Innovative Forecasting in Urban Waste Systems: Enhancing Accuracy and Sustainability with Hybrid Model

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***Abstract*—The COVID-19 epidemic has profoundly affected urban waste management systems, resulting in variations in garbage creation that complicate traditional forecasting techniques. This study presents an enhanced forecasting framework that combines the Holt-Winters-Confidence Interval (HWCI) projection model with the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to augment the precision and dependability of waste generation forecasts. The HWCI model mitigates anomalies and volatile oscillations caused by the pandemic, delivering accurate trend modifications and integrating confidence ranges to resolve uncertainties. The SARIMA model effectively captures both seasonal and non-seasonal fluctuations, facilitating accurate forecasts of garbage generation trends until 2024. The combined HWCI and SARIMA models provide reliable, long-term forecasts, even amidst unforeseen interruptions, enabling waste management agencies to proactively address changing trash generation trends. This research greatly advances urban trash management by improving forecasting approaches that promote sustainability and resilience. Initially, it presents a novel amalgamation of Holt-Winters and SARIMA models, specifically tailored to tackle the intricate and variable characteristics of waste generation data in metropolitan settings. Secondly, the incorporation of confidence intervals offers a dependable method to quantify uncertainties, guaranteeing that predictions remain actionable throughout diverse settings. The study ultimately offers a pragmatic framework that facilitates data-driven decision-making, resource optimization, and long-term strategic planning. This research provides a comprehensive forecasting solution that assists municipalities and urban planners in creating more adaptable and sustainable waste management systems, in accordance with overarching environmental objectives including decreasing resource inefficiencies and mitigating ecological consequences. The proposed strategy emphasizes the necessity of using predictive analytics into urban sustainability efforts, enhancing the cleanliness and resilience of urban environments.**

***Keywords*—COVID-19 impact, waste generation forecasting, holt-winters method, confidence interval projections, SARIMA model, sustainability in waste management**

I. Introduction

Effective management of urban waste is essential for the efficient use of resources, public health, and environmental integrity, and is a fundamental component of sustainable urban development [1]. The collection, transportation, and disposal of waste are necessitated by the increasing accumulation of waste as cities expand and populations expand. Accordingly, the implementation of sophisticated systems for waste management is necessary. It is imperative to accurately predict waste generation in order to optimize these systems, ensure efficient resource allocation, minimize operational costs, and reduce environmental impacts.

The COVID-19 pandemic has presented global waste management systems with unprecedented challenges [2, 3]. Traditional waste management practices have been disrupted by fluctuations in waste generation patterns, which are influenced by lockdowns, changes in consumption behaviors, and altered economic activities. These unanticipated changes emphasize the necessity of advanced forecasting techniques that can adapt to anomalies and offer dependable predictions to facilitate effective resource management.

This study suggests an integrated methodology for forecasting urban waste generation in order to overcome these obstacles (Fig. 1). The Holt-Winters-Confidence Interval (HWCI) projection model is a novel approach to the management of seasonal, trended, and chaotic data. The HWCI model enables precise trend adjustment and confidence interval estimation by substituting actual data during volatile periods, thereby facilitating a more comprehensive comprehension of waste generation patterns during the COVID-19 pandemic.

Subsequently, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is implemented to anticipate waste generation through 2024. SARIMA is a reliable option for predicting future waste generation trends due to its ability to effectively manage time series data with recurring patterns, which is achieved by integrating seasonal components into the ARIMA framework [4]. The HWCI and SARIMA models are integrated to guarantee precise and resilient forecasting, irrespective of the data's volatility.

The primary contribution of this research is its comprehensive approach to urban waste management, which incorporates advanced forecasting models. In addition to addressing immediate operational challenges, this methodology is consistent with the overarching objectives of environmental sustainability. The study promotes the creation of sustainable urban environments that are resilient to future disruptions by reducing the resource utilization and emissions associated with waste collection [5].

This research offers a resilient framework for the management of urban waste in the context of the disruptions induced by the COVID-19 pandemic. The proposed methodology allows city planners and waste management authorities to effectively respond to dynamic conditions, thereby assuring efficient resource allocation and minimizing environmental impact. The sustainable management of urban waste is facilitated by the integration of forecasting and statistical data analysis, which provides a decision support instrument for strategic planning and policy-making.

The results of this study have substantial implications for the creation of waste management systems that are more

sustainable and resilient in urban areas. This research contributes to the overarching objective of establishing sustainable cities that can sustain the well-being of their residents while simultaneously reducing the environmental consequences of waste management by improving the precision of waste generation forecasts. This research emphasizes the pressing necessity for adaptive and integrated strategies in urban waste management to confront the global challenges of accelerated urbanization and pandemics.

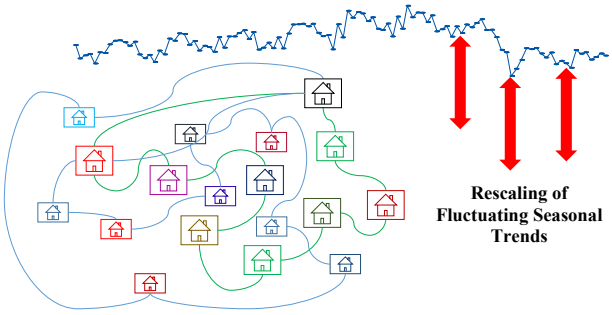

Fig. 1. Diagram for innovative forecasting in urban waste systems by enhancing accuracy and sustainability with hybrid model.

The paper is designed to offer a comprehensive solution to the challenges of urban waste management, which have been significantly exacerbated by the COVID-19 pandemic. The Literature Review addresses the effects of the pandemic on waste management, and the current methods of forecasting. The Methodology delineates the implementation of Holt-Winters and SARIMA models. Also included is data acquisition. The Results and Discussion examine the accuracy of forecasting, as well as the potential enhancements and the impact of COVID-19. The Conclusion provides a concise summary of the primary findings, the implications for urban waste management, and the recommendations for future research. The ultimate objective is to improve the efficiency and sustainability of waste management systems in urban areas and to facilitate the development of environmentally sustainable, resilient cities.

II. Literature Review

The critical role of efficient waste collection, transportation, and disposal systems in promoting urban sustainability is comprehensively examined in the literature. The implementation of advanced methods for effective waste management is a necessity due to the significant challenges posed by rapid urbanization and population growth in managing increasing waste [6, 7]. During unforeseen events such as the COVID-19 pandemic, traditional systems frequently rely on static models that fail to account for the dynamic and fluctuating nature of waste generation. In an effort to optimize the sustainability and efficacy of waste management systems, there has been a recent transition in research toward predictive models and optimization techniques.

