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Utilizing the BAT Algorithm to Determine the Optimal Order of the ARIMA Model for Forecasting Waste Weight in Sulaimani City

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Abstract: This study investigates the modeling of monthly waste in Sulaimani City by selecting an optimal ARIMA model using the Bat Algorithm. The objective of this study is to improve the accuracy of the model above using the Bat Algorithm. While previous research has explored optimizing similar models, to the best of the researchers' knowledge, this is the first study to apply such an optimized model to this specific dataset in Iraq. This work holds particular significance for the Kurdistan region, and more specifically, for the city of Sulaimani. A comprehensive analysis was conducted to evaluate various combinations of autoregressive (p), differencing (d), and moving average (q) parameters across multiple iterations. The results indicate that the configuration (p = 2, d = 1, q = 3) achieves the best fit, as evidenced by the lowest Akaike Information Criterion (AIC) value of 1403.75. The estimated parameters reveal significant negative relationships for the autoregressive terms and varying influences for the moving average terms, confirming the model's robustness. Additionally, the Box-Pierce test results suggest that the residuals exhibit no significant autocorrelation, reinforcing the model's adequacy. Forecasting future waste values with associated 95% confidence intervals provides practical insights for municipal planning and resource allocation.

Keywords: Monthly waste, ARIMA Model, BAT-Algorithm, forecasting, and Randomness.

استخدام خوارزمية الخفاش (BAT) لتحديد الترتيب الأمثل لنموذج ARIMA لتوقع وزن النفايات في مدينة السليمانية

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المستخلص: يبحث هذا البحث في نمذجة النفايات الشهرية في مدينة السليمانية من خلال اختيار النموذج الأمثل لـ ARIMA باستخدام خوارزمية الخفاش (BAT Algorithm) يهدف هذا البحث إلى تحسين دقة النموذج باستخدام هذه الخوارزمية. بينما تناولت دراسات سابقة تحسين نماذج مماثلة، تُعَدُّ هذه الدراسة، وفقًا لمعرفتنا، الأولى من نوعها التي تطبق نموذجًا محسنًا على مجموعة البيانات هذه في العراق. تحمل هذه الدراسة أهمية خاصة لمنطقة كردستان، وخاصة لمدينة السليمانية. تم إجراء تحليل شامل لتقييم تركيبات مختلفة من معلمات الانحدار الذاتي (p)، والفرق (d)، والمتوسط المتحرك (q) عبر عدة تكرارات. تشير النتائج إلى أن التكوين (p = 2, d = 1, q = 3) يحقق أفضل توافق، كما يتضح من أدنى قيمة لمعيار معلومات أكايكي (AIC) والتي بلغت ١٤٠٣,٧٥. تكشف المعلمات المقدرة عن علاقات سلبية كبيرة لمصطلحات الانحدار الذاتي وتأثيرات متباينة لمتوