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Enhancing waste management forecasting in Taiwan with the nonlinear gray Bernoulli model and genetic algorithms

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Abstract: According to statistics from the Ministry of Environment, Taiwan's total waste has consistently increased over the past decade. Annual maintenance of public incinerators has led to a reduction in incineration capacity, resulting in the steady accumulation of untreated temporary waste, which negatively impacts the ecological environment and considerably reduces the quality of life for local residents. Previous solutions, such as expanding incineration capacity and coordinating inter-county waste dispatch, have proven insufficient due to the continuous growth in waste volume. This study proposes a predictive method for Taiwan's total waste, providing accurate forecasts to support proactive planning. Historical waste data from the past decade and forecasts for the next five years were analyzed using the nonlinear gray Bernoulli model ((NGBM(1,1)), which effectively predicts nonlinear trends. To enhance prediction accuracy, the model incorporates parameter optimization through a genetic algorithm (GA) and integrates an indifference zone (IZ) mechanism. Incorporating the IZ reduced the mean absolute percentage error (MAPE) of the NGBM(1,1) model to 9.13%, a 75% improvement over GA alone, while accelerating convergence. By enhancing prediction accuracy and efficiency, the findings of this study enable stakeholders to plan incineration capacity, allocate resources, and manage temporary waste storage more effectively, ultimately addressing waste disposal challenges in Taiwan.

Introduction

Statistics from Taiwan's Ministry of Environment show that the total amount of waste in Taiwan has consistently increased over the past decade (Figure 1). Annual maintenance of public incinerators has reduced incineration capacity, leading to a steady accumulation of untreated temporary waste, which negatively affects the ecological environment and significantly reduces the quality of life for local residents. These issues underscore the need to address Taiwan's waste problem and highlight the importance of adopting proactive and predictive strategies for effective waste management planning.

Governmental and nongovernment organizations focus on waste management strategies, including expanding incineration capacity, coordinating inter-county waste dispatch, and promoting waste classification policies. However, these measures mainly address the problem retrospectively and have proven insufficient in curbing the rising waste trend. This shortfall not only exacerbates the problem but also leads to substantial economic expenditures. Consequently, employing predictive analysis for proactive planning emerges as an effective approach for managing the growing waste volume.

Advancements in predictive techniques have enabled the use of various forecasting methods such as exponential smoothing, time series models, regression analysis, and gray prediction in practical contexts. However, exponential smoothing requires precise adjustment of weighted values, while time series and regression analysis necessitate large datasets and strong statistical foundations. By contrast, gray prediction excels in analyzing small and uncertain datasets to generate accurate forecasts (Lin, 2012). Given that this study utilizes only 10 years of historical waste data, the gray prediction model serves as an appropriate and effective forecasting method. Specifically, the nonlinear gray Bernoulli model (NGBM(1,1)), which combines the GM(1,1) with the Bernoulli differential equation, facilitates the handling of nonlinear data and maintains computational simplicity while achieving high predictive performance (Chen et al., 2008).

To further enhance the accuracy of the NGBM(1,1), parameter-optimization techniques are incorporated. The genetic algorithm (GA), an optimization method inspired by Darwin's theory of evolution, is employed due to its simplicity, rapid convergence, and effectiveness in locating global optimal solutions. GA has been widely applied in various sectors, including power systems (Cadini et al., 2010), supply chain management (Chang, 2010), and industrial engineering (Huang et al., 2010). Nonetheless, GAs exhibit certain limitations in parameter optimization. During the later stages of convergence,

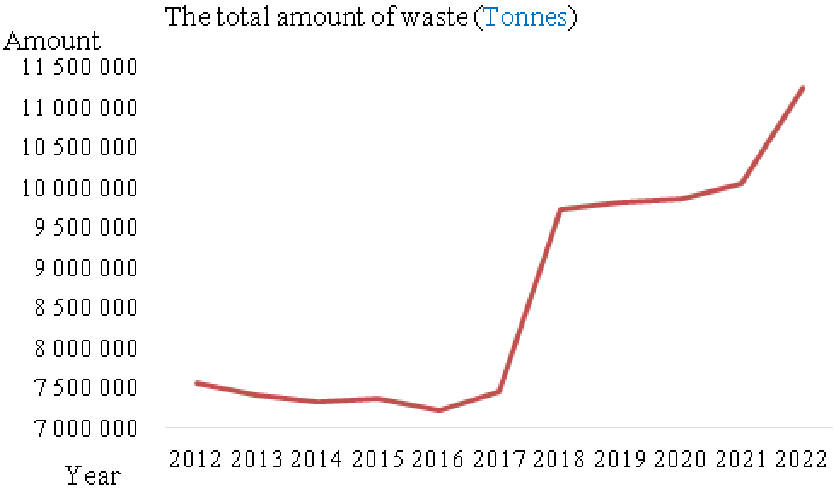

Figure 1. Total amount of waste in Taiwan in 10 years (Statistics Department)