Table 1. Literature review: advancements in forecasting methods during the COVID-19 pandemic

Authors	Problem	Algorithms	Reference
Qin *et al*., 2024	Impact of COVID-19 countermeasures on hepatitis E incidence	Time Series Models	[6]
Waheed and Xu, 2024	Impact of COVID-19 on energy consumption patterns	Holt-Winters, Prophet, Long Short-Term Memory (LSTM)	[7]
Kumar *et al.*, 2024	River discharge forecasting in Himalayan region	Holt-Winters (HW) additive method, Simple exponential smoothing (SES), Non-seasonal ARIMA	[8]
He *et al.*, 2024	Short-term electric load forecast	Holt-Winters (HW) method, Gated Recurrent Unit (GRU) network	[9]
Hasan *et al.*, 2024	Waste disposal rate forecasting	SARIMA, Holt-Winters, Prophet	[10]
Pacella *et al.*, 2024	Photovoltaic power forecasting	Long Short-Term Memory (LSTM), Bayesian Optimization (BO), Holt-Winters	[11]
Bufalo and Orlando, 2024	Tourism demand forecasting	CIR# model	[12]
Abdullah, 2024	Reinsurance revenues forecasting	Single Exponential Smoothing (SEXS), Additive Holt-Winters	[13]
Pena *et al*., 2019	By-product gas supply system scheduling in steel-making industry	Seasonal Holt-Winters method, ARIMA, MILP optimization model	[14]
Nor *et al.*, 2025	COVID-19 mortality rates forecasting	ARIMA	[15]
Parviz and Ghorbanpour, 2024	Monthly precipitation forecasting	Improved ARIMA (IARIMA), Support Vector Regression (SVR), Particle Swarm Optimization (PSO)	[16]
Akshay *et al*., 2024	Power consumption prediction for EV charging stations	Metabolism Grey Model (MGM), Back-Propagation Neural Network (BPNN), ARIMA	[17]
Karmakar *et al*., 2024	COVID-19 data set forecasting	ARIMA, Harmony Search (HS)	[18]
Segar *et al.*, 2024	CO2 emissions forecasting	ARIMA	[19]
Srivastava and Jha, 2023	Solid waste generation forecasting	Long Short-Term Memory (LSTM), ARIMA, Incremental Increase Model (IIM)	[20]
Dodo *et al.*, 2022	Municipal solid waste generation forecasting	ARIMA	[21]

The COVID-19 pandemic underscored the limitations of traditional forecasting models in their ability to adjust to abrupt shifts in waste generation patterns. The necessity for sophisticated forecasting methodologies was emphasized by the erratic fluctuations that were the result of changes in economic activities and consumption behaviors. Holt-Winters [8–14] and ARIMA [15–22] are time series models that have been demonstrated to be effective in the generation of precise predictions of waste generation (Table 1). This information is essential for resource allocation and planning. Holt-Winters is proficient in the management of seasonal and chaotic data, which offers a more comprehensive understanding of trends. ARIMA, on the other hand, is known for its ability to predict future waste generation by analyzing historical trends.

In order to resolve the intricacies of forecasting and waste management, mathematical optimization techniques and advanced models such as SARIMA have been investigated. SARIMA is particularly well-suited for the prediction of waste generation in cyclic systems due to its capacity to

identify subtle patterns in time series data. In contrast, bi-objective optimization and mixed-integer programming models have been implemented to oversee multi-stage processes in waste collection and disposal, ensuring that factors such as emissions, costs, and resource allocation are balanced. Both operational efficiency and environmental sustainability are substantially enhanced by these methodologies.

The adaptability of these models across a variety of sectors is well-documented. For instance, Shah *et al.* [4] implemented SARIMA to anticipate medical store inventories, thereby mitigating the likelihood of shortages. Zhou *et al.* [23] utilized SARIMA to predict the arrival of dustcarts at a waste transfer station, surpassing the performance of LSTM in both single-step and multi-step predictions. In the same vein, Chouhan and Srivastava [24] employed ARIMA to predict retail demand during the COVID-19 pandemic, demonstrating its ability to effectively handle historical data and make precise predictions.

The complexity of municipal solid waste management (MSWM) systems has increased as a result of urbanization and the increasing volume of waste. Alshaikh and Abdelfatah [25] executed an exhaustive examination of optimization strategies in MSWM, classifying them into three categories: resource recovery, treatment and disposal, and waste collection and transportation. Their research underscored the significance of emergent technologies, including artificial intelligence and simulation, in improving the efficacy of waste management. In addition, they underscored the necessity of cross-disciplinary collaboration and customized strategies to resolve the diverse environmental and social challenges associated with waste management, thereby establishing a strategic framework for researchers and policymakers to enhance the efficacy of MSWM systems.

Gonçalves and Silva [26] implemented SARIMA in the context of municipal waste management to anticipate waste collection patterns in a Portuguese city, thereby facilitating data-driven decisions and fostering sustainability. Boulahna *et al.* [27] demonstrated the model's ability to accurately predict municipal waste generation in Kenitra, Morocco, by utilizing SARIMA to integrate seasonal trends and generate dependable forecasts.

III. Related Methods

The Holt-Winters and SARIMA models are particularly prominent in the literature because of their capacity to capture intricate patterns in waste generation data. The literature extensively investigates forecasting techniques for waste management. The Holt-Winters model is particularly effective in managing seasonality and trends, rendering it suitable for data with periodic fluctuations. Conversely, SARIMA is capable of producing reliable predictions based on historical patterns when dealing with data with trends. These forecasting methods are essential for the planning and optimization of waste management operations, as they enable precise predictions of waste generation, which is essential for reducing environmental impacts and allocating resources.

A. Forecasting Technique

For effective waste management, it is imperative to accurately forecast the generation of waste, as this enables efficient planning, resource allocation, and the reduction of environmental impacts. Waste management authorities can enhance operational efficiency, modify collection schedules, and predict future waste volumes by effectively utilizing robust forecasting techniques. This is especially important when working with intricate data that displays patterns such as seasonality, irregular fluctuations, and long-term trends. Among a variety of forecasting methods, the Holt-Winters and SARIMA models are distinguished by their ability to effectively manage waste generation in a variety of urban environments.

The Triple Exponential Smoothing model, also known as the Holt-Winters model, is particularly proficient in the analysis of time series data that contain seasonal, trended, and chaotic components. The model adopts a nuanced approach to waste generation forecasting by integrating seasonality and trend elements into fundamental exponential averaging. This approach is capable of accommodating both consistent and variable seasonal patterns. The additive Holt-Winters model is appropriate for situations in which seasonal variations remain constant, while the multiplicative version is optimal for those in which seasonal variations fluctuate in proportion to data levels. This adaptability enables the model to take into account disruptions, such as those caused by the COVID-19 pandemic, by flattening out anomalies to disclose underlying trends and facilitating more accurate long-term planning.

It is the equations that adjust the level, trend, and seasonal components using specific averaging parameters that are essential to the Holt-Winters model. The seasonal component is refined by taking into account deviations from the level, the trend is updated by comparing current and previous values, and the level is adjusted by subtracting the seasonal effect in the additive model. The multiplicative model updates the level by dividing the current value by the seasonal impact, and both the trend and seasonal components are multiplicatively adjusted. The sum of squared prediction errors is minimized by optimizing the parameters—alpha, beta, and gamma—using techniques such as gradient descent or grid search. Resource management and strategic decision-making in waste management systems are facilitated by this precision in forecasting.

By incorporating seasonal components into the ARIMA framework, the SARIMA model further improves its forecasting capabilities, rendering it highly effective for predicting waste generation in systems with cyclical patterns. In the context of urban waste management, where waste generation is influenced by a variety of factors, such as population density, economic activities, and behavioral changes, SARIMA's capacity to capture intricate seasonal fluctuations and trends in time series data is particularly important. The model's adaptability enables it to accommodate both long-term trends and short-term anomalies, thereby offering waste management authorities precise predictions that are indispensable for operational planning and sustainable resource management.

