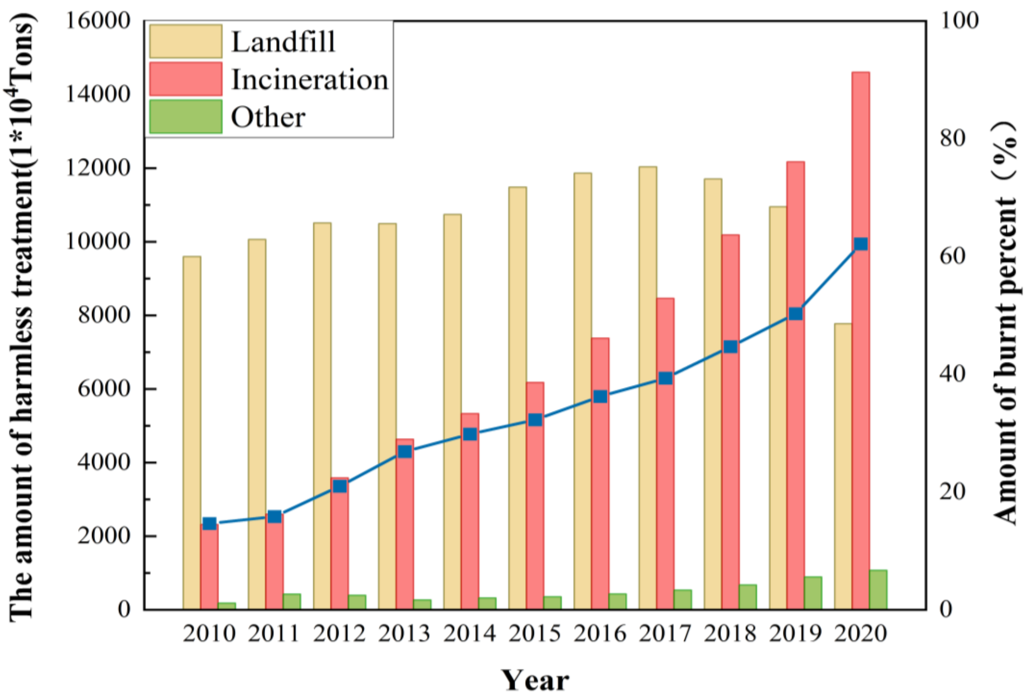

Figure 1. The amount of harmless disposal of MSW in China

The core of MSW processing is recycling. Based on the original intention of recycling, scholars have conducted research on converting municipal solid waste into renewable resources [7]. Waste incineration simultaneously reduces pollutant emissions and supplements urban energy. It has the following advantages: (1) After incineration, the original volume of the waste will be significantly reduced, thus avoiding land occupation and achieving resource utilization and waste reduction; (2) Incinerating the waste can convert the heat generated during the process into thermal energy and electricity, supporting applications such as power generation, heating, and cogeneration. At present, China has invested heavily in technological innovation to convert MSW into energy reuse. The number of harmless municipal solid waste treatment plants has increased significantly, reaching 1,287 in 2020, an increase of 104 from 2019, representing a year-on-year growth of 8.8%.

Facing the challenge of sustainable development, waste-to-energy (WTE) disposal strategies are gaining popularity among governments [8], because they not only address the dramatic increase in MSW, but also meet the huge energy demand at a manageable environmental and economic cost. This demonstrates the application of the sustainable development principle. It significantly reduces reliance on traditional fossil fuels, while alleviating the pressure of carbon emissions and air pollution control [9]. These environmental benefits and economic advantages have made this technology increasingly accepted by more and more countries and governments. As China's special economic zone, the population of Shenzhen continues to net inflow, solid waste generation continues to grow at a high rate, the daily population of Shenzhen is about 20 million people, each person produces 1 kg of waste per day, the city's daily solid waste of more than 20,000 tons, Shenzhen land resources are tight, dense population, landfill disposal is unsustainable, cracking the waste siege of the city is imminent. After exploration and practice, Shenzhen has achieved a change in the concept of waste disposal. In 2019, Shenzhen was selected as a pilot “waste-free city”and became the first in the country to achieve full-scale incineration of its solid waste, completely solve the problem of "garbage around the city". Therefore, accurately predict the output of MSW into the potential energy can be estimated, and meet certain energy demands while ensuring effective management of MSW and overcoming environmental pollution.

This study explored the generation and reuse potential of MSW in Shenzhen, emphasizing the importance of sustainable development in converting waste into energy. This paper considers the dual advantages of indicator selection and deep learning, and constructs a combined prediction model to estimate the MSW production in Shenzhen in 2035 under different development scenarios. We also estimated the low heat value of MSW in Shenzhen using the LHV calculation formula, evaluated its potential for energy conversion, and proposed corresponding sustainable development suggestions. The research contributions of this study to the exploration of the potential for MSW incineration power generation can be summarized as follows:

- A combined MSW power generation prediction model based on GRA-BiLSTM was trained, achieving high-precision prediction.
- Utilization of GRA to identify nine key indicators (including economic, social, and population indicators) for improved prediction accuracy.
- Based on a reasonable prediction of the power generation potential of municipal solid waste incineration in Shenzhen, and an assessment of the treatment methods.

LITERATURE REVIEW

MSW's Factors Affecting Research

MSW is different from other types of waste. The sources of urban domestic waste are characterized by their wide range, diversity and complexity. The above problems have led to many factors affecting the generation of MSW. According to the current mainstream research, it can be summarized that these influencing factors mainly include economic factors, social factors and demographic factors. Among them, urban population is an important factor that directly leads to the generation of MSW [10]. In particular, the income level of each household in a city will also directly affect MSW, it affects the structure of the aggregate, such as the increased content of recyclables generated by high-income households. On the contrary, income poverty leads to a higher proportion of organic waste in the total amount of MSW generated [11]. Now, many regions and countries use carbon tax as a means of managing municipal solid waste, which significantly reduces the total carbon emissions through standardized management of the classification and screening of waste items, indicating that policy has a direct role in influencing waste generation [12].

Through the literature review, it can be obtained that factors such as residents' disposable income, consumption expenditure and the total retail sales of consumer goods will have a strong correlation with the generation of MSW [13]. It was found that the growth of urban tertiary industry output value and MSW generation showed a positive correlation [14]. Some study found that higher urban green cover would have a suppressive effect on MSW generation and higher road density would generate more MSW [15]. The researchers discovered through the management of construction solid waste that the attitudes, subjective norms, and perceived behavioral control of construction industry practitioners would affect the amount of construction solid waste generated [16]. Another important finding is that by enhancing awareness, strengthening education, and implementing incentive policies on construction sites, the amount of construction waste can be effectively reduced [17]. The above studies provide data indicators that can support the prediction of MSW production volume, which serve as input indicators for the prediction model.