improvements in fitness values tend to plateau, resulting in redundant calculations and decreased search efficiency, which ultimately impacts the accuracy of the model.

To address these drawbacks, this study integrates the indifference zone (IZ) mechanism into GA, forming an improved algorithm known as GA with IZ. The IZ mechanism introduces a small threshold (δ) to monitor changes in fitness values between consecutive generations. When a change in fitness values falls below the threshold, the algorithm terminates early to avoid redundant computations and improve computational efficiency. By combining GA with IZ, this study significantly boosts the effectiveness of parameter search and increases the predictive accuracy of the NGBM(1,1).

This study proposes a predictive framework featuring the NGBM(1,1) with GA and GA-with-IZ optimization methods to forecast Taiwan's total waste volume for the next five years. Leveraging the optimization capability of GA along with the efficient control offered by the IZ mechanism, we aim to minimize prediction errors and achieve precise forecasting results. Using the total amount of waste generated in Taiwan over the past decade as a detailed case study, this research provides insights that can support policy formulation and planning. These insights can assist Taiwan as well as other countries in crafting and executing effective waste-management policies and regulations. The proposed predictions offer a scientific basis for authorities planning incineration capacity, allocating resources, and effectively managing temporarily waste storage, thereby improving overall waste-management efficiency and addressing increasingly severe waste-disposal challenges.

The article is structured as follows: Section 2 provides a literature review of total waste generation and the gray model (GM). Section 3 outlines the methodology, including the application of NGBM(1,1), GA, and the proposed GA variant. Section 4 presents the numerical analysis, and Section 5 concludes the paper with a summary of findings and suggestions for future research.

Literature Review

Waste Management and Forecasting Methods

According to definitions provided by the Ministry of Environment, 'general waste' refers to routine waste other than business waste as defined by the Waste Disposal Act. The statistics on total waste include general waste, bulky waste, recyclables, and kitchen waste. Over the past few years, the total amount of waste has continued to increase, prompting the government to implement various policies to address waste-management challenges.

(1) Increase in incinerator capacity: This strategy involves upgrading existing equipment, expanding current incineration facilities, and constructing new ones.
(2) Intercounty waste dispatch: County and city governments negotiate and jointly sign "Administrative Contracts for Regional Cooperation in Waste Management," with the signing witnessed by the Ministry of Environment. Alternatively, administrative agreements may be signed directly between the Ministry of Environment and local governments. Counties with surplus waste-treatment capacity commit to providing a specified treatment volume each year. The Ministry of Environment coordinates regional cooperation to assist counties facing waste crises or temporary situations, such as incinerator shutdowns for maintenance or the surge of waste generated after natural disasters.

In pursuit of a circular economy, the issue of waste management has been widely examined. Chen (2020) investigated the relationship between demographic factors and waste generation across counties and cities in Taiwan, revealing that differences in age, education level, and economic status significantly influence waste production - insights that can help policymakers design more effective waste-management strategies. Izquierdo-Horna et al. (2022) conducted a comprehensive literature review to deepen understanding of the complex factors influencing municipal solid waste generation. Their study identified a predictor set spanning sociocultural, environmental, and economic dimensions, emphasizing its importance in supporting the development of reliable predictive models. Ke (2022) analyzed how local governments select waste-disposal methods and found that waste reduction and sorting alone are insufficient to address inadequate waste treatment capacity. The study highlighted that, in addition to existing incineration plants, anaerobic digestion facilities and waste-to-energy plants offer economic benefits and reduce carbon emissions, thereby improving disposal rates. Accurate