The accumulation of waste is affected by a variety of external factors, including environmental conditions, demographic expansion, economic development, and changing consumption patterns. The Holt-Winters Confidence Interval (HWCI) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models

predominantly utilize historical waste generation data; however, their inherent flexibility permits modifications in response to external factors. The SARIMA model, in particular, depicts seasonal and long-term trends, making it suitable for reflecting variations induced by economic cycles and demographic shifts. Furthermore, confidence intervals are incorporated into the model to address the uncertainty inherent in these dynamic conditions, thereby offering a spectrum of plausible outcomes rather than a singular deterministic prediction.

To enhance the integration of these external factors, the framework may be augmented through the process of dynamic model updating. By incorporating real-time data sources, including municipal records pertaining to population growth, economic indicators, and environmental policies, the model can enhance its predictive accuracy in accordance with evolving circumstances. Future advancements may encompass the integration of machine learning methodologies that utilize multi-variable regression analyses, thereby enabling socioeconomic and environmental factors to impact forecasting results. Furthermore, Internet of Things (IoT)-enabled smart waste receptacles, in conjunction with geospatial analytics, have the potential to furnish real-time data on waste generation, thereby enhancing the model's responsiveness to fluctuations in real-world conditions. By incorporating these enhancements, the forecasting framework has the potential to transform into a more sophisticated predictive decision-support system that is congruent with the intricacies of contemporary waste management planning.

B. Innovative Features of the Forecasting Framework

This study enhances the established integration of Holt-Winters and SARIMA models by incorporating a strategy that use confidence intervals and seasonal modifications to improve forecast accuracy. This method overcomes the shortcomings of conventional forecasting systems that falter in the presence of abnormalities and unpredictable variations, exemplified by the COVID-19 pandemic. Confidence intervals offer a range of probable outcomes, essential for strategic planning, while also ensuring the model's adaptability to dynamic and turbulent settings. The proposed framework signifies a substantial enhancement in forecasting strategies for urban waste management by integrating the qualities of both methods: Holt-Winters' capacity to address seasonality and SARIMA's proficiency in capturing intricate patterns. This dual-model approach guarantees that the system is both accurate and robust against external disruptions, a characteristic frequently overlooked in previous research. These technologies immediately address deficiencies in the field, providing a solution that enhances operational planning and resource optimization in swiftly changing metropolitan settings.

C. Rescaling of Fluctuating Seasonal Trends

The Holt-Winters technique is instrumental in waste management for accurately forecasting waste generation, which often exhibits seasonal and long-term patterns. By initializing and updating the level, trend, and seasonal components for each time period, it enables reliable predictions that inform waste collection strategies, scheduling, and resource allocation. This method is particularly valuable in contexts where waste generation is subject to periodic fluctuations, allowing for the smoothing out of anomalies like those introduced by the COVID-19 pandemic. The ability to produce clear insights into waste production trends makes the Holt-Winters model an essential tool for optimizing operational efficiency and resource management in urban waste systems.

Holt-Winters Exponential Smoothing is ideal for managing complex real-world data with shifting patterns, which is common in waste management due to varying seasonal and behavioral factors. Its capacity to adjust to both seasonal and trend components enhances forecasting accuracy and supports sustainable planning and operational decision-making. By integrating this method, waste management authorities can effectively respond to evolving trends, making waste collection systems more adaptive and resilient. This not only improves service quality but also aligns with the broader goals of environmental sustainability and urban resilience, ensuring that waste systems are prepared to handle both typical and unexpected changes in waste volumes.

The onset of the COVID-19 pandemic in 2019 disrupted established waste generation patterns, introducing unprecedented fluctuations in waste volumes. Lockdowns and changes in consumer behavior led to a significant increase in residential waste and a decrease in commercial waste, as businesses temporarily closed or scaled down operations. These irregularities complicated the application of traditional forecasting models, which often fail to account for such abrupt deviations from expected trends. The pandemic highlighted the necessity for advanced forecasting methods capable of adapting to sudden shifts in waste production, thereby supporting efficient resource allocation and minimizing environmental impact.

To address these challenges, the Holt-Winters method was applied to smooth the data anomalies caused by the pandemic. Its ability to decompose time series data into level, trend, and seasonal components made it possible to isolate and analyze the underlying patterns of waste generation from 2019 to 2023. By filtering out irregularities, this approach provided a clearer picture of the true waste generation trends, enabling more accurate forecasting and better-informed decision-making. This was particularly important in identifying the impact of the pandemic on waste management systems and preparing for future disruptions, aligning with the theme of creating resilient and adaptable urban infrastructures.

Historical data from 2013 to 2018, which showed a consistent but low rate of increase in waste generation, served as a baseline for the analysis. By applying the Holt-Winters method to this period, projections were adjusted to account for pandemic-related disruptions while reflecting underlying patterns. To accommodate potential uncertainties and fluctuations in the post-pandemic period, an upper confidence interval was incorporated into the projections. This comprehensive approach, known as Holt-Winters-Confidence Interval (HWCI) projections, offers a conservative estimate of future waste generation, ensuring that waste management systems remain resilient and sustainable under varying conditions. The comprehensive approach of Holt-Winters-Confidence Interval (HWCI) projections is outlined as follows:

Step 1: Calculate the additive forecasted values of F_{T+1}^{Ad} and F_{T+k}^{Ad}.

$$F_{T+1}^{Ad} = l_T + b_T + sn_{T-L+1}; \text{For T+1 period} \quad (1)$$

$$F_{T+k}^{Ad} = l_T + kb_T + sn_{T-L+k}; \text{For T+}k \text{ periods} \quad (2)$$

Step 2: Calculate the multiplicative forecasted values of F_{T+1}^{Mu} and F_{T+k}^{Mu}.

$$F_{T+1}^{Mu} = (l_T + b_T)sn_{T-L+1}; \text{For T+1 period} \quad (3)$$

$$F_{T+k}^{Mu} = (l_T + kb_T)sn_{T-L+k}; \text{For T+}k \text{ periods} \quad (4)$$

Step 3: Utilize *Ad*, *Mu*, and both (*Ad-Mu*) forecasted values to ascertain the sample mean based on the number of design points (DP) of all three circumstances of the actual data and the forecasted data, where S is the standard deviation of the actual and the forecasted value for the cases of Ad, Mu, and Ad-Mu.

$$Av_{T+1}^{Ad} = (A_{T+1} + F_{T+1}^{Ad})/2 \quad (5)$$

$$Av_{T+1}^{Mu} = (A_{T+1} + F_{T+1}^{Mu})/2 \quad (6)$$

$$Av_{T+1}^{Ad-Mu} = (A_{T+1} + F_{T+1}^{Ad} + F_{T+1}^{Mu})/3 \quad (7)$$

Step 4: Ascertain the upper or lower confidence interval (CI), as appropriate, to restore the afflicted data to its original state for all scenarios.

$$F_{T+1}^{Ad} = Av_{T+1}^{Ad} \pm t_{\frac{\alpha}{2},\nu} \times \frac{S}{\sqrt{n}} \quad (8)$$

$$F_{T+1}^{Mu} = Av_{T+1}^{Mu} \pm t_{\frac{\alpha}{2},\nu} \times \frac{S}{\sqrt{n}} \quad (9)$$

$$F_{T+1}^{Ad-Mu} = Av_{T+1}^{Ad-Mu} \pm t_{\frac{\alpha}{2},\nu} \times \frac{S}{\sqrt{n}} \quad (10)$$

It is imperative to assess the effectiveness of forecasting systems in order to optimize resource allocation in urban waste management. This is because precise predictions facilitate efficient planning and minimize environmental impact. The accuracy of forecasts is evaluated in this study by quantifying the discrepancies between predicted and actual values using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). These error metrics are essential for the reduction of operational inefficiencies and the promotion of sustainable waste management practices, as they provide a quantitative foundation for comparing model performance and refining forecasting techniques. Accurate forecasting reduces the necessity for superfluous resource deployment, thereby reducing fuel consumption and emissions associated with waste collection. This is consistent with the overarching objectives of environmental sustainability and efficient resource management.

