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Forecasting Municipal Solid Waste Removal Volume Based on Socioeconomic Indicators for Carbon Reduction Strategy in Beijing's Waste Management

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Municipal solid waste (MSW) management poses a significant challenge amidst global population growth and urbanization. With Beijing as a focal point due to its substantial contribution to MSW generation and greenhouse gas (GHG) emissions, this study employs two-stage Bayesian-optimized Artificial Neural Network models to forecast MSW removal volume and evaluate associated GHG emissions in Beijing. The analysis integrates socioeconomic indicators, including population and GDP, to elucidate the complex relationship between MSW generation and economic development. Various MSW treatment scenarios are assessed by alternating the configuration of sanitary landfills, incineration, and composting. Results indicate a projected MSW removal volume of approximately 14 Mt by 2060, a 63.16 % reduction compared to 2023. Scenario 2 (50 % incineration and 50 % composting) demonstrates the potential to reduce GHG emissions by approximately 4.11 Mt of CO_2e compared to the current practice. The findings underscore the need for comprehensive waste management strategies integrating waste segregation, incineration, and composting to achieve sustainable MSW treatment.

1. Introduction

Municipal solid waste (MSW) is emerging as a significant environmental issue due to global population expansion, economic development, and urbanization trends. Around 2.01 Gt of MSW are produced annually worldwide, and it is expected to surge to 3.40 Gt by 2050 (Kaza et al., 2018). As MSW treatment accounts for 5 % of the total GHG emissions into the atmosphere (Gautam and Agrawal, 2021), its rapid growth will exacerbate the already alarming rate of global warming and climate change. East Asia and the Pacific generate the most MSW (23 %), followed by Europe and Central Asia (20 %), with China being a prominent contributor of 15.5 % of the global MSW generation (Tiseo, 2023).

Considering China's major role in GHG emissions and its "30·60 dual-carbon" goal to reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060, an endeavor towards carbon-neutral MSW management is crucial. Various studies have focused on China's MSW review, forecast, and technological developments. Li et al. (2024) concluded that China has shifted from landfill to incineration and power generation as their predominant MSW treatment method, reaching 72.55 % in 2021. Zhang et al. (2022) noted a surge in China's MSW-related GHG emissions from 43 Mt in 2010 to 80 Mt in 2019. They also predicted China's carbon neutrality of MSW treatment only after China implemented a full garbage sorting policy under Shared Socioeconomic Pathway 1. In terms of waste-to-energy conversion, Awasthi et al. (2022) recommended a combination of unconventional technology, such as pyrolysis and gasification, as well as conventional technology, like incineration and sanitary landfill, to realize a resource recovery loop in MSW management.

To date, no study has evaluated GHG emissions of MSW by employing forecasted MSW removal volume derived from socioeconomic indicators in Beijing. The MSW production rate is correlated with economic

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development level, average family size, monthly income, and employment status. Similarly, albeit not proposing a quantitative model to show their correlation, Mian et al. (2017) showed that urban population and economic growth are important factors affecting MSW generation. As a highly populated urbanized city, Beijing is chosen as the region for the study. Being the capital of China, Beijing tops the nominal GDP per capita and is the second most populated city in the country. Since China has grown to be the fastest developing economy worldwide, Beijing underpins remarkable values as a reference to other Chinese regions within the context of urbanization and MSW treatment policy.

This study aims to evaluate GHG emissions associated with MSW by employing forecasted MSW removal volume derived from socioeconomic indicators using a Bayesian-optimized Artificial Neural Network (ANN). The forecasting model projects MSW removal volume and subsequently examines GHG emissions, while past studies directly forecasted the latter only. Considering China's rapid economic and social development, this study can comprehensively understand the drivers behind MSW volume and the pertinent GHG emissions. Ultimately, this study can promote the development of a more robust and efficient MSW treatment system by presenting a precipient understanding of future MSW trends to the stakeholders in China to advocate environmental conservation.