Table 1. Research and techniques used in waste generation forecasting

Type	Reference	Dataset	Models	Application Area
Statistical Model	Oroye et al. (2024)	1/2019-12/2023	Seasonal Exponential Smoothing	Monthly waste generation in Nigeria
	Xu et al. (2024)	2010-2021	Interval Time-Delayed Gray Model	Construction waste prediction in China
Machine Learning Model	Adu et al. (2025)	2019-2023	Linear Regression, Random Forest (RF), Long Short-Term Memory	Municipal solid waste generation in Ghana
	Zhang et al. (2022)	2000-2019	Linear Regression, Polynomial Regression, Support Vector Machine, RF, Extreme Gradient Boosting (XGBoost)	Municipal solid waste generation in China
Hybrid Model	Soni et al. (2019)	1993-2011	GA + Neural Networks	Annual municipal solid waste production in India
	Wang et al. (2021)	2003-2015, 2007-2019	Variational Mode Decomposition + Exponential Smoothing + Gray Modeling	The electronic waste quantity in the US and UK
	Konyalıoğlu et al. (2025)	2004-2023	Firefly Algorithm + NGBM(1,1)	Medical waste estimation in Istanbul

estimation of waste growth rates was shown to be essential for enhancing net profits and the operational efficiency of incinerators. From a strategic perspective, Adewuyi et al. (2024) emphasized that advancements in forecasting future waste trends play a critical role in promoting sustainable waste management and long-term environmental resilience.

As forecasting waste volume becomes increasingly important, numerous studies have focused on developing sophisticated predictive models to improve accuracy. Traditional time series models, such as ARIMA, weighted moving averages, and exponential smoothing, can work effectively with limited historical data by identifying patterns and correlations, thereby producing reliable results (Adewuyi et al., 2024). Regression models, meanwhile, are well suited for examining relationships between variables. In recent years, machine learning and artificial intelligence (AI) techniques have gained popularity; however, these methods typically require large datasets to achieve optimal performance. Table 1 summarizes recent research and methodologies used in waste-generation forecasting.

Given the inherent limitations of each method, the choice of suitable model hinges on data availability, computational resources, and the desired degree of interpretability (Adu et al., 2025). AI and advanced modeling techniques have shown strong performance; however, they do not represent a one-size-fits-all solution. When dealing with limited or incomplete data, selecting a method that delivers high-quality outcomes while maintaining computational efficiency remains a significant challenge.

Gray Model (GM)

Gray theory, proposed by Deng (1989), primarily addresses the uncertainty and incomplete information in system modeling. It involves conducting correlation analyses and constructing models for systems in which the available data are ambiguous or partial. The theory aims to facilitate system exploration and understanding through prediction and decision-making methods while effectively managing uncertainties, multivariate inputs, discretized data, and information gaps. Key research domains within gray system theory include gray generation, gray relational analysis, the gray model (GM), gray prediction, gray decision-making, and gray control.

GM serves as the foundation and core of gray system theory, requiring only a small amount of data for prediction. To enhance predictive accuracy, numerous improved models have been developed and widely applied across diverse fields, such as machinery production, agriculture, water resource management, transportation, information technology, and business. Evans (2014) applied gray Verhulst model to analyze steel intensity of use in the UK; the data exhibited an inverted U shaped pattern, and the model produced accurate and unbiased predictions. Zhou et al. (2023) proposed an improved time-varying parameter gray Bernoulli model (TVBGM) to forecast electric vehicle stock and sales in France and globally using six benchmarks. They employed the cuckoo search algorithm to identify optimal time-varying parameters and the power exponent. Their findings indicated that the TVBGM can reliably capture the nonlinearity, complexity, and uncertainty present in the data, and empirical analyses demonstrated its stability and reliability.

Zeng et al. (2023) reported that the three-parameter gray prediction model offers the advantage of optimizing parameter combination, enabling the model structure to adapt to datasets with varying characteristics. The order *r* has been expanded from positive real numbers to all real numbers, significantly broadening the model's application scope. The model was used to forecast new-energy vehicle sales in China for the next 10 years. Ou (2012) forecasted agricultural output using an improved gray forecasting model based on GA; the results indicated that the IGM generated appropriate parameters through GA and reduced prediction errors, demonstrating its effectiveness in modeling and forecasting agricultural outputs.

Methodology

NGBM(1,1)

The NGBM(1,1) model integrates the classic GM(1,1) with the Bernoulli equation. It retains the advantages of GM(1,1) while providing higher prediction accuracy when dealing with small sample sizes.