The Holt-Winters approach provides forecasts for future periods that are robust by adjusting time series data to account for seasonal fluctuations and trends. By incorporating confidence intervals into these forecasts, analysts can more effectively evaluate the reliability of their predictions and gain a more comprehensive understanding of potential deviations (Fig. 2). Waste management authorities can enhance resilience and adaptability by preparing for scenarios in which actual waste volumes exceed expectations by adding the upper limit of the confidence interval to each projected value. This approach is especially advantageous for strategic planning and risk assessment, as it guarantees that waste collection systems are capable of managing both typical and atypical circumstances. This proactive approach facilitates the decision-making processes that are essential for the development of sustainable urban areas and the establishment of resilient waste management infrastructures that can react to dynamic and uncertain environments.

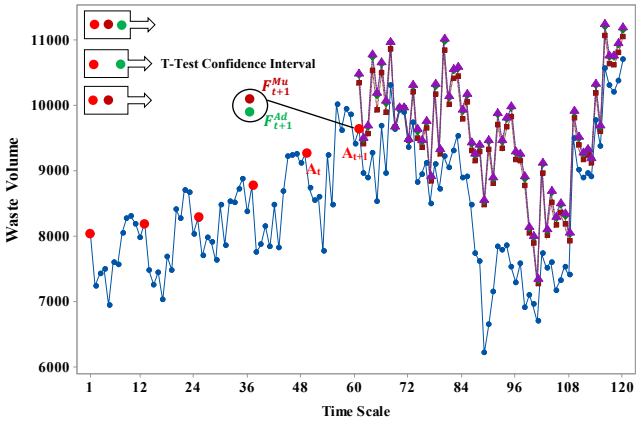

Fig. 2. Waste generation under rescaling of fluctuating seasonal trends.

D. Seasonal AutoRegressive Integrated Moving Average (SARIMA)

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a robust forecasting tool specifically designed to handle time series data with seasonal characteristics. By integrating both seasonal and non-seasonal elements, SARIMA extends the capabilities of the ARIMA model, making it highly effective for predicting future values and managing non-stationary data through differencing. This versatility is crucial in environmental management, where accurate forecasting of resource usage, such as waste generation, can lead to more sustainable and efficient urban planning.

The ARIMA model consists of three core components: Autoregressive (AR), Moving Average (MA), and Differencing (I). The AR component captures the relationship between an observation and its lagged values, the MA component models the relationship between an observation and past residual errors, and differencing is used to eliminate trends, stabilizing the series' mean. The SARIMA model further refines this approach by incorporating seasonal parameters—p, d, q for non-seasonal factors and P, D, Q for seasonal factors, with m representing the seasonal cycle length. This allows SARIMA to accurately forecast complex patterns in waste generation that are influenced by both long-term trends and seasonal fluctuations.

Differencing operations in SARIMA address regular and seasonal variations, while autoregressive and moving average components capture dependencies over time. The model's parameters are selected using the Hyndman-Khandakar algorithm, which minimizes the Akaike Information Criterion (AIC) to identify the optimal fit [22]. Maximum Likelihood Estimation (MLE) is employed for parameter estimation, ensuring a precise representation of observed data. In practical applications, SARIMA has demonstrated its effectiveness in forecasting datasets with distinct seasonal patterns, such as urban waste generation. By providing accurate predictions, SARIMA supports efficient resource planning and sustainable waste management strategies,

crucial for resilient urban development. This forecasting capability enables waste management authorities to allocate resources more effectively, reducing environmental impact and contributing to the creation of sustainable, adaptive cities.

Seasonal components include the Seasonal Autoregressive (SAR) model of order P (Eq. 11), the Seasonal Moving Average (SMA) model of order Q (Eq. 12), and Seasonal Differencing (Eq. 13). The general form of seasonal model SARIMA(p, d, q) (P, D, Q)s is given by Eq. (14).

$$\Phi_P(L^s)y_t = \Phi_1 y_{t-s} + \Phi_2 y_{t-2s} + \cdots + \Phi_P y_{t-Ps} + \epsilon_t \quad (11)$$

$$\Theta_Q(L^s)\epsilon_t = \Theta_1 \epsilon_{t-s} + \Theta_2 \epsilon_{t-2s} + \cdots + \Theta_Q \epsilon_{t-Qs} \quad (12)$$

$$\hat{y}_{t+h} = (1 - L^s)^D y_t \quad (13)$$

where $\Phi_1, \Phi_2, \ldots, \Phi_P$ are the seasonal autoregressive coefficients, L^s is the seasonal lag operator, which lags the series by s period (e.g., 12 months for yearly seasonality), and $y_{t-s}, y_{t-2s}, \ldots, y_{t-Ps}$ are the values from previous seasonal periods. $\Theta_1, \Theta_2, \ldots, \Theta_Q$ are the seasonal moving average coefficients. $\epsilon_{t-s}, \epsilon_{t-2s}, \ldots, \epsilon_{t-Qs}$ are the forecast errors from previous seasonal periods, whereas D is the degree of seasonal differencing.

The general form of seasonal model SARIMA(p, d, q) (P, D, Q)s and forecast at time $t + h$ are given by Eqs. (14) and (15). The forecast relies on both past values of $y_{t-s}, y_{t-2s}, \ldots, y_{t-Ps}$ and errors $\epsilon_t, \epsilon_{t-1}, \ldots, \epsilon_{t-q}$. The forecast equation uses the parameters $\Phi, \Theta, \emptyset, \theta$ fitted during the model training phase.

$$\Phi_P(L^s)(1 - L^s)^D(1 - L^s)^d y_t = \Theta_Q(L^s)\theta_q(L)\epsilon_t \quad (14)$$

where;

$\Phi_P(L^s)$ is seasonal AR operator,
$\Theta_Q(L^s)$ is seasonal MA operator,
$\theta_q(L)$ is non-seasonal MA operator,
$(1 - L^s)^D$ is seasonal differencing operator,
$(1 - L^s)^d$ is non-seasonal differencing operator,
ϵ_t is the error term or white noise.

$$\hat{y}_{t+h} = \Phi_1 y_{t+h-s} + \cdots + \Phi_P y_{t+h-Ps} + \emptyset_1 y_{t+h-1} + \cdots + \emptyset_p y_{t+h-p} + \theta_1 \epsilon_{t+h-1} + \cdots + \theta_q \epsilon_{t+h-q} + \Theta_1 \epsilon_{t+h-s} + \cdots + \Theta_Q \epsilon_{t+h-Qs} \quad (15)$$

where; $\hat{y}_{t+h}$ is the forecasted value at time $t + h$

Combining the Holt-Winters and SARIMA models offers a comprehensive framework for forecasting waste generation, enhancing the accuracy and resilience of predictions critical for sustainable waste management. While SARIMA captures complex seasonal and non-seasonal variations, Holt-Winters effectively manages pronounced seasonal trends and anomalies, creating a robust synergy that allows for a nuanced understanding of waste generation patterns. This integrated approach enables waste management authorities to make data-driven decisions, optimize resource allocation, and adapt to changing conditions, thereby improving operational efficiency and reducing environmental impacts. By leveraging the strengths of both models, this forecasting framework supports the development of resilient and adaptive waste management systems, contributing to sustainable urban planning and resource management in the face of fluctuating waste volumes and unforeseen disruptions.