2. Methodology

2.1 Phase 1: AI predictive modelling for the volume of MSW removal

With a 2019 MSW removal rate of 20,300 tpd (Beijing Municipal Ecology and Environment Bureau, 2023), Beijing's MSW primarily comprises food residue (Figure 1). In 2019, 24 % of MSW was disposed of in sanitary landfills, 50 % of MSW was treated in incineration, and 26% of MSW was treated in composting (Li et al., 2022). The MSW treatment has mainly developed in the direction of incineration, and the sanitary landfill rate of MSW generally declined from 2006 to 2019 in Beijing. Understanding the socioeconomic indicators becomes crucial in elucidating these trends, as studies affirm the strong association between population, GDP, and MSW removal (Hoy et al., 2022).

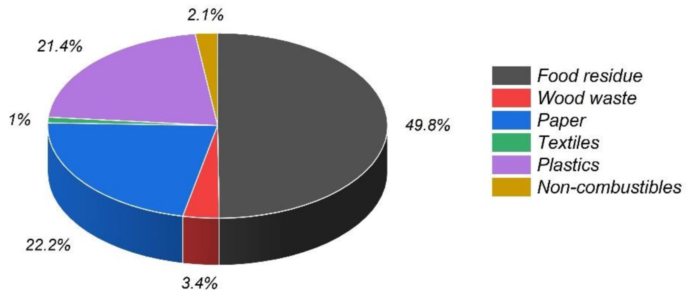

Figure 1: The proportion of MSW composition in Beijing in 2019 (Li et al., 2022).

A two-stage artificial neural network (ANN) model is used to forecast municipal solid waste (MSW) removal volumes from 2022 to 2060, developed using MATLAB R2021. Optimized with Bayesian methods, the first ANN model predicts MSW removal volume based on historical data collected from the Beijing Municipal Bureau of Statistics (1992-2022) database. Bayesian optimization, which uses the Bayesian conditional probability rules, iteratively estimates the best hyperparameter combination to minimize error, reducing the need for manual feature engineering and computational resources (Hoy et al., 2024). Historical socioeconomic data (population and GDP) and MSW removal volumes are normalized and partitioned into training and testing sets (80:20 ratio), as recommended by Hoy et al. (2022). The Bayesian-optimized ANN model is used to train on data from 1991 to 2021 and learn the relationship between socioeconomic patterns and MSW removal volume. Bayesian optimization optimizes two critical hyperparameters: the number of hidden layer neurons and the learning rate, aiming to minimize the root mean square error (RMSE), as presented in Eq(1).

$$RMSE = \sqrt{\sum_{i=0}^{N} (Y_i - X_i)^2 / N} \quad (1)$$

where *RMSE* is the root mean square error; Y_i is the predicted value; X_i is the actual value; N is the number of data samples.

The model undergoes 30 iterations, with training halting after 1,000 epochs or upon no further improvements. After the 30 iterations, the optimized hyperparameter combination is automatically identified based on the combination that yields predictions with the smallest RMSE. The optimal hyperparameters are identified by the lowest RMSE, with recommended ranges for the learning rate (1×10^{-1} to 1×10^{-5}) (Goodfellow et al., 2016) and the number of neurons (1 to 12), which is calculated based on a formula involving the number of inputs, outputs, and a constant, as presented in Eq(2) (Zhang et al., 2021).

$$l = \sqrt{n+m} + a \tag{2}$$

where *l* is the number of neurons; *n* is the number of inputs (i.e., two inputs – population and GDP); m is the number of outputs (i.e., one output – annual MSW emissions); a is a constant between [0, 10].
The second ANN level forecasts Beijing's population and GDP from 2023 to 2060. This model is trained using historical and government-projected population and GDP data of China, sourced from the National Bureau of Statistics of China (1992-2022) database. The trained model then uses Beijing's historical data to project its population and GDP from 2023 to 2060. These projected data and data from 2022 are input into the trained Bayesian-optimized ANN model (i.e., the first model) to predict Beijing's MSW removal volume for 2022 to 2060. An ensemble learning approach with 10 trials reduces forecast bias, and the forecasted MSW removal volumes are analyzed based on the ensemble mean.