The following steps describe the procedures of NGBM(1,1):

Step 1: Define the original of data series $X^{(0)}$:

$$X^{(0)} = [X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(k)], \qquad k = 1,2,\dots n \quad (1)$$

Step 2: Perform the first-order accumulated generating operation (1-AGO)

Apply the 1-AGO to obtain the accumulated sequence $X^{(1)}$

$$X^{(1)} = [X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(k)] \quad (2)$$

Where:

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i), \qquad k = 2,3,\dots n \quad (3)$$

Step 3: Compute the background value $Z^{(1)}(k)$

The background sequence $Z^{(1)}$ is defined as:

$$Z^{(1)}(k) = [Z^{(1)}(1), Z^{(1)}(2), \dots, Z^{(1)}(n)] \quad (4)$$

where the background value is calculated using:

$$Z^{(1)}(k) = P * X^{(1)}(k) + (1-P) * X^{(1)}(k-1) \quad (5)$$

P is usually given as 0.5, then the background value is:

$$Z^{(1)}(k) = 0.5 * [X^{(1)}(k) + X^{(1)}(k-1)] \quad (6)$$

Step 4: NGBM (1,1) model equation:

$$X^{(0)}(k) + aZ^{(1)}(k) = b[Z^{(1)}(k)]^r, \qquad r \neq 1 \quad (7)$$

where a is the development coefficient, b is the gray action quantity, and r is the power exponent.

When $r = 0$, the NGBM(1,1) reduces to GM(1,1); when $r = 2$, the NGBM(1,1) becomes the gray Verhulst model.

Step 5: The whitening differential equation corresponding to NGBM(1,1):

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b[X^{(1)}]^r \quad (8)$$

Step 6: Parameter estimation using ordinary least square:

The parameters a and b are obtained by:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (9)$$

where the matrices B and Y are defined as:

$$B = \begin{bmatrix} -Z^{(1)}(2) & (Z^{(1)}(2))^r \\ -Z^{(1)}(3) & (Z^{(1)}(3))^r \\ \vdots & \vdots \\ -Z^{(1)}(n) & (Z^{(1)}(n))^r \end{bmatrix}, \qquad Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \vdots \\ X^{(0)}(n) \end{bmatrix}$$

Step 7: The time-response function of NGBM(1,1) is:

$$\hat{X}^{(1)}(k+1) = \left\{\left[(X^{(0)}(1))^{1-r} - \frac{b}{a}\right] e^{-a(1-r)k} + \frac{b}{a}\right\}^{\frac{1}{1-r}}, \qquad r \neq 1, k = 1,2,\dots \quad (10)$$

The restored values can be obtained by using the 1-IAGO:

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1), \qquad k = 2,3,\dots,n \quad (11)$$

Genetic Algorithm (GA)

To enhance the prediction accuracy of the NGBM(1,1) model, the genetic algorithm (GA) is employed to determine the optimal parameter $\hat{r}$. The GA-based NGBM(1,1), denoted as GANGBM(1,1), integrates GA with NGBM(1,1). This approach improves parameter estimation and strengthens forecasting performance.

The procedures of GA are as follows:

(1) For a given optimization problem, specify the optimization objective.
(2) Select intervals for the parameter to be optimized.
(3) Encode the parameters to be optimized in binary code.
(4) Randomly generate the parameters to form an initial population.
(5) Set the evaluation function to calculate fitness value for each individual in the population.
(6) Perform the crossover operation between two parent genomes (parameter to be optimized) in the population.
(7) Generate an offspring's genome by mutation.
(8) Go back to 5 - 7 after repeated iterations until the optimal individual goals are achieved or after genetic algebra is maximized and then stop the operation.

Proposed Genetic Algorithm (GA)

After applying GA to the NGBM(1,1), the converge rate is not sufficiently satisfactory. Hence, we refine the GA by incorporating an indifference-zone (IZ) mechanism during the initialization stage.

The IZ method, originally proposed by Sullivan and Wilson (1989), aims to select a subset of m systems from a set of k candidate systems. The parameters m, the indifference parameter d, and the lower bound of the probability of correct selection $P*$ are predetmined by the user. The procedure relies on Rinott's constant and consists of two stages. In the first stage, n0 samples are used to estimate the mean and standard deviation of each system. In the second stage, a sampling formula determines the additional number of observations required for each system, and the m systems with the smallest W_i values are selected.

In this study, the integration of an IZ mechanism into the GA is intended to enhance the algorithm's computational efficiency and convergence performance, particularly during the later stages of optimization. A small threshold value δ is defined for the monitoring of changes in fitness values (e.g., mean absolute percentage error, MAPE) between consecutive generations. An the absolute difference in fitness values falls below δ, the algorithm is considered to have entered the IZ, indicating that further iterations would produce negligible improvements. At this point, the algorithm terminates early, thereby avoiding unnecessary computations.