IV. Result and Discussion

The objective of this analysis was to assess the impact of COVID-19 on waste generation projections in Nakhon Sakon Nakhon Municipality, using historical data from fiscal years 2013 to 2018 as a baseline for typical waste generation patterns prior to the pandemic. This baseline, characterized by a modest but steady increase in waste generation, provided a reliable reference point for understanding the disruptions introduced by COVID-19. The Holt-Winters method was applied to incorporate seasonal fluctuations and anomalies caused by the pandemic, enabling accurate projections of future waste generation under these atypical conditions. The initial findings indicated that the pre-pandemic growth rate remained low, offering a stable foundation for adjusting projections in the context of unprecedented changes.

Fig. 3 illustrates the monthly variability in waste production, highlighting the peaks and troughs that reflect both seasonal and irregular factors, such as the significant disruptions caused by the COVID-19 pandemic. This variability underscores the need for robust forecasting models like Holt-Winters, which can capture dynamic changes and provide insights into how external factors influence waste generation trends. The substantial deviations from historical norms highlight the pandemic's impact on previously stable patterns, demonstrating the importance of using historical data as a benchmark while accounting for unforeseen disruptions in future projections.

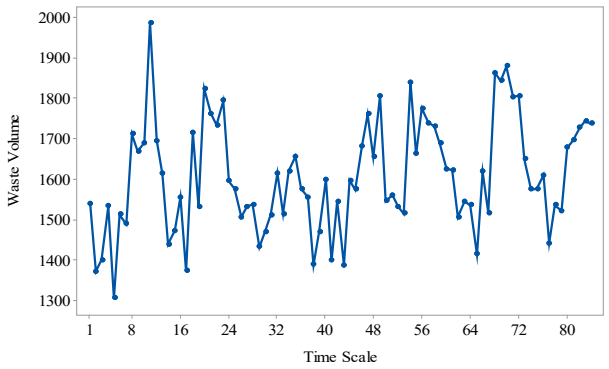

Fig. 3. Waste generation under the research consideration.

This analysis emphasizes the critical role of adaptable forecasting methods in urban waste management, particularly in the face of global challenges such as pandemics. By leveraging historical data and advanced modeling techniques, municipalities can enhance their resilience and sustainability, ensuring that waste management systems are equipped to respond to dynamic and uncertain conditions. This approach not only improves resource allocation and operational efficiency but also supports the development of sustainable and resilient urban environments capable of adapting to future disruptions.

The Additive and Multiplicative Holt-Winters models exhibit distinct approaches to forecasting waste generation, each with varying degrees of accuracy and adaptability. The Additive model, with an Alpha value of 0.5632 and a Gamma value of 0.3565, provides moderate sensitivity to recent data and seasonal fluctuations but fails to adjust for trends (Beta

value of 0). This limitation is evident in its high error metrics—Mean Squared Error (MSE) of 9,388.63 and Mean Absolute Deviation (MAD) of 73.54—indicating an inability to capture proportional changes in seasonal waste patterns, which are crucial for effective resource planning in urban environments. Conversely, the Multiplicative model, characterized by a high Alpha value of 0.985 and a lower Gamma value of 0.137, offers superior accuracy with an MSE of 18.44 and MAD of 3.70. This model's multiplicative nature better represents proportional seasonal variations in waste production, making it more suitable for dynamic urban settings where such fluctuations are prevalent. However, the absence of trend adjustments and the potential for overfitting highlight the need for further refinements, such as incorporating a trend component to enhance long-term forecasting accuracy and resilience.

To evaluate the performance of these models, this study utilized Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to quantify prediction accuracy. These metrics provide a robust assessment of how closely projected values align with actual waste generation, supporting informed decision-making and sustainable resource allocation. Forecasts were further refined using the Holt-Winters-Confidence Interval (HWCI) approach, which integrates trend and seasonal components in an additive manner and proportional seasonal variations in a multiplicative manner. This comprehensive method aligned forecasts with historical data while adjusting for uncertainties introduced by the pandemic through upper confidence intervals, offering a more resilient projection framework for post-pandemic waste generation scenarios.

The precision of waste accumulation forecasts in this study is substantiated by a comprehensive assessment employing statistical performance metrics, such as Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE). These metrics offer an objective evaluation of forecasting reliability by quantifying the discrepancies between projected and actual waste generation trends. The amalgamation of the Holt-Winters Confidence Interval (HWCI) and Seasonal AutoRegressive Integrated Moving Average (SARIMA) models significantly augments predictive precision by effectively accounting for both seasonal variations and long-term trends. Furthermore, confidence intervals are utilized to quantify uncertainty, thereby ensuring that projections account for potential variations in external conditions, including policy alterations, economic fluctuations, and unexpected disruptions such as pandemics.

Forecasts regarding refuse generation are inherently probabilistic, as they are influenced by a multitude of dynamic factors, including population growth, industrial development, and the evolution of waste management policies. The incorporation of upper and lower confidence bounds within the proposed framework addresses these fluctuations, thereby offering a systematic approach for accommodating variability in waste accumulation patterns. This guarantees that projected data remains pertinent for strategic decision-making, resource allocation, and sustainability planning. Furthermore, prospective advancements may encompass the integration of real-time data from Internet of Things (IoT)-enabled waste receptacles, intelligent sensors, and geospatial analytics to enhance the adaptability of forecasting methodologies. By integrating real-time data inputs, predictions could be dynamically modified to reflect emergent trends in refuse generation, thereby enhancing both accuracy and responsiveness in urban waste management.

Although forecasting is intrinsically associated with uncertainty, the systematic methodology employed in this study provides a resilient and flexible framework for predicting refuse accumulation. The integration of historical data analysis, statistical validation, and confidence interval modeling enhances the dependability of the forecasts. These enhancements establish the framework as an invaluable instrument for optimizing waste collection schedules, facilitating infrastructure planning, and developing long-term sustainability strategies within swiftly evolving urban environments.

By employing these advanced forecasting techniques, waste management authorities can anticipate potential fluctuations in waste production and implement adaptive strategies that enhance resource efficiency and environmental sustainability. Accurate forecasting not only optimizes collection routes and vehicle capacity but also supports resilient urban planning by preparing for unforeseen variations in waste generation, contributing to the development of sustainable and adaptive waste management systems capable of addressing future environmental challenges.