2.2 Phase 2: GHG emissions evaluation for various MSW treatment scenarios

In Phase 2, the study quantifies the greenhouse gas (GHG) emissions from MSW treatment facilities, focusing on sanitary landfills, incineration, and composting. Methane emissions are quantified for sanitary landfills using the waste model from the 2006 IPCC guidelines (2019 Refinement) (IPCC, 2019). Landfill gases are collected and recovered at a 75 % efficiency rate for electricity generation (Cudjoe et al., 2021). The avoided emissions from this electricity, which displaces fossil-based grid electricity, are calculated using Equations (3) and (4). The net GHG emissions, denoted as $CO_2e_{net\,(Landfill)}$, are determined by subtracting the avoided emissions from the fugitive landfill gas emissions, as shown in Eq(5).

$$E_{Gen\,(Landfill)} = \frac{R_{CH_4} \times 37.2 \times \alpha \times 0.9 \times \beta}{\gamma} \tag{3}$$

$$CO_2e_{avoided\,(Landfill)} = E_{Gen\,(Landfill)} \times 0.1229 \times 2.64 \times 10^{-3} \tag{4}$$

$$CO_2e_{net\,(Landfill)} = \left(CH_4\ Emissions - R_{CH_4}\right) \times 25 - CO_2e_{avoided\,(Landfill)} \tag{5}$$

where $E_{Gen\,(Landfill)}$ represents the electricity generated from landfill methane; 37.2 MJ/m^3 is the methane heating value; 0.9 is the landfill oxidation factor; β is the electricity generation efficiency (i.e., 35 %); α is the capacity factor (i.e., 85 %), and γ is the conversion factor from MJ to kWh (i.e., 3.6) (Cudjoe et al., 2021). The conversion factor for translating electricity generation to its equivalent in standard coal is 0.1229 kg of standard coal per kWh (NBS, 2022), with standard coal producing 2.64 t of CO_2e per t of coal (NDRC, 2016).
For incineration, flue gases emitted to the atmosphere during the treatment of MSW contribute to GHG emissions, while the heat energy produced is converted into electricity, which substitutes fossil-based electricity. Every tonne of MSW is estimated to produce 441 kWh of electricity (Beijing Municipal Commission of Urban Management, 2024). Only 75.8 % of electricity generated can be transmitted into the power grid (Gao, 2016). The formula for calculating net GHG emissions, denoted as $CO_2e_{net\,(Incineration)}$, is provided in Eq(7).

$$CO_2e_{avoided\,(Incineration)} = MSW_I \times E_{Gen\,(Incineration)} \times 75.8\% \times 0.1229 \times 2.64 \times 10^{-3} \tag{6}$$

$$CO_2e_{net\,(Incineration)} = MSW_I \times \sum_i (PC_i \times CC_i \times MC_i) \times EF \times \frac{44}{12} - CO_2e_{avoided\,(Incineration)} \tag{7}$$

where $CO_2e_{avoided\,(Incineration)}$ represents the reduced GHG emissions from the electricity generated during the incineration process; MSW_I represents the amount of incinerated MSW in tonnes; $E_{Gen\,(Incineration)}$ is the electricity generated from incineration; PC represents the physical composition of waste type i^{th}; CC represents the carbon content in i^{th} waste; MC represents the proportion of mineral carbon in the total carbon content of i^{th} waste; EF represents the combustion efficiency of the incinerator.
In terms of composting, the biogas generated (i.e., methane and nitrous oxide) is calculated using the equation from the 2006 IPCC guidelines (2019 Refinement) (IPCC, 2019). All the biogas escapes to the atmosphere, while the products produced are used as biofertilizers, substituting chemical fertilizers and avoiding the GHG emissions associated with their production. According to Alengebawy et al. (2022), 1 t of biocompost can avoid 0.183 t CO_2e from chemical fertilizer. The net GHG emissions, denoted as $CO_2e_{net\,(Composting)}$, are determined by subtracting the avoided emissions from the composting gas emissions, as shown in Eq(9).

$$CO_2e_{avoided\,(Composting)} = MSW_C \times CPR \times CO_2e_{chemf} \tag{8}$$

$$CO_2e_{net\,(Composting)} = CH_4\ Emissions \times 25 + N_2O\ Emissions \times 298 - CO_2e_{avoided\,(Composting)} \tag{9}$$

where MSW_C represents the amount of composted MSW in tonnes; CPR represents the compost production rate; CO_2e_{chemf} represents the amount of CO_2e from chemical fertilizer that can be avoided by 1 t of compost.