After the incorporation of the IZ mechanism, the GA reduces redundant searches and accelerates convergence while maintaining solution accuracy. This approach is particularly effective for optimizing nonlinear models such as the NGBM(1,1), where parameter searches may otherwise be time-consuming and prone to inefficiency. The resulting GA with IZ achieves accurate predictions with reduced computational overhead, as demonstrated by the considerable reduction in MAPE compared to the standard GA.

Applying the IZ approach to the GA is described in the following steps:

Steps 1–4: are identical to those used in the in NGBM(1,1) procedure.

Step 5: Formulate the whitening differential equation of the NGBM(1,1):

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b[X^{(1)}]^r \tag{12}$$

Step 6: GA is applied to find the optimal parameter $\hat{r}$.

The GA is an efficient random search algorithm that, when provided with an appropriate fitness function, can approximate the optimal search direction and identify high-quality solutions. To minimize forecasting error, the following fitness function is used:

$$MAPE = \sum_{k=2}^{n} \frac{\frac{X^{(0)}(k) - \hat{X}^{(0)}(k)}{X^{(0)}(k)}}{n-1}, k = 2,3, \dots n \tag{13}$$

$X^{(0)}(k)$ is the actual value, whereas $\hat{X}^{(0)}(k)$ is the prediction value.

Step 6.1: Randomly generate parameters in the new range to form an initial population.
Step 6.2: Calculate the fitness and make an evaluation.
Step 6.3: Select the best half of the solution as the parent.
Step 6.4: Perform a crossover operation between the two parent genomes in the population.
Step 6.5: Generate an offspring's genome by mutation.
Step 6.6: Go back to 2–5 after repeated iterations until the optimal individual goals are achieved or genetic algebra is maximized, and then stop the operation.
Step 6.7: IZ monitoring: Check fitness value changes between generations, stop iterations early if changes are below δ.

In the proposed GA, the optimum parameter $\hat{r}$ is selected according to the criterion of minimal MAPE. Once $\hat{r}$ is determined, the corresponding optimal parameters $\hat{a}$ and $\hat{b}$ can be obtained as follows:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{14}$$

$$B = \begin{bmatrix} -Z^{(1)}(2) & (Z^{(1)}(2))^{\hat{r}} \\ -Z^{(1)}(3) & (Z^{(1)}(3))^{\hat{r}} \\ \vdots & \vdots \\ -Z^{(1)}(n) & (Z^{(1)}(n))^{\hat{r}} \end{bmatrix}, \quad Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \vdots \\ X^{(0)}(n) \end{bmatrix}$$

Step 7: The forecasting function is:

$$\hat{X}^{(1)}(k+1) = \left\{ \left[(X^{(0)}(1))^{1-\hat{r}} - \frac{\hat{b}}{\hat{a}} \right] e^{-\hat{a}(1-\hat{r})k} + \frac{\hat{b}}{\hat{a}} \right\}^{\frac{1}{1-\hat{r}}}, \quad \hat{r} \neq 1, k = 1,2, \dots \tag{15}$$

The restored values can be obtained by using the 1-IAGO as:

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1), k = 2,3, \dots n \tag{16}$$

Numerical Analysis

Genetic Algorithm (GA) with Indifference Zone (IZ)

In this section, we employ Taiwan's total waste data from the past 10 years as the basis for forecasting future waste generation using the NGBM(1,1). Changes in waste generation are closely influenced by environmental policies, economic activities, and social behaviors. These changes often exhibit nonlinear and uncertain characteristics, making parameter optimization crucial for obtaining accurate predictions. Therefore, two optimization methods are adopted: the GA and the improved GA incorporating an IZ (GA with IZ). Both methods are employed to optimize the parameters of the NGBM(1,1), enabling a comparison of their performance in terms of prediction accuracy and computational efficiency.

In the analysis, we first construct the NGBM(1,1) model for waste generation forecasting and use the MAPE as the criterion for evaluating model performance. The GA is then used to optimize the model parameters and . To further improve the convergence efficiency of the GA, the GA with IZ method is introduced. By specifying an IZ threshold δ, the algorithm terminates iterations early when changes in fitness values become negligible. This study compares the performance of GA and GA with IZ in parameter optimization and evaluates their applicability to long-term waste generation forecasting.