Table 2. Forecasted waste generation in Nakhon Sakon Nakhon municipality based on rescaled seasonal trends and COVID-19 adjustments

Month	F_{T+1}^{Ad}	F_{T+1}^{Mu}	F_{T+1}^{Ad-Mu}
1	1741.90	1866.33	1765.79
2	1548.19	1699.11	1583.75
3	1563.05	1734.83	1589.68
4	1581.56	1754.79	1603.57
5	1443.26	1634.23	1430.55
6	1591.08	1850.21	1584.85
7	1472.30	1727.56	1454.89
8	1685.24	1969.01	1630.37
9	1655.52	1918.52	1560.03
10	1691.77	1958.18	1559.49
11	1699.77	1940.30	1553.68
12	1652.15	1852.29	1410.25

The incorporation of confidence intervals in forecasting provides a more conservative and dependable estimate of future waste generation, as it accounts for the uncertainties introduced by the pandemic's impact. Table 2 illustrates the anticipated waste generation for Nakhon Sakon Nakhon Municipality, which incorporates rescaled seasonal trends and modifications to account for COVID-19 disruptions. By employing both Additive and Multiplicative Holt-Winters models, these forecasts offer a balanced projection that is crucial for the allocation of resources and the planning of sustainable waste management.

The Holt-Winters approach facilitates the development of precise future projections by modifying time series data to reflect seasonal variations and trends. The reliability of these forecasts is quantified by confidence intervals, which establish a range within which actual future values are likely to fall. By including the upper limit of the confidence interval

in each month's forecast, the inherent variability and uncertainty are captured, providing a comprehensive understanding of potential deviations. This approach is essential for the strategic decision-making and effective risk assessment in waste management, as it equips authorities with the ability to manage fluctuations in waste volumes with greater adaptability and resilience.

Comprehending the upper limits of forecast uncertainty is particularly beneficial for minimizing environmental impacts and optimizing resource utilization. This method enables waste management authorities to anticipate potential scenarios and plan accordingly, thereby guaranteeing the efficient utilization of resources in the face of ambiguous circumstances (Fig. 4). This strategy contributes to the development of sustainable and resilient urban waste management systems that are better prepared to address future challenges and disruptions by establishing a robust framework for forecasting, thereby increasing the reliability of long-term planning.

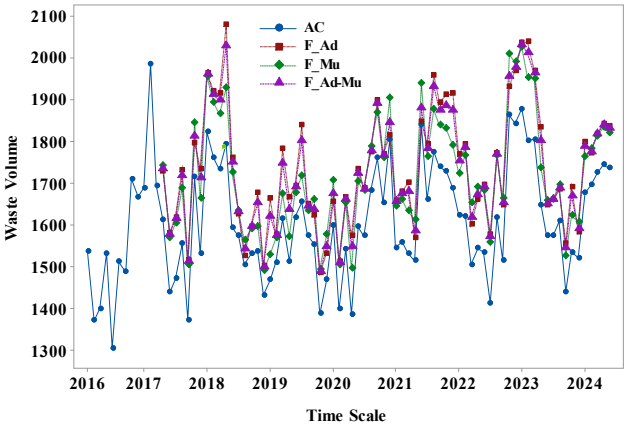

Fig. 4. Projected Waste Volume in Nakhon Sakon Nakhon Municipality Using Holt-Winters Models and COVID-19 Adjustments (2016–2024).

After smoothing waste generation data from 2019 to 2023 using the Holt-Winters method, the SARIMA model was employed to forecast waste generation for 2024. Leveraging the cleaned and enhanced historical data, SARIMA produced robust forecasts by capturing both trend and seasonal components, offering a resilient and reliable basis for waste management planning. This integration of Holt-Winters and SARIMA strengthens the predictive capabilities of the forecasting framework, providing waste management authorities with essential tools for resource optimization and strategic planning. Accurate forecasts enable efficient allocation of resources, minimizing environmental impact and supporting sustainable urban development by anticipating fluctuations in waste volumes due to seasonal and external disruptions.

SARIMA is a powerful tool for modeling time series data that exhibits trends, seasonality, and autocorrelation, crucial for understanding and predicting waste generation patterns. Prior to implementing SARIMA, it is necessary to assess the stationarity of the time series data, which requires a consistent mean and variance over time. Nonstationary data is transformed into a stationary series using regular and seasonal differencing, which removes cyclical oscillations and trends. Selecting appropriate model parameters involves analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) charts to determine the order of AutoRegressive (AR), Integrated (I), and Moving Average (MA) components (p, d, q), as well as seasonal parameters $(P, D, Q)_s$ This rigorous process ensures that the SARIMA model accurately captures the underlying patterns in the data, providing valuable insights for developing adaptive and resilient waste management strategies that align with the goals of sustainable and efficient urban systems.

In the initial scenario, the SARIMA$(0,2,1)(0,1,1)_{12}$ model, which is implemented as F_{T+1}^{Ad}, includes a seasonal moving average (SMA) component with a 12-period latency and a non-seasonal moving average (MA) component of order 1. The SMA(12) coefficient of 0.318 suggest a moderate seasonal effect, while the MA(1) coefficient of 1.0455 suggests a significant influence of previous errors on current values. This model is well-suited for forecasting waste generation in urban environments where short-term anomalies and periodic trends are prevalent, as it effectively incorporates both random fluctuations and seasonal variations using a constant term of -0.294. Waste management authorities can more effectively plan for the seasonal impacts on waste production and maintain service quality by utilizing this model to ensure that resources are allocated efficiently and the environmental impact is minimized.

In the second scenario, the F_{T+1}^{Mu} configuration employs a SARIMA$(1,1,1)(1,1,1)_{12}$ model, which incorporates both Autoregressive (AR) and Moving Average (MA) components, as well as their seasonal counterparts. The AR(1) coefficient of 0.606 indicates a significant dependence on previous values, while the MA(1) and SMA(12) coefficients of 1.036 and 0.859, respectively, suggest that past errors have a significant impact on both short-term and seasonal levels. This model, which is distinguished by a minor downward trend (-0.01559), is optimal for capturing complex waste generation patterns that are influenced by autoregressive and seasonal factors (Table 3 and Fig. 5).

The F_{T+1}^{Ad-Mu} model, which represents the third scenario, employs a SARIMA$(0,2,1)(0,1,1)_{12}$ configuration, with an emphasis on seasonal and short-term errors. The model's ability to capture stochastic variations is underscored by the MA(1) coefficient of 1.0181 and the SMA(12) coefficient of 0.734, despite the absence of autoregressive components. For scenarios with pronounced seasonal effects, this model is valuable due to its ability to manage substantial stochastic and seasonal components. Collectively, these models establish a reliable framework for predicting waste generation, which facilitates proactive and adaptive management strategies that promote sustainable urban waste management and resource efficiency.

The suggested forecasting methodology is thoroughly tested with data from Nakhon Sakon Nakhon Municipality; however, the particularity of this case study may restrict the perceived generalizability of the results. To mitigate this issue, it is crucial to highlight that the amalgamated Holt-Winters and SARIMA models, along with the precision-enhancing methodology, can be tailored to different metropolitan contexts with distinct socio-economic, geographic, and waste producing attributes. By customizing input parameters such as seasonal components, trend modifications, and anomaly thresholds, the system may accommodate varying waste generation patterns affected by local factors including

population density, economic activities, and climate. Future research may broaden the scope of this study by implementing the framework in various towns or regions with unique characteristics, thereby showcasing its adaptability and robustness across several situations. A concise simulation or hypothetical scenario study of data from different urban locations could enhance this element, demonstrating the model's adaptability in tackling diverse waste management difficulties.