Table 1: The composition, carbon content, and mineral carbon content of MSW in Beijing (NCSC, 2011).

	Physical composition (%)	Carbon element (%)	Mineral carbon (%)
Food residue	49.85	50.60	11.73
Paper	22.17	46.13	8.90
Plastics	21.45	78.77	68.10
Textiles	0.98	61.03	52.30
Wood waste	3.43	53.03	18.53

2.3 Phase 3: Scenario analysis and policy recommendations

This study establishes five scenarios to project GHG emissions for 2025, 2030, and 2060, aiming to determine a more optimal balance between incineration and composting for MSW management. Scenario 1 utilizes the business-as-usual treatment practice of 2019 as a baseline for estimating GHG emissions. Scenario 2 proposes full-scale composting of food waste, which accounts for 50 % of MSW, while the remaining MSW undergoes incineration. Scenarios 3 and 4 increase the proportion of incineration, aligning with Chinese policy directives, with waste incineration and composting ratios set at 65:35 and 80:20, respectively. Scenario 5 adopts exclusive incineration treatment. These scenarios assess the impact of global warming on different treatment ratios, identifying the most effective methods for GHG mitigation and determining the superior treatment approach. The findings offer valuable insights for government agencies and urban planners to devise tailored policies and measures based on the scenario analyses.

3. Results and Discussion

3.1 Bayesian-optimized ANN models for forecasting MSW removal volume

Figure 2 illustrates the temporal trends in Beijing's population, GDP, and MSW removal volume. From 1992 to 2015, Beijing witnessed sustained population growth, culminating in approximately 2.19×10^7 population by 2020. However, in line with the broader demographic shifts in China, the overall population is expected to exhibit a marginal decline in the foreseeable future, as reflected in the projected population curve for Beijing. Conversely, Beijing's GDP consistently grew, surpassing 41.6 trillion CNY by 2022. Despite potential fluctuations in future growth rates, the trajectory of GDP is anticipated to maintain an upward trend. The volume of MSW removal, influenced by both population and GDP dynamics, peaked in 2019 but experienced a notable downturn in 2020 due to the impact of the pandemic. While population and GDP contribute to fluctuations in MSW removal volumes, population emerges as a dominant predictor, consistent with prior research (Mian et al., 2017). Notably, despite the upward trajectory of GDP, the projected MSW removal volume is expected to plateau around 2030, hovering close to 13 Mt, with only a slight increase anticipated thereafter. This stabilization is primarily attributed to minimal anticipated changes in population dynamics in the future.

3.2 Calculate GHG emissions for five scenarios

Table 2 analyses various scenarios regarding CO_2e emissions, revealing significant disparities among waste management approaches. Scenario 1 stands out with the highest CO_2e output by 2060, totaling 8.55 Mt, while Scenario 2 demonstrates the lowest emissions for the same period, with only 4.44 Mt CO_2e. The result underscores that Scenario 1 yields CO_2e emissions approximately 1.92 times higher than those of Scenario 2. Despite variations in CO_2e emissions among the scenarios, all scenarios show an increasing trend over time due to a slight rise in the MSW removal volume. Particularly concerning is the escalating trend in CO_2e emissions within Scenario 1 across the years 2025, 2030, and 2060, indicative of the environmental drawbacks of landfill-based waste management practices. Despite their prevalence, traditional landfill methods are not aligned with sustainable waste management goals, mainly due to challenges in methane recovery (Woon and Lo, 2014). Composting emerges as a more environmentally friendly alternative, boasting advantages over incineration and landfilling. A gradual decrease in composting treatment across scenarios correlates with an increase in CO_2e emissions, underscoring the pivotal role of composting in mitigating environmental impact. Prioritizing composting over incineration proves beneficial, particularly for scenarios featuring substantial food waste volumes, such as Scenario 2, which has a 50:50 ratio between incineration and composting.