MSW's Prediction Research

Accurate prediction of MSW is an important basis for promoting sustainable urban development. Currently, research methods for MSW generation forecasting are divided into traditional statistical prediction methods [18], including Regression model forecasting and Time series forecasting methods [19], Machine learning prediction algorithms [20], and Deep learning prediction algorithm [21]. Based on the correlation between MSW generation and other predictors, a regression model was developed [22]. In existing studies, MSW predictions have used multiple linear regression and single linear regression [23]. MSW generation and composition have been predicted by regression analysis with time series analysis [24]. In recent years, researchers and scholars mostly use supervised machine learning algorithms to predict and evaluate the future development of MSW by predicting the amount of MSW production [25]. For the assessment of MSW generation quantities in areas with incomplete and difficult-to-obtain data, most of the time, KNN models are constructed for prediction [26]. System dynamics has always been a common tool in data analysis research, and scholars have used it to construct many models to evaluate the carbon emission potential of waste recycling and recycling treatment [27]. The process that needs to be represented determines which neural model should be utilized, and since the prediction of solid waste creation depends on a complicated web of variables, NAR models with various lagged inputs were employed to forecast future MSW generation [28]. Then, deep learning models has gradually become an important tool to evaluate the development potential of circular economy [27,29]. Due to the special three-layer architecture of LSTM cell, it can accurately capture long-term temporal patterns and their durations during the training process.

Data used to assess the potential for MSW generation is the primary factor affecting model prediction performance [30]. Sometimes the data needs to be reduced in dimensionality, and tools such as Principal Component Analysis (PCA) are often used in combination, and use Wavelet Transform (WT) for data feature identification [31]. To capture the correlation features between indicators and output targets, Grey Relational Analysis (GRA) is used to quantify the strength of the correlation between key factors of urban solid waste generation, thereby improving the prediction accuracy [32]. On the basis of the deep integration of information management and data preprocessing, the introduction of Grey Relational Analysis (GRA) not only realizes the reduction of data dimension, but also effectively eliminates more data noise through correlation screening before model prediction, thus significantly improving the prediction accuracy of the model. This paper proposes a hybrid model to enhance the accuracy of MSW generation volume assessment. This hybrid model combines the GRA and BiLSTM framework, namely the so-called GRA-BiLSTM model. The model integrates the methodological advantages of both the GRA and the bidirectional LSTM structure. It more efficiently understands the differences between data sequences in data prediction and also takes into account the influence relationships of interrelated factors. The GRA - BiLSTM model applies GRA to assess correlations between the original metrics using mathematical techniques. This combined model possesses the excellent fault-tolerant capability of neural networks, and at the same time, it can effectively improve the accuracy of predictions, thereby reliably assessing the potential of MSW incineration power generation in Shenzhen.

MATERIAL AND METHODS

GRA-BiLSTM

In this paper, the influencing factors summarized in the literature are firstly sorted by the correlation degree through GRA, and then suitable input indicators are selected according to the ranking for BiLSTM training and prediction. Then, the BiLSTM model is trained for prediction, and the optimal parameters suitable for predicting the MSW production in Shenzhen are obtained. The third step is to simulate the growth scenarios of MSW in Shenzhen to explore the possible range of MSW generation and estimate its future power conversion capacity. The following part details the operational logic of the prediction model and the formulas used to estimate the MSW incineration capacity.

Gray Relational Analysis

The core principle of GRA is to determine the degree of closeness between multiple comparison sequences by measuring their geometric similarity to the reference data sequence. This is a multi-factor statistical technique used to evaluate the relationships between data sets [32]. The geometric similarity in the output results of this method can be used as an indicator of the strength of correlation [33]. There are often differences in the size and units of different input indicators, and direct comparison may not be reliable. Therefore, before conducting the GRA analysis, the data will be standardized to a dimensionless form.

We use xi(k) to denote the k value of the i factor, and use x0(k) to denote the parent sequence and i ≥ 1 to denote the subsequence, which is the sequence of the elements to be analyzed, the reference series $x_0 = \{x_0(1), x_0(2), \cdots, x_0(n)\}$, where n represents the number of total input indicators, compare series $x_i = \{x_i(1), x_i(2), \cdots, x_i(n)(i = 0,1,2,\cdots, m-1)\}$, where m is the number of all indicators. Each indicator is used as a reference series, and the rest of the indicator series are used as comparison series.

Firstly, the m-group metrics are averaged to eliminate the effect of dimensionality, as shown in Equation (1).

$$y_i(t) = \frac{x_i(t)}{\overline{\overline{x_i}}} \tag{1}$$

Then calculate the gray correlation coefficients of $y_i(t)$ and $y_0(t)$ at moment t, as shown in Equation (2).

$$\xi_i(t) = \frac{\min_i \min_t |y_0(t) - y_i(t)| + \rho \max_i \max_t |y_0(t) - y_i(t)|}{|y_0(t) - y_i(t)| + \rho \max_i \max_t |y_0(t) - y_i(t)|} \tag{2}$$

Among them, $\xi_i(t)$ is the number of gray correlations, adjustment parameters $\rho \in (0,1)$ enables increased correlation of indicators, calculating the correlation coefficient between the y_0 and y_i is shown in Equation (3).

$$\gamma(y_0, y_i) = \frac{1}{n}\sum_{t=1}^{n} \xi_i(t) \tag{3}$$

Each indicator is used as a reference series, and the correlation coefficient matrix of each indicator is calculated with the help of Equation (3) as shown in Equation (4).

$$\gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \gamma_{n1} & \gamma_{n2} & \cdots & \gamma_{nn} \end{bmatrix} n \times n \tag{4}$$

The average of the correlation coefficients is calculated as a quantitative measure of the correlation between the comparison series and the reference series, with the corresponding weights for each indicator determined.

Bi-Directional Long Short-Term Memory

As a special variant of recurrent neural network, LSTM network effectively alleviates the problem of gradient disappearance and gradient explosion by introducing the gating mechanism of cell state and regulation of information flow [34]. In the LSTM structure diagram f_t, i_t, o_t and $\overline{C}_t$ denote forget gate, input gate, output gate and state function respectively, as shown in Figure 2.