To validate the effectiveness of GA and GA with IZ in optimizing the NGBM(1,1), the resulting MAPE values are calculated and summarized in Tables 2 and 3, respectively. Table 2 shows that using GA for optimization results in a MAPE of 36.59453% for NGBM(1,1). This outcome reflects the baseline performance of a GA-optimized model in forecasting. However, the effectiveness of GA faces certain limitations in optimizing parameters for complex nonlinear models. First, the inherent randomness of GA can lead to ineffective searches as fitness values approach convergence, resulting in redundant iterations and unnecessary computational effort. Second, because GA lacks mechanisms for controlling local convergence, its global search efficiency declines substantially when improvements in fitness plateau. Thus, identifying well-performing parameter combinations becomes more difficult, ultimately reducing the accuracy of model predictions.

To address these issues, we adopt the GA with IZ. Table 3 illustrates that using GA with IZ optimization, the MAPE of the NGBM(1,1) considerably decreases to 9.129584%, representing an approximately 75% reduction in prediction error compared to GA-alone approach. This result demonstrates that the IZ mechanism effectively enhances the optimization performance of GA, particularly during the later stages of convergence. By introducing an IZ threshold δ, redundant

Table 2. Forecasting results using GA method

Year	Period	Actual Value (Tonnes)	Forecast Value (Tonnes)	MAPE (%)
2012	0	7554589	-	-
2013	1	7403948	2179362	70.56486
2014	2	7332694	2721541	62.88484
2015	3	7369439	3389429	54.00696
2016	4	7229290	4211550	41.74325
2017	5	7461342	5222837	30.00138
2018	6	9740671	6466071	33.61781
2019	7	9812418	7993637	18.5355
2020	8	9869675	9869675	1.43E-06
2021	9	10049062	12172708	21.13278
2022	10	11238654	14998868	33.45787
Total	-	-	-	36.59452

Table 3. Forecasting results using GA with IZ method

Year	Period	Actual Value (Tonnes)	Forecast Value (Tonnes)	MAPE (%)
2012	0	7554589	-	-
2013	1	7403948	5254580	29.03002
2014	2	7332694	6432472	12.27682
2015	3	7369439	7431757	0.845622
2016	4	7229290	8250532	14.12645
2017	5	7461342	8896752	19.23796
2018	6	9740671	9383622	3.665547
2019	7	9812418	9726865	0.871881
2020	8	9869675	9943064	0.743584
2021	9	10049062	10048648	0.004116
2022	10	11238654	10059288	10.49384
Total	-	-	-	9.129584

iterations are automatically eliminated, reducing unnecessary computations. The incorporation of IZ also increases the GA's sensitivity in parameter searching, enabling more targeted local optimization and consequently improving a model's predictive capability. These findings confirm the potential and superiority of the GA with IZ over other methods in the context of nonlinear prediction model applications.

Additionally, the prediction trends can be visually observed in Figures 2 and 3. In both, the orange lines represent the model's predicted values. After the GA with IZ optimization method is applied, the predicted values align closely with the actual data trends, showcasing enhanced fitting ability and precision. Compared with the noticeable deviations in Figure 2, which uses GA alone, Figure 3 demonstrates that GA with IZ optimization produces a predictive curve that more accurately captures the changes in the data.

In summary, the GA with IZ optimization method offers considerable benefits that improve the prediction accuracy of the NGBM(1,1), offering an efficient and precise solution for parameter optimization and forecasting. This makes it a promising approach for nonlinear prediction tasks.

Forecasting

Based on the aforementioned analysis, we employ the improved GA with IZ to optimize the NGBM(1,1), achieving a considerably reduced MAPE. After the optimal model parameters are determined, the optimized model is further applied to forecast Taiwan's total waste generation over the next five years.

Table 4 presents the forecasting results for the next five years using the NGBM(1,1) optimized with GA with IZ. The model relies on historical cumulative data, performs cumulative calculations for each year, and then applies differencing to obtain annual waste generation predictions. This forecasting process fully leverages the optimization capabilities of the GA with IZ method, enabling the model to maintain high accuracy while effectively capturing the nonlinear trends in waste generation.

According to the model predictions, Taiwan's total waste generation over the next five years is expected to exhibit certain fluctuations. The forecasted values reveal potential variations in total waste over time, providing scientific insights for policy-making and waste management planning. These results demonstrate the practicality and accuracy of the GA with IZ method in handling complex nonlinear sequence forecasting. The specific forecast values presented in Table 4 can serve as valuable references for related research and practical applications.