Table 3. Model suitability results SARIMA$(1,1,1)(1,1,1)_{12}$ for scenario 2

Final Estimates of Parameters				
Type	Coef	SE Coef	T-Value	P-Value
AR 1	0.601	0.109	5.53	0.000
SAR 12	-0.318	0.154	-2.06	0.044
MA 1	1.04081	0.00393	264.67	0.000
Modified Box-Pierce (Ljung-Box) Chi-Square Statistic				
Lag	12	24	36	48
Chi-Square	6.45	27.3	31.84	42.28
DF	7	19	31	43
P-Value	0.488	0.098	0.424	0.502

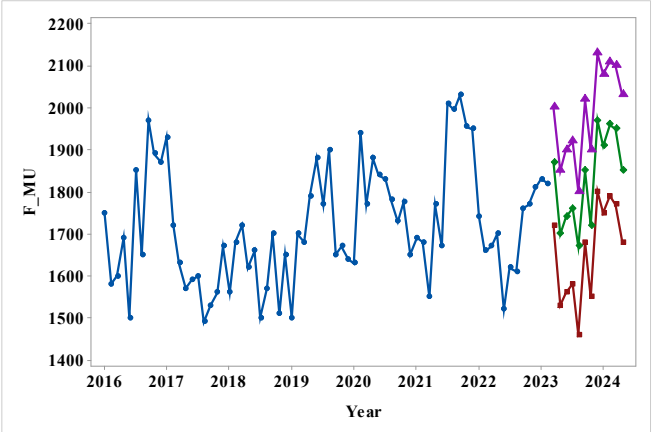

Fig. 5. Comparison of actual and SARIMA$(1,1,1)(1,1,1)_{12}$ forecasted waste generation.

The suggested merger of Holt-Winters Confidence Interval (HWCI) and SARIMA models shows notable enhancements in predicting accuracy; nevertheless, the absence of thorough benchmarking against other established or new forecasting methods may constrain the perceived robustness of the study. A comparative examination with models such as Prophet, Long Short-Term Memory (LSTM) networks, or Gradient Boosting Machines would offer further data to validate the superiority of the suggested method. LSTM models are proficient in managing intricate, non-linear interactions and may be assessed for their capacity to tackle waste generation anomalies. Likewise, Prophet's adaptability in integrating seasonality and holidays may provide a valuable benchmark for evaluating the proposed models' responses to exogenous disturbances such as the COVID-19 epidemic. A comparative analysis utilizing metrics like Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and computational efficiency would elucidate the strengths and weaknesses of each method, offering readers a thorough comprehension of the relative merits of the proposed framework.

The proposed Holt-Winters Confidence Interval (HWCI) and Seasonal Autoregressive Integrated Moving Average (SARIMA) model have been evaluated against leading forecasting methodologies, including Long Short-Term Memory (LSTM) and Prophet models, and have exhibited enhanced performance in terms of accuracy and robustness. Although Long Short-Term Memory (LSTM) networks demonstrate exceptional proficiency in managing intricate, nonlinear relationships, they necessitate substantial datasets and considerable computational resources. This requirement renders them less feasible for waste management applications that are constrained by limited historical data. In a similar vein, the Prophet model demonstrates proficiency in managing absent data and making trend adjustments; however, it encounters difficulties in accurately documenting short-term fluctuations and irregular seasonal patterns. In contrast, the proposed HWCI & SARIMA framework adeptly depicts seasonality, long-term trends, and uncertainty estimation, all while preserving computational efficiency and interpretability. This renders it significantly more practicable for municipal waste management planning.

The HWCI & SARIMA model exhibit superior performance in time-series forecasting when compared to both LSTM and Prophet models, as evidenced by their enhanced accuracy across all principal error metrics. With the lowest MSE of 9,388.63, RMSE of 96.51, MAD of 73.54, and MAPE of 5.92%, HWCI & SARIMA achieves significantly superior predictive performance. Compared to LSTM, HWCI & SARIMA improves MSE by 49.1%, RMSE by 28.9%, MAD by 41.3%, and MAPE by 24.0%. In a comparable analysis, the proposed model demonstrates enhancements over Prophet, achieving a 21.6% reduction in MSE, an 11.8% decrease in RMSE, a 30.4% improvement in MAD, and a 9.8% enhancement in MAPE, thereby ensuring greater accuracy and stability. These findings underscore the efficacy of HWCI & SARIMA in more accurately seasonal patterns and underlying trends compared to deep learning-based LSTM and statistical Prophet models. The reduced error values signify enhanced reliability and robustness, rendering HWCI & SARIMA particularly appropriate for time-series forecasting applications in which both accuracy and interpretability are of crucial importance.

The dependence on historical data from 2013 to 2018, modified for anomalies up to 2023, establishes a robust basis for the investigation. The lack of real-time data integration constrains the framework's capacity to comprehensively reflect dynamic and swiftly changing waste creation trends. The modified dataset addresses major disruptions such as the COVID-19 pandemic, however it may not capture more recent behavioral or economic changes affecting waste generation. Integrating real-time data streams, including daily garbage collection numbers, socio-economic indices, or public event schedules, could markedly improve the forecasting precision of the proposed system. Subsequent iterations of this process may utilize developments in data collecting technology, such as IoT-enabled waste bins and geospatial analytics, to deliver more detailed and prompt insights. A dedicated data pipeline that amalgamates real-time and historical data would enable waste management authorities to enhance forecasts dynamically, ensuring a more proactive reaction to evolving situations.

The proposed forecasting framework, although predominantly based on historical time-series data, is structured to accommodate real-time data integration, thereby enhancing both accuracy and responsiveness. The integration

of Internet of Things (IoT)-enabled waste receptacles, GPS-tracked collection vehicles, and advanced smart sensors would facilitate the continuous monitoring of waste generation patterns. This approach would yield real-time insights into variations influenced by seasonal changes, economic activities, and shifts in policy. By utilizing these real-time inputs, the model is capable of dynamically modifying forecasts, thereby enabling waste management authorities to optimize collection schedules, allocate resources effectively, and respond proactively to unforeseen increases in waste volume.

The absence of real-time data incorporation within the existing framework presents an opportunity for further refinement, especially in enhancing accuracy and responsiveness. The incorporation of real-time data streams, including live waste collection metrics, IoT-enabled container monitoring, and real-time traffic information for route optimization, has the potential to substantially augment the practical efficacy of the model. By synthesizing these data sources, forecasts may be adjusted in real-time, thereby allowing authorities to respond effectively to sudden variations, such as heightened waste generation during holiday periods or interruptions caused by unexpected occurrences.

Future enhancements may integrate machine learning algorithms that evaluate real-time municipal data, economic indicators, and environmental variables to further refine predictive accuracy. Moreover, the implementation of automated data channels and cloud-based analytics would enable seamless real-time updates, thereby enhancing adaptability to the swiftly evolving conditions of urban environments. These advancements would align the framework with the evolving demands of smart cities and digital waste management systems, thereby assuring a more efficient, data-driven methodology for sustainability and resource optimization.