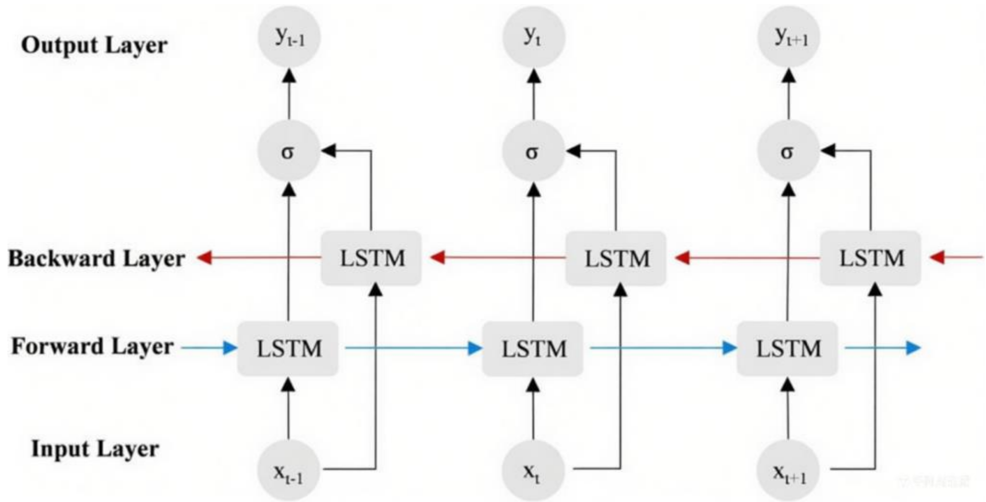

Figure 2. Bidirectional Long Short-Term Memory (BiLSTM) model structure

Where forget gate, input gate, output gate can be expressed as equations (5) ~ (7):

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{5}$$
$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{6}$$
$$f_o = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{7}$$

The state function can be represented in LSTM by the following Equation (8):

$$\overline{C_t} = f_t C_{t-1} + i_t \tanh h \left(W_{xc} x_t + W_{hc} h_{t-1} + b_c \right) \tag{8}$$

The output from the LSTM neuron is represented by Equation (9):

$$h_t = o_t \tanh h \left(\mathrm{c}_t \right) \tag{9}$$

where in equations, W and b express the structural weights and structural biases, respectively.

The core mechanism of BiLSTM (Bidirectional Long Short-Term Memory network) is to introduce a bidirectional structure, which processes time series data through two independent LSTM branches: forward and backward, so as to simultaneously model past and future context information [35]. By jointly encoding the forward and backward temporal dependencies in the sequence, the model significantly enhances the representation ability of complex temporal dynamic features, effectively improves the generalization performance of the model, and can capture the potential bidirectional correlation structure in the time series more comprehensively. Additionally, the bidirectional LSTM has a chain-like structure with complex hidden layer repetition modules, as shown in Figure 2.

In the forward layer, computation proceeds sequentially from time 1 to time t, and the output at each time step is calculated and stored. The backward layer does the opposite. At time t, information from both t − 1 and t + 1 is utilized. The final output is then obtained by combining the corresponding outputs from the Forward and Backward layers at each time step, as shown in the Equations. (10) ~ (12).

$$h_t = f \left(w_1 x_t + w_2 h_{t-1} + b \right) \tag{10}$$

$$h_t{}' = f \left(w_3 x_t + w_5 h_{t-1} + b' \right) \tag{11}$$

$$y_t = w_4 h_t + w_6 h_t{}' + b_y \tag{12}$$

In equation, where w_1~w_6 are the corresponding weight coefficients, x_t is the input layer, y_t is the output layer, h_t is the forward layer, h_t' is the backward layer, and b, b', b_t are the corresponding deviation vectors.

Power Generation Estimation Formula

With the progress of our waste management policy, MSW generation is no longer a burden to our country. However, waste is increasingly being viewed as a form of energy, and incineration technology is currently an important method for recycling MSW [36], and the combustible components of waste release a large amount of heat during incineration. The heat generated during waste incineration is closely related to its physical composition, and the captured heat can be converted into the energy we normally use. Existing research recognizes the potential of incinerated MSW to be converted into energy by calculating LHV of MSW. Urban MSW in China mainly includes components such as plastic and rubber, wood and bamboo, food, paper, textiles, and inorganic materials [37]. Based on this composition, the LHV prediction model is defined as:

$$LHV = \beta_{pl}P_{pl} + \beta_{pa}P_{pa} + \beta_{wo}P_{wo} + \beta_{Te}P_{Te} + \beta_{Fo}P_{Fo} + \beta_{Ino}P_{Ino} \tag{13}$$

Where, $\mathrm{P_{pl}}$, $\mathrm{P_{pa}}$, $\mathrm{P_{wo}}$, $\mathrm{P_{Te}}$, $\mathrm{P_{Fo}}$ and $\mathrm{P_{Ino}}$ representing the mass fraction of plastic and rubber, paper, wood and bamboo, textiles, food waste and inorganic substances in MSW; β_{pl}, β_{pa}, β_{wo}, β_{Te}, β_{Fo} and $\beta_{\mathrm{Ino}}$is the coefficient of the corresponding waste composition. The estimation of LHV of MSW in China has been abundantly studied in recent years, among which Xuebin Lin has proposed a well-recognized estimation tool. It was also found that the weighted average high pressure could accurately predict the high pressure of combustible materials and food waste. The effect of inorganic waste on waste high pressure is negligible. Therefore, Equation (13) can be described as Equation (14):

$$LHV = LHV_{pl}P_{pl} + LHV_{pa}P_{pa} + LHV_{wo}P_{wo} + LHV_{Te}P_{Te} + LHV_{Fo}P_{Fo} \tag{14}$$

Shenzhen is a large city in China. The municipal solid waste (MSW) is rather complex and it is difficult to comprehensively understand its composition through sampling tests. However, it can be inferred from the statistical data of urban domestic waste that the reported quality fractions are food waste (25% - 75%), combustible materials (16% - 50%), and inorganic waste (30% - 70%) [37]. Obviously, the combustible components in MSW contribute the most to the calorific value. Therefore, when ignoring the influence of food residues and inorganic substances on the low calorific value (LHV), urban solid waste can be roughly divided into four categories: plastics, paper, wood, and textiles. For the estimation method of Low heat value

(LHV), existing studies usually analyze the influence of fuel, food residue and ash content on LHV, and then estimate it by classification. This method includes measuring the calorific value of clean combustibles. The weighted average heating value (HV) is then used to accurately predict the MSW heating value. According to daily statistics, the proportion of waste paper products such as tissues and milk cartons is 5:5, and the mass ratio of leaves in wood waste and the mass ratio of disposable tableware to plastic bags are both 1:9. The most difficult part of the statistics is food waste, whose complex composition and different moisture contents. Current research generally holds that the calorific value of food can be calculated as 0 MJ/kg [38]. Summarizing the component ratios in the literature, when calculating the weighted average low calorific value of urban domestic waste, the model as shown in Equation (15) can be constructed.