Food waste, primarily organic matter, offers a valuable resource for recycling. Current practices of mixing food waste with general household waste for landfilling or incineration result in resource inefficiency and loss (Awasthi et al., 2022). Food waste contains nutrients and organic materials that could be harnessed for various beneficial purposes, including soil enrichment through composting (Alengebawy et al., 2022). While incineration presents a viable option for reducing overall waste volumes and mitigating environmental impact, it is not without its challenges. The high moisture and salt content inherent in food waste can pose difficulties during incineration. These elements contribute to low combustion efficiency, increased energy consumption and emissions during incineration (Chin et al., 2023), potentially undermining the environmental benefits sought through waste management efforts. Addressing these challenges requires further advancements in incineration technology to enhance its efficiency. Achieving the ‘zero landfill’ ambition demands a multifaceted approach, beginning with robust waste segregation policies and advocating for the incineration of MSW and composting food waste. Effective waste segregation forms the cornerstone for subsequent treatment modalities, enabling the diversion of organic waste streams towards beneficial reuse and recycling. Integrating waste separation with incineration and composting aligns with minimizing landfill dependency and fostering sustainable resource management practices. Waste minimization strategies are crucial for reducing CO_2e emissions by decreasing the overall amount of MSW. These efforts collectively contribute to a more efficient and environmentally friendly waste management system.

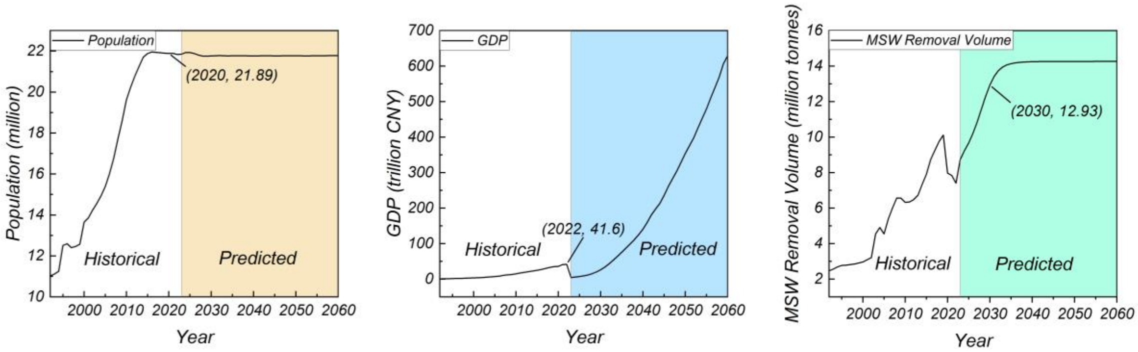

Figure 2: Historical and predicted values of population, GDP, and MSW removal volume in Beijing

Table 2: CO_2e emissions of MSW treatment (landfill, incineration, composting) in Beijing under five scenarios.

	Treatment configuration (%)			Total CO_2e emissions (Mt)		
	Landfill	Incineration	Composting	2025	2030	2060
Scenario 1	24	50	26	5.10	6.53	8.55
Scenario 2	0	50	50	3.01	4.02	4.44
Scenario 3	0	65	35	3.55	4.75	5.24
Scenario 4	0	80	20	4.09	5.47	6.04
Scenario 5	0	100	0	4.82	6.44	7.11

4. Conclusions

The study underscores the importance of MSW management strategies in mitigating GHG emissions associated with MSW. By leveraging Bayesian-optimized ANN models, forecasted results indicate that the MSW removal volume is expected to stabilize around 2030, reaching approximately 14 Mt by 2060. Scenario analysis highlights the significant potential of prioritizing composting alongside incineration, with a projected reduction of approximately 4.11 Mt CO_2e emissions by 2060 compared to landfill-focused approaches. These findings underscore the pivotal role of composting in promoting sustainability and advocating for integrated waste management approaches to achieve environmental conservation goals. Addressing challenges such as directing food waste to compost and enhancing incineration efficiency are pivotal in realizing low-carbon MSW management and reducing reliance on landfilling.

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