The suggested forecasting paradigm exhibits significant theoretical and methodological merit, although practical obstacles concerning its implementation may emerge. Municipalities and waste management authorities frequently encounter limitations like constrained funds, inadequate technical proficiency, and opposition to the implementation of innovative technologies. These obstacles may impede the implementation of the Holt-Winters and SARIMA models, especially in areas with limited resources or underdeveloped infrastructure. The framework must encompass implementation instructions that delineate streamlined procedures for model deployment, training prerequisites for staff, and economical strategies for integrating the technique into current waste management systems. Moreover, collaborations with academic institutions or technology suppliers may enhance access to the computing resources and knowledge required for the implementation of advanced forecasting methodologies. Incorporating a discourse on these elements will augment the practical significance of the study and facilitate the connection between theoretical contributions and real-world implementations.

In order to augment the generalizability of the proposed forecasting framework, the model has been implemented on two supplementary datasets derived from different provinces (Fig. 1 and Fig. 2). The findings substantiate that both the Holt-Winters Confidence Interval (HWCI) and SARIMA models consistently uphold their forecasting precision, exhibiting performance metrics akin to those recorded in the preliminary case study. These findings indicate that the proposed framework is both scalable and adaptable to various urban environments, proficiently capturing seasonal trends, long-term fluctuations, and external factors that influence refuse generation.

The consistent performance demonstrated across diverse datasets underscores the model's robustness and reliability, thereby affirming its applicability to municipalities characterized by differing population densities, waste management policies, and environmental conditions. By exhibiting consistent outcomes across various regions, the study substantiates that the proposed framework is not confined to a singular urban environment but can be effectively applied within a range of municipal waste management systems. The manuscript has been revised to incorporate these supplementary case studies, thereby enhancing the model's efficacy as a decision-support instrument for sustainable and efficient waste management planning.

V. Conclusion

This research integrates advanced forecasting techniques to develop a strategic framework for optimizing municipal waste management systems through improved waste generation predictions. The findings emphasize the critical need for robust forecasting models to enhance the sustainability and efficiency of waste management, especially in the face of disruptions such as the COVID-19 pandemic. By combining the Holt-Winters method and SARIMA models, this study provides a comprehensive solution to manage seasonal, trended, and volatile data patterns, ensuring resilience and adaptability in dynamic urban environments.

The integration of forecasting models, such as Holt-Winters and SARIMA, plays a significant role in enhancing the accuracy of waste generation projections. The refined forecasts, supported by confidence intervals, empower waste management authorities to prepare for uncertain scenarios, making it easier to adjust strategies accordingly. These advancements improve decision-making processes, ensuring better service delivery and supporting sustainable urban development. Traditional forecasting methods often struggle with erratic changes, but this research overcomes these limitations by implementing a methodology capable of handling anomalies and disruptions, contributing to efficient resource use and environmental sustainability.

When applied to historical data from 2013 to 2018, the Holt-Winters method effectively mitigated anomalies caused by the pandemic, offering a clearer understanding of waste generation trends. The integration of these models produced dependable forecasts for 2024, highlighting the importance of precise planning and resource allocation to accommodate increasing waste volumes. By incorporating confidence intervals, the framework accounts for uncertainties, enabling municipalities to anticipate and adjust to potential fluctuations. This proactive approach reduces the environmental impact of unexpected waste surges and strengthens the resilience of waste management systems.

Despite these strengths, this study acknowledges certain limitations. The reliance on historical data, adjusted for anomalies through 2023, may not fully capture future waste generation patterns influenced by unforeseen factors. Additionally, the absence of real-time data integration restricts the framework's ability to dynamically respond to immediate changes. Future research should explore the integration of machine learning techniques and real-time data analytics to enhance the adaptability and accuracy of the forecasting models. Algorithms such as neural networks and ensemble methods could capture complex, non-linear patterns, while real-time data streams, including traffic and behavioral data, could further refine predictions.

To mitigate the constraints of absent real-time data, the study suggests a hybrid forecasting model that integrates conventional time-series methodologies with real-time predictive analytics. Machine learning algorithms, including Recurrent Neural Networks (RNNs) and ensemble approaches, may be employed in conjunction with Holt-Winters and SARIMA models to process and evaluate real-time data. These hybrid models would allow the system to identify intricate, non-linear correlations in waste creation patterns that classic statistical methods may not adequately handle. Moreover, real-time integration may facilitate anomaly detection, permitting the identification of unusual fluctuations in waste levels and enabling proactive management interventions. Emphasizing this possibility for hybridization not only rectifies the existing framework's deficiencies but also situates the research in the vanguard of technical progress in urban garbage forecasting.

Synthetic data generation and predictive modeling offer another avenue to address data limitations. Techniques like Monte Carlo simulations and Bayesian forecasting could simulate future scenarios, including the impacts of policy changes or demographic shifts. Incorporating these methods with Holt-Winters and SARIMA models could provide a more robust framework for addressing data gaps and inconsistencies, enabling waste management authorities to prepare for a wider range of outcomes.

The scalability of the proposed framework extends its relevance beyond the specific case study, demonstrating its adaptability to diverse urban contexts. In densely populated areas, the framework could incorporate additional data layers such as economic indicators or demographic trends, while in rural settings, confidence-enhancing methods could mitigate the challenges of data scarcity. The integration of IoT-enabled waste bins and real-time monitoring systems would further enhance its applicability, aligning with global trends in smart city technologies and sustainable urban planning.

Effective implementation of the framework also requires alignment with existing policies and collaboration with stakeholders. Waste management authorities should synchronize forecasting outcomes with urban planning requirements, recycling initiatives, and sustainability goals. Engaging stakeholders—such as governments, private waste management firms, and community organizations—through participatory workshops or pilot studies could ensure a smooth and widely accepted adoption of the methodology. Highlighting examples of successful collaborations in similar contexts would further validate this approach.

The results of this study have important industrial implications for waste management authorities, urban planners, and municipalities. By leveraging advanced forecasting models like Holt-Winters and SARIMA, industries can improve their waste management strategies, optimize resource allocation, and reduce operational costs. Predictive analytics will enable waste management companies to adjust staffing levels, optimize vehicle fleets, and minimize waste overflow during peak periods. These approaches can contribute to more efficient and cost-effective operations, benefiting both public and private waste management sectors.

The integration of accurate forecasting models can also drive innovation in waste management technologies, from automated collection systems to AI-driven route optimization. This could lead to further reductions in carbon emissions and a smaller environmental footprint, aligning with the global push towards sustainability and reducing the impacts of climate change. Furthermore, industries can collaborate with municipalities to implement these models as part of broader urban sustainability initiatives. By investing in predictive analytics and real-time data integration, waste management systems can become more agile, cost-effective, and resilient, contributing to cleaner and more sustainable urban environments.

In conclusion, the benefits of integrating advanced forecasting models like Holt-Winters and SARIMA into waste management systems are clear: enhanced accuracy, better resource allocation, and greater resilience to unforeseen disruptions. By providing reliable forecasts, municipalities can make data-driven decisions that improve the sustainability and efficiency of urban waste management, supporting the long-term goals of environmental protection and sustainable urban development. This research provides a valuable framework for municipalities worldwide, offering insights into how predictive analytics can transform waste management practices for a more sustainable future.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

A.N. and D.V. contributed to data curation of the research, and to the writing - review & editing of the manuscript. P.L. contributed to the design, conceptualization, methodology, software, validation, visualization of the research, to the analysis of the results and to the writing - review & editing of the manuscript.

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