$$LHV = 219P_{pl} + 112P_{pa} + 108P_{wo} + 115P_{Te}(kJ/kg) \tag{15}$$

where P_{pl}, P_{pa}, P_{wo}, and P_{Te} represent the plastic, paper, wood, andtextile content (wt%), respectively. Paper, wood and textiles (especially cotton) are chemically similar and their coefficients are approximately equal in Equation (15). Thus, these three coefficients can be consolidated into a single one. Based on statistical data for various regions in China, the mass ratio of paper, wood, and textiles is typically 5:3:2. Therefore, Equation (15) can be further simplified as follows:

$$LHV = 219Pl + 109(Pa + W + T)(\mathrm{kJ/kg}) \tag{16}$$

where, *Pl* represents the plastic content, *Pa* represents the paper content, *W* represents the wood content, *T* represents the textile content.

Next, Equation (17) is used to calculate the heat released during waste incineration treatment.

$$Q = MSW * LHV(kJ) \tag{17}$$

MSW represents the total quality of MSW. The amount of heat that can be released during waste incineration treatment depends on the weighted average *LHV* of the waste.

Data Resource

In order to realize the assessment of 2035, the total amount of domestic waste generated in the history of Shenzhen was counted. The data includes MSW generation statistics for Shenzhen from 1986 to 2022. They are used as prediction target indicators to train the prediction model to achieve the function of prediction. Based on this target value, calorific value conversion can be used to evaluate the potential of energy conversion more accurately. The original data is divided into two groups according to the principle that the training set is 80% and the test set is 20%. The data from 1986 to 2022 are used for training and testing of the prediction model, in which the data from 1986 to 2014 are used as the training set and the data from 2015 to 2022 are used as the testing set.

Based on the literature review of the impact factors of MSW in the previous section, this study collected and integrated 442 historical data, covering 12 indicators such as society, economy and population, and constructed a relatively comprehensive set of impact factors, numbering them for easier discussion. The input indicators are t1 to t12, while w represents the total amount of urban solid waste generated in Shenzhen. Indicators t1 to t5 are macroeconomic indicators reflecting the development quality of Shenzhen and the consumption capacity of residents; t6 to t9 are population-related indicators directly affecting the generation volume of domestic waste in Shenzhen; t10 to t12 are social-related indicators. For detailed information on the indicators, please refer to the annotations in Table 1. The data used in the experiment for training the prediction model all come from the Shenzhen Statistical Yearbook published by the Shenzhen Statistics Bureau over the years.

Table 1. Index relevance ranking

Economic Indicators			Population Indicators			Social Indicators		
Index name	Correlation	Sorting	Index name	Correlation	Sorting	Index name	Correlation	Sorting
t1	0.8477	1	t7	0.7785	1	t10	0.7357	1
t2	0.8138	2	t8	0.8340	2	t11	0.6152	2
t3	0.8009	3	t6	0.8312	3	t12	0.5978	3

Economic Indicators			Population Indicators			Social Indicators		
Index name	Correlation	Sorting	Index name	Correlation	Sorting	Index name	Correlation	Sorting
t4	0.7435	4	t9	0.6109	4			
t5	0.6358	5						

RESULTS AND DISCUSSION

Influencing Factor Screening

Using the GRA method, a correlation survey was conducted on the initial 12 influencing factors. Table 1 presents the ranked results of the strength of the relationships among five economic-related indicators, four population statistics-related indicators, and three social-related indicators. From this table, it is clearly observable that per capita consumption expenditure has the most obvious connection with the amount of urban solid waste; conversely, the green coverage area in the built environment has the least correlation. Therefore, from this empirical listing, it is clearly evident that the economic variables shaping household waste volume hold the primary position. Based on the ranking of correlations, this study selected the top 9 indicators as the key variables for prediction.

Variables are: Per capita consumption expenditure (t1), GDP (t2), Tertiary industry output (t3), Disposable income per capita (t4), Total retail sales of social consumer goods (t5), Number of resident population at the end of the year (t6), Overnight visitor arrivals (t7), Number of households with the registered population at the end of the year (t8), Employed persons at the end of the year (t9), Urban road area (t10), Actual buses at the end of the year (t11), Area of greenery coverage in built-up areas (t12).

Evaluation and Comparison of Models

In this study, a key difference between the deep learning prediction model and other models lies in its ability to effectively adjust the structural parameters. The performance of other MSW prediction models adopted was compared and verified, including Support Vector Regression (SVR), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), as well as mixed models such as GRA-SVR, GRA-GRU, and GRA-LSTM.

At the beginning of the experiment, the default hyperparameter configuration was used to observe the change of loss value, so as to define the initial range of each hyperparameter. Subsequently, the optimal configuration is finally determined by adjusting the parameters one by one and monitoring the corresponding changes in the loss values.

In this stage, in order to highlight the applicability of the deep learning model, a cross-comparison of common prediction models including the combined model was conducted through the use of evaluation functions. Mean Absolute Percentage error (MAPE) is often used to evaluate model performance in prediction research. The Mean absolute error (MAE) and root mean square error (RMSE) are also used as references. The optimal model parameters derived from this study are detailed in Table 2, while the evaluation indicators of the structural performance of each prediction model are listed in Table 3.

Table 2. Proposed parameter setting for the BiLSTM neural network

Algorithms	Time Step	Hidden_layer	Batch Size	Lr	Epoch	validation_split	MAPE (%)
GRA-BiLSTM	2	10	3	0.011	5000	0.05	3.588
	2	9	3	0.012	5000	0.05	6.674
	2	8	3	0.012	5000	0.05	5.576
	2	6	3	0.011	7500	0.05	8.093
	2	5	3	0.01	7500	0.05	9.196
	2	5	3	0.011	7500	0.05	8.683

Table 3. Prediction accuracy of each group of models

Model	MAE	RMSE	MAPE (%)
GRA-BiLSTM	22.747	28.325	3.588
GRA-LSTM	36.030	43.979	5.576
GRA-GRU	38.914	39.616	6.122
GRA-SVR	83.297	86.919	10.201
BiLSTM	34.105	36.618	5.232

LSTM	59.127	75.610	9.196
GRU	68.450	83.657	9.917
SVR	72.762	94.964	13.381

The average absolute error is calculated by the Equation shown in (18).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{18}$$

The Equation for calculating the root mean square error is shown in (19).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{19}$$

The Equation for calculating the average absolute percentage error is shown in (20).