Discussion

This study presents a comparative analysis of the conventional GA and GA with IZ for enhancing the predictive performance of the NGBM(1,1) model in forecasting waste generation in Taiwan. The primary objective is to assess whether incorporating a statistical threshold δ for performance differences can lead to significant improvements in convergence behavior, reduce redundant computations, and ultimately enhance prediction accuracy.

Table 4. Forecasting results for the next five years using GA with IZ method

Future Period	Forecast Value (Tonnes)
1	9852740
2	19085188
3	26542987
4	30754599
5	30823387

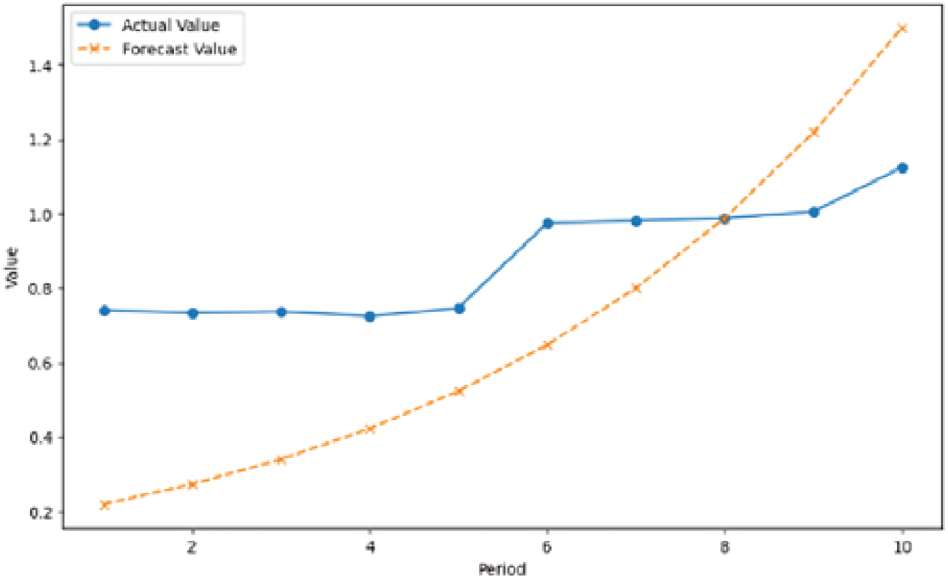

Figure 2: Line chart comparing predicted and actual values with the GA method

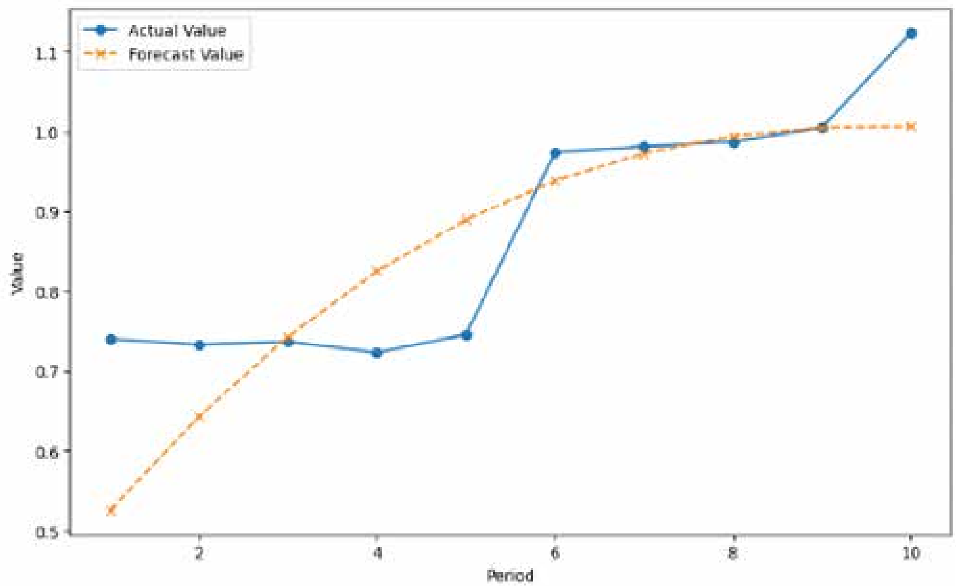

Figure 3: Line chart comparing predicted and actual values with GA with IZ method

The findings indicate that GA with IZ outperforms the standard GA in terms of predictive performance. As illustrated in Figure 2, applying GA alone to optimize NGBM(1,1) parameters results in greater deviations between forecasted and actual values, especially in later periods, suggesting potential overfitting or sensitivity to noise due to the absence of a filtering mechanism. In contrast, Figure 3 demonstrates that GA with IZ produces forecasts that more closely follow actual values across all periods, reflecting better generalization and smoother convergence.