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{20}$$

Among them, $\hat{y} = \{\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_n\}$ is the predicted value, $y = \{y_1, y_2, \cdots, y_n\}$ is the true value, n is the number of indicator variables.

The analysis results at this stage show that combining the GRA method with the prediction model can significantly improve the prediction accuracy of the model. Among the eight models participating in the performance comparison, GRA-SVR has the largest prediction error, followed by SVR algorithm. The MAE, RMSE and MAPE values of GRA-SVR are 83.2968, 86.9185 and 13.2010%, respectively, while the corresponding values of SVR are 72.7622, 94.9643 and 10.3807%. In contrast, the prediction accuracy of the combined models GRA-GRU and GRA-LSTM is better than that of the traditional GRU and LSTM models. In particular, the GRA-BiLSTM model has the lowest MAE, RMSE and MAPE values of 22.7468, 28.3250 and

3.5882%, respectively, and has the best performance. This indicates that this combined model has excellent performance in predicting the MSW generation volume of the Shenzhen city.

Forecasting of the MSW Generation

Setting the Scenarios

In this part, the relevant macroeconomic development trends of the input indicators are set up with three different scenarios for each factor: low growth scenario, benchmark scenario and high growth scenario. Within the scenario framework, the change in each input indicator is characterized by an average annual growth rate. The growth rate assumption of the baseline scenario forms the basis for the setting of the low growth and high growth scenarios, so it can be seen that the latter two are established in reference to the former. It is especially important to note that the definitions of low growth scenario and high growth scenario mentioned in this article are in relation to the baseline scenario, not in relation to the current level.

The factors affecting GDP growth are complex and complex. According to the current policy of high-quality development of China's economy, future economic growth will be maintained or slowed down. The baseline scenario for tertiary industry output is set at 10%, taking into account the year - on - year growth in value-added of the tertiary industry in Shenzhen over the past five years. Referring to the 7th Party Congress report of Shenzhen, the growth of residents' income has generally kept pace with the city’s economic expansion, and it is projected that per capita disposable income will exceed 90,000 RMB in the next five years. However, due to sudden social emergencies across the country and other factors, the proposed benchmark growth rate for per capita disposable income is 3%, the growth rate for per capita consumption expenditure is set at 2%, and the growth rate for total retail sales of consumer goods is set at 8%. As a city of immigrants, Shenzhen has continued to relax the threshold for settlement, and has maintained a high rate of increase in the household registration population when other cities have seen a decrease in their resident population. Referring to the "Statistical Bulletin on National Economic and Social Development of Shenzhen 2022" released by the Shenzhen Bureau of Statistics, the benchmark scenarios for the end resident population and year-end household registration population households are set at 5% and 1.3%. With its superior investment environment and strong external attraction, Shenzhen has always ranked in the forefront of business and foreign trade in China. However, in view of the impact of recent social emergencies and historical data over the past five years, the baseline scenario growth rate of inbound overnight visitors is set at 3%. The overall road network density in the built-up area of Shenzhen's central city ranked first among 36 major cities in China, and According to the "Opinions on Further Strengthening Urban Planning, Construction and Management", the area of urban roads is generally set at 0.3%. Based on the future assessment of the above input indicators, the annual rate of change of the input indicators under different scenarios is shown in Table 4.

Table 4. Growth rates of influence factors of MSW (in %)

Scenarios	Low-growth	Benchmark	High-growth
GDP	6	7	8
Tertiary industry output	9	10	11
Per capita consumption expenditure	2	3	4
Disposable income per capita	1	2	3
Total retail sales of social consumer goods	6	8	10
Number of resident population at the end of the year	2	5	6
Overnight visitor arrivals	2	3	4
Number of households with the registered population at the end of the year	1.2	1.3	1.4
Employed persons at the end of the year	0.2	0.3	0.4

Forecasting Results of the MSW Generation

By comparing the results of different models, the GRA-BiLSTM model was verified to be applicable for predicting the amount of urban solid waste generated in Shenzhen in 2035. Its input indicators only cover three different scenarios. The simulation results of the low growth, base, and high growth scenarios are shown in Figure 3. Specifically, MSW generation will increase moderately in the low-growth scenario, from 846 million tons in 2022 to 150.771 million tons in 2035. In the baseline scenario, it shows steady growth, rising from 846 million tons to 194.053 million tons over the same period. The high growth scenario shows a similar pattern to the base scenario, but with a more significant growth rate, reaching 278,885 million tons by 2035. It is estimated that by 2035, Shenzhen's MSW production will be in the range of 1.508 billion tons to 2.789 billion tons.

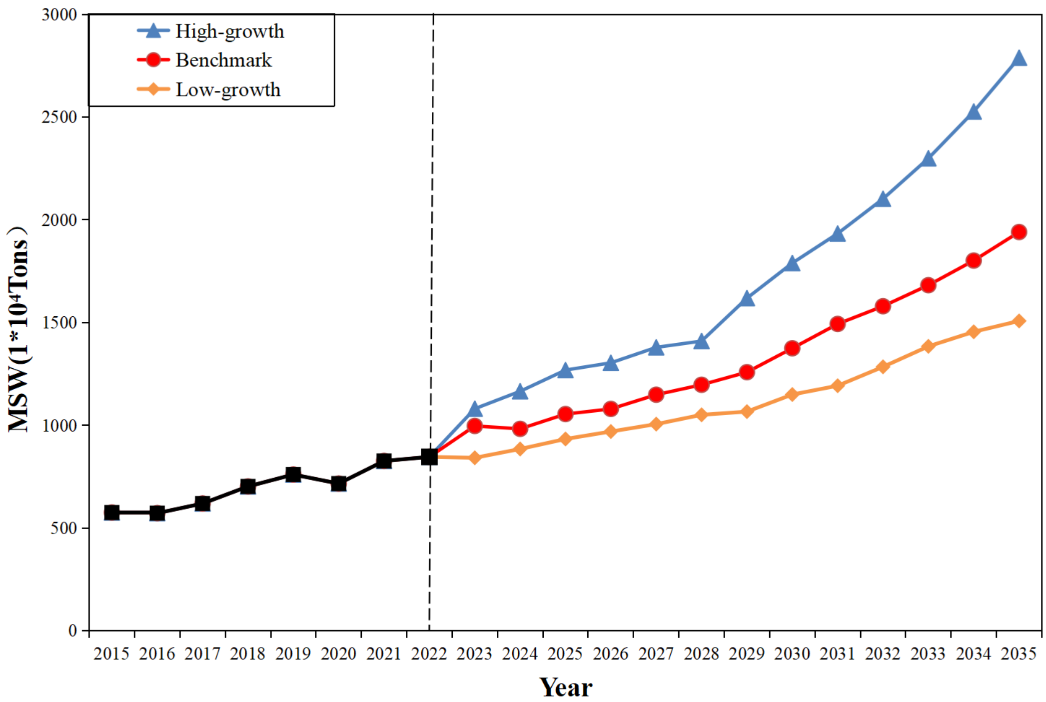

Figure 3. The prediction results of the three scenarios

Shenzhen is treating the solid waste system as the core regulatory link of the city's metabolism. Through institutional integration of sorting practices and facility operations, it is promoting the transformation of waste from a linear disposal model to a controllable material flow closed loop, and comprehensively enhancing the system's resilience and spatial adaptability. Additionally, in the future development of the city, it is planned to achieve 100% coverage of medical waste collection and disposal systems, harmless sludge disposal, hazardous waste management, and environmental pollution liability insurance for public service units, as well as a high standard for the proportion of green buildings in new construction projects.

Estimation of Heat

Shenzhen is committed to building a zero-waste city, aiming to reduce solid waste while enhancing the capacity for solid waste incineration. Therefore, accurately estimating the heat generated during the incineration process of solid waste is of vital importance for achieving Shenzhen's sustainable development goals. Based on the prediction results of different development scenarios, further discusses the potential of converting MSW incineration into energy, providing data support for related development plans. As people's living standards and habits gradually stabilize, the annual changes in the physical composition ratio of domestic waste in Shenzhen do not show a clear trend. Based on the literature review, the composition ratios of MSW in Shenzhen were used to estimate the calorific value. According to the technical bulletin of the five largest waste incineration treatment plants in Shenzhen, the incineration ratio used in this study was adjusted, as shown in Table 5. Then, heat generation from MSW incineration in Shenzhen was evaluated, and the conversion potential results are shown in Figure 4. Under the base growth scenario, the heat generation amount increased from 129,551.50 GJ in 2023 to 252,269.23 GJ in 2035. And the heat generation amount increased from 109,386.20 GJ in 2023 to 196,001.75 GJ in 2035 by the low growth scenario. Therefore, the heat generation amount increased from 140,450.7 GJ in 2023 to 362,550.5 GJ in 2035 by the high growth scenario.

Table 5. Physical composition and LHV of MSW in Shenzhen

Project	Food	Paper	Plastic	Textile	Wood	Others	LHV(MJ/kg)
Physical composition (wt%)	47.16	13.03	8.73	12.44	9.98	9.04	/
Incinerate composition (wt%)	/	29.50	19.75	28.15	22.6	/	13.07

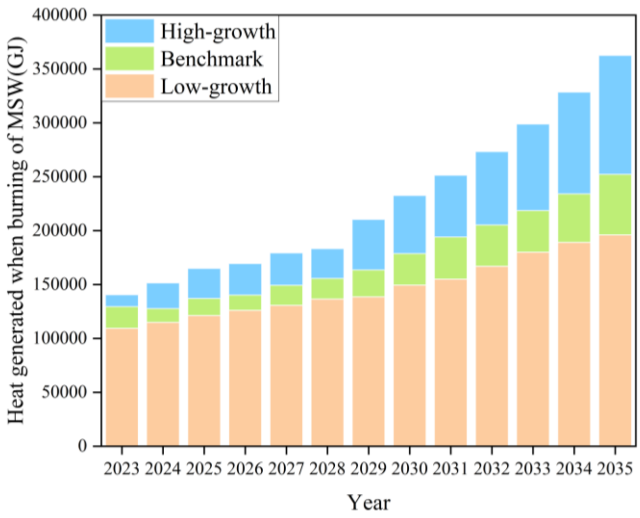

Figure 4. The prediction results of Heat

The waste incineration method is a high-temperature thermal treatment technology that can recycle waste heat generated by incineration while achieving harmless, reduced, and resourceful waste. Under three scenarios, the heat generated by incineration tends to rise as the amount of MSW generated increases, so more available clean energy is obtained. With the rapid economic development and high population gathering, China's MSW disposal is still facing serious challenges, in order to solve the problem of "garbage siege", Shenzhen City, September 1, 2020, the official implementation of the "Shenzhen Municipal Regulations on the Management of Solid Waste Classification", Shenzhen's waste classification from "initiative classification Shenzhen has changed from "initiative classification" to "compulsory classification", and has achieved remarkable results by reducing solid waste from the source and managing the whole process through legislation. In the "Shenzhen Municipal Committee of the Communist Party of China on the formulation of the fourteenth five-year plan for the national economic and social development of Shenzhen and the 2035 Visionary Goals", it is clearly pointed out that to promote the construction of "waste-free city", comprehensive promotion of waste reduction and classification, and promote the source of solid waste reduction, harmless and resource management.

Waste separation lays the foundation for waste to be effectively incinerated. MSW incineration can generate heat for heating, power generation, and combined heat and power, which effectively reduces over-reliance on primary energy sources such as coal. The determination of its energy conversion into potential energy is not only dependent on the physical calorific value, but is also deeply coupled with the influence of classification purity on the stability of combustion, as well as the secondary reduction potential contained in the unburned carbon and metal oxides in the ash and slag. Therefore, this paper draws on the actual investigation results of researchers on the Shenzhen waste incineration plant to obtain the potential parameters for converting domestic waste into energy. Finally, the quantitative assessment of the potential for converting urban waste into energy in Shenzhen is shown in Table 6. From these calculation results, it can be seen that by 2035, the potential capacity for generating electricity through the incineration of urban waste in Shenzhen will increase to 24.9 TWh. In the future, vigorously promoting MSW incineration for power generation will be beneficial for large cities like Shenzhen to accelerate their energy transition and reduce carbon emissions in the power system.

Table 6. Conversion of MSW to energy: estimated potential

Year	Electricity generation potential (TWh)
2025	10.30
2030	16.20
2035	24.90

CONCLUSION AND POLICY IMPLICATIONS

Conclusions

MSW has become an important indicator to show the changes of urban metabolic intensity and consumption structure. During the rapid urbanization process in developing countries, its growth inertia often exacerbates the nonlinear cumulative effect of environmental load and governance costs. This study takes Shenzhen as a case and constructs a collaborative prediction framework (GRA-BiLSTM) that integrates system correlation identification and temporal dynamic modeling, aiming to assess and predict the future production volume and energy conversion potential of urban MSW. This framework first decomposes the structural coupling relationship between population structure, economic activity density, consumption pattern evolution and waste output through gray correlation analysis, achieving mechanism-oriented screening of input variables. And the prediction model captures its inherent time-varying characteristics and sensitivity to sudden changes, significantly enhancing the representation ability of waste production fluctuations under the disturbance of complex urban systems. The average absolute percentage error (MAPE) of this model is 3.5882%. Furthermore, this study conducted a reverse adjustment for the dynamic range of low calorific values, while also incorporating the unique thermodynamic boundary constraints of the incineration system. Under different scenarios, the potential adaptability of the pathways for converting waste into energy was evaluated. It is expected that by 2035, the proportion of electricity generated from waste incineration in the total power generation of Shenzhen will increase year by year, rising from 4.2% in 2023 to 14.6%.