Table 4 shows the projected waste generation over the next five years, showing a consistent upward trend, with estimates increasing from around 9.85 million to more than 30.8 million tons. This sharp increase in waste amount in Taiwan within five years highlights the need for effective planning, resource allocation, and infrastructure development. Additionally, the substantial volume of waste calls for strategic interventions by Taiwan policymakers and waste management authorities to ensure efficient and sustainable waste handling. The results also serve as a cautionary signal to global policymakers regarding the escalating environmental pressures that may arise in the future. The amount of waste produced in Taiwan tends to mirror similar trends worldwide, underscoring the urgency of proper global waste management systems. Beyond traditional approaches, developing sustainable waste management strategies requires integrating regulatory frameworks, advanced technologies, and active public engagement.

Overall, the results confirm that GA with IZ offers a more practical and effective approach for modeling complex, noisy environments. By focusing on statistically meaningful improvements, GA with IZ enables more robust and decision-aligned forecasting for non-linear and fluctuating waste generation trends. This approach can be extended to other countries and regions, particularly where data constraints are similar. Implementing such frameworks can significantly enhance the accuracy of waste forecasting models, supporting timely and well-informed policy decisions across various jurisdictions.

Conclusion

This study utilized total waste data from Taiwan over the past decade to forecast future waste generation using NGBM(1,1) model. Given that changes in waste volume are influenced by multiple factors, including environmental policies, economic activities, and social behavior, the data exhibit nonlinear and uncertain characteristics. Therefore, optimizing model parameters is critical for enhancing prediction accuracy. To this end, two optimization methods were adopted: the conventional GA and an improved GA incorporating the IZ (GA with IZ). Their performance in improving prediction accuracy and computational efficiency was evaluated through comparative analysis.

Compared to GA alone, the GA with IZ optimization significantly reduced the MAPE of the NGBM(1,1) to 9.13%, representing an approximate 75% reduction in relative prediction error. This result demonstrates the effectiveness of the IZ mechanism in enhancing GA's optimization performance, particularly during the later stages of convergence. By setting an IZ threshold δ, redundant iterations are automatically terminated, reducing unnecessary computations. Moreover, the incorporation of IZ improves GA's sensitivity in parameter searches, enabling precise local optimization and considerably enhancing the model's predictive capability. Consequently, this approach proves effective for tackling nonlinear prediction problems and serving as a robust instrument for addressing various complex forecasting tasks.

The results in this study have important implications for policy-making in various areas. First, they provide a scientific foundation for relevant authorities to construct incineration strategies. Variability in waste volume complicates the planning of incineration facilities, potentially leading to overcapacity, which wastes financial and material resources, or undercapacity, which strains operational staff. Accurate forecasting aids decision-makers in planning incineration capacity and determining whether to upgrade equipment, expand, or construct new incineration facilities to manage large waste volumes. Additionally, the forecasting outcomes inform policymakers in establishing inter-county waste treatment regulations. By implicitly pinpointing factors that affect waste generation, the study can also guide initiatives aimed at educating residents to minimize waste production.

From an operational perspective, the forecasts provide a framework for resource allocation during fluctuates in waste volume, assist incineration facilities in adjusting operational schedules, manage temporary waste storage, and plan maintenance. These applications ultimately enhance operational efficiency, improve overall waste management effectiveness, and help to handle severe challenges associated with the increasing volume of waste.

This study has certain limitations that suggest avenues for future research. The forecasts are based solely on data from Taiwan between 2012 and 2022, which restricts the generalizability of the findings. Future research could extend the timeframe and examine different regions to identify new trends. Furthermore, while this study employed a nonlinear gray Bernoulli model combined with GA and IZ to refine predictions, future work could investigate alternative methods to further enhance forecasting accuracy. These advancements in predictive techniques can help to promote more sustainable waste management practices in the face of changing waste generation trends.

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