Policy Implications

At present, the extensive application of waste incineration technology in China aims to improve the energy consumption structure, reduce pollution emissions, and enhance environmental quality, thereby contributing to the country's sustainable development goals. Although some domestic waste incineration and power generation technologies in China have reached international advanced levels, there are still significant gaps in the broader waste incineration industry, especially in meeting high-quality development standards and addressing the insufficient supervision during certain stages of the incineration process. Given the actual constraints faced by megacities such as Shenzhen in the treatment of domestic waste through incineration, including high facility load, significant neighborhood opposition effects, and insufficient granularity in the entire process supervision, policy optimization urgently needs to consider urban adaptability. Measures could include shifting the regulatory framework from end-of-pipe compliance review to a full lifecycle governance covering site selection assessment, dynamic emission traceability, fly ash collaborative disposal, and public participation. Only through the coordinated integration of differentiated emission standards, cross-departmental data sharing mechanisms, and third-party performance auditing systems can the long-standing imbalance between technical rigidity and governance flexibility in the industry be effectively resolved, thereby supporting the green transformation from a conceptual consensus to institutional implementation.

The current waste classification and recycling system implemented in Shenzhen, although it has formally established a complete framework covering the entire process from collection, transportation to disposal, its environmental benefits have not been fully realized in the incineration stage. The main problem lies not in the deficiency of the classification system design, but in the insufficient technical compatibility between the classification results and the incineration system. (Silva 2020). Therefore, it is necessary to strengthen environmental management during the MSW incineration process in Shenzhen, establish a comprehensive information management system for incineration ash, odors and leachate, and implement continuous monitoring to achieve the goal of effectively preventing and controlling environmental risks. What is even more alarming is that the solid waste generation pattern in Shenzhen is undergoing a structural transformation. The population density is approaching the physical limit, the developed area is reaching saturation, and the proportion of electronic and packaging waste is continuously rising. Under the constraints of extremely scarce land resources and an approaching environmental capacity threshold, simply relying on the construction or expansion of incineration plants is no longer sufficient to support the goal of sustainable management. Therefore, the solution does not lie in adding capacity, but in redefining the functional positioning of the incineration system within the urban metabolic network. It shifts from a terminal disposal node to a hub-type infrastructure that links classification quality feedback, thermal power generation scheduling, and the pre-extraction of high-value components.

Author Contributions

Conceptualization – Lai M; methodology – Lai M; formal analysis – Wang Y; investigation – Lai M; Software – Lai M; Data curation – Wang Y; Validation – Liu A; Visualization – Liu A; writing-original draft preparation – Liu A; writing-review and editing – Lai M and Liu A. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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Availability of Data and Materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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REFERENCES

[1] Zhang M, Wei J, Li H, et al. Comparing and optimizing municipal solid waste (MSW) management focused on air pollution reduction from MSW incineration in China. Science of The Total Environment. 2024;

907:167952. doi: 10.1016/j.scitotenv.2023.167952

[2] Yan M, Zhang S, Wibowo H, et al. Biochar and pyrolytic gas properties from pyrolysis of simulated municipal solid waste (SMSW) under pyrolytic gas atmosphere. Waste Disposal & Sustainable Energy. 2020; 2(1):37-46. doi: 10.1007/s42768-019-00030-y

[3] Ashani PN, Shafiei M, Karimi K. Biobutanol production from municipal solid waste: Technical and economic analysis. Bioresource Technology. 2020; 308:123267. doi: 10.1016/j.biortech.2020.123267

[4] Katakojwala R, Kopperi H, Kumar S, et al. Hydrothermal liquefaction of biogenic municipal solid waste under reduced H2 atmosphere in biorefinery format. Bioresource Technology. 2020; 310:123369. doi: 10.1016/j.biortech.2020.123369

[5] Wang D, Tang YT, He J, et al. Generalized models to predict the lower heating value (LHV) of municipal solid waste (MSW). Energy. 2021; 216:119279. doi: 10.1016/j.energy.2020.119279

[6] Peng J, Zhang S, Wang Y, et al. Time-space patterns of groundwater contamination in a closed MSW landfill: Insights from long-term monitoring and SOM-based clustering analysis. Environmental Pollution. 2025; 382:126659. doi: 10.1016/j.envpol.2025.126659

[7] Kasataka K, Kumagai S, Kameda T, et al. Enhancement of gasification and liquefaction during fast co-pyrolysis of cedar wood and polyethylene through control of synergistic interactions. Bioresource Technology Reports. 2020; 11:100431. doi: 10.1016/j.biteb.2020.100431

[8] Luo X, Gong X, Xia J. Assessment of the waste-to-energy potential for industrial steam supply and carbon emission reduction in Hainan, China. Renewable and Sustainable Energy Reviews. 2025; 217:115749. doi: 10.1016/j.rser.2025.115749

[9] Istrate IR, Iribarren D, Gálvez-Martos JL, et al. Review of life-cycle environmental consequences of waste-to-energy solutions on the municipal solid waste management system. Resources, Conservation and Recycling. 2020; 157:104778. doi: 10.1016/j.resconrec.2020.104778

[10] Ayeleru OO, Fajimi LI, Oboirien BO, et al. Forecasting municipal solid waste quantity using artificial neural network and supported vector machine techniques: A case study of Johannesburg, South Africa. Journal of Cleaner Production. 2021; 289:125671. doi: 10.1016/j.jclepro.2020.125671

[11] Chen X, Sun Z, Kuo PC, et al. Zero direct carbon emission renewable natural gas production from municipal solid waste via chemical looping. Renewable and Sustainable Energy Reviews. 2026; 226:116501. doi: 10.1016/j.rser.2025.116501

[12] Liu J, Li Y, Wang Z. The potential for carbon reduction in construction waste sorting: a dynamic simulation. Energy. 2023; 275:127477. doi: 10.1016/j.energy.2023.127477

[13] Nguyen XC, Nguyen TTH, La DD, et al. Development of machine learning-based models to forecast solid waste generation in residential areas: A case study from Vietnam. Resources, Conservation and Recycling. 2021; 167:105381. doi: 10.1016/j.resconrec.2020.105381

[14] Li B, Li D, Hu J, et al. Carbon emission of municipal solid waste under different classification methods in the context of carbon neutrality: A case study of Yunnan Province, China. Fuel. 2024; 372:132167. doi: 10.1016/j.fuel.2024.132167

[15] Ghosh A, Maji D, Roy S, et al. Forecasting Organic Waste and Biomethane Generation Potential of a non industrial district of Eastern India: A Data-Driven Approach to Sustainable Energy and Waste Management. Cleaner Waste Systems. 2025: 100378. doi: 10.1016/j.clwas.2025.100378

[16] Liu B, Zhang L, Wang Q. Demand gap analysis of municipal solid waste landfill in Beijing: Based on the municipal solid waste generation. Waste Management. 2021; 134:42-51. doi: 10.1016/j.wasman.2021.08.007

[17] Liu J, Chen Y, Wang X. Factors driving waste sorting in construction projects in China. Journal of Cleaner Production. 2022; 336:130397. doi: 10.1016/j.jclepro.2022.130397

[18] Fu H, Chen L, Fang W, et al. Characteristics and life cycle carbon emission reduction potential of waste recycling after implementing new waste classification policy in China: From case study to national perspective. Journal of Environmental Sciences. 2025; 155:645-657. doi: 10.1016/j.jes.2024.05.045

[19] Denafas G, Ruzgas T, Martuzevičius D, et al. Seasonal variation of municipal solid waste generation and composition in four East European cities. Resources, Conservation and Recycling. 2014; 89:22-30. doi: 10.1016/j.resconrec.2014.06.001

[20] Zhang C, Dong H, Geng Y, et al. Machine learning based prediction for China's municipal solid waste under the shared socioeconomic pathways. Journal of Environmental Management. 2022; 312:114918. doi: 10.1016/j.jenvman.2022.114918

[21] Alidoust P, Keramati M, Hamidian P, et al. Prediction of the shear modulus of municipal solid waste (MSW): An applicatn of machine learning techniques. Journal of Cleaner Production. 2021; 303:127053. doi: 10.1016/j.jclepro.2021.127053

[22] Adamović VM, Antanasijević DZ, Ristić MĐ, et al. Prediction of municipal solid waste generation using artificial neural network approach enhanced by structural break analysis. Environmental Science and Pollution Research. 2017; 24(1):299-311. doi: 10.1007/s11356-016-7767-x

[23] Ghinea C, Drăgoi EN, Comăniţă ED, et al. Forecasting municipal solid waste generation using prognostic tools and regression analysis. Journal of Environmental Management. 2016; 182:80-93. doi: 10.1016/j.jenvman.2016.07.026

[24] Paulauskaite-Taraseviciene A, Raudonis V, Sutiene K. Forecasting municipal solid waste in Lithuania by incorporating socioeconomic and geographical factors. Waste Management. 2022; 140:31-39. doi: 10.1016/j.wasman.2022.01.004

[25] Liu J, Li J. Economic benefit analysis of the carbon potential of construction waste resource management based on a simulation of carbon trading policy. Environmental Science and Pollution Research. 2023; 30(36):85986-86009. doi: 10.1007/s11356-023-28417-9

[26] Adu TF, Mensah LD, Rockson MAD, et al. Forecasting municipal solid waste generation and composition using machine learning and GIS techniques: A case study of Cape Coast, Ghana. Cleaner Waste Systems. 2025; 10:100218. doi: 10.1016/j.clwas.2025.100218

[27] Liu Y, Li R, Cai W, et al. Greenhouse gas emissions and mitigation strategies in China's municipal solid waste sector under the impact of the COVID-19 pandemic. Environmental Research, 2025, 266: 120497. doi: 10.1016/j.envres.2024.120497

[28] Lin K, Zhao Y, Tian L, et al. Estimation of municipal solid waste amount based on one-dimension convolutional neural network and long short-term memory with attention mechanism model: A case study of Shanghai. Science of the Total Environment. 2021; 791:148088. doi: 10.1016/j.scitotenv.2021.148088

[29] Lin K, Zhao Y, Kuo JH, et al. Toward smarter management and recovery of municipal solid waste: A critical review on deep learning approaches. Journal of Cleaner Production. 2022; 346:130943. doi: 10.1016/j.jclepro.2022.130943

[30] Will R, Hirota M, Chaffe PLB, et al. Socioeconomic development role in hospitalization related to air pollution and meteorology: A study case in southern Brazil. Science of The Total Environment. 2022; 826:154063. doi: 10.1016/j.scitotenv.2022.154063

[31] Li X, Zhang Y, Du M, et al. The forecasting of passenger demand under hybrid ridesharing service modes: A combined model based on WT-FCBF-LSTM. Sustainable Cities and Society. 2020; 62:102419. doi: 10.1016/j.scs.2020.102419

[32] Han Y, Cui S, Geng Z, et al. Food quality and safety risk assessment using a novel HMM method based on GRA. Food Control. 2019; 105:180-189. doi: 10.1016/j.foodcont.2019.05.039

[33] Mahmoudi A, Javed SA, Liu S, et al. Distinguishing coefficient driven sensitivity analysis of GRA model for intelligent decisions: application in project management. Technological and Economic Development of Economy. 2020; 26(3):621-641. doi: 10.3846/tede.2020.11890

[34] Graves A, Schmidhuber J. Framewise phoneme classification with bidirectional LSTM and other neural network architectures. Neural Networks. 2005; 18(5-6):602-610. doi: 10.1016/j.neunet.2005.06.042

[35] Ghasemlounia R, Gharehbaghi A, Ahmadi F, et al. Developing a novel framework for forecasting groundwater level fluctuations using Bi-directional Long Short-Term Memory (BiLSTM) deep neural network. Computers and Electronics in Agriculture. 2021; 191:106568. doi: 10.1016/j.compag.2021.106568

[36] Hoang QN, Vanierschot M, Blondeau J, et al. Review of numerical studies on thermal treatment of municipal solid waste in packed bed combustion. Fuel Communications. 2021; 7:100013. doi: 10.1016/j.jfueco.2021.100013

[37] Zhou H, Meng AH, Long YQ, et al. An overview of characteristics of municipal solid waste fuel in China: physical, chemical composition and heating value. Renewable and Sustainable Energy Reviews. 2014; 36:107-122. doi: 10.1016/j.rser.2014.04.024

[38] Lin X, Wang F, Chi Y, et al. A simple method for predicting the lower heating value of municipal solid waste in China based on wet physical composition. Waste Management. 2015; 36:24-32. doi: 10.1016/j.wasman.2014.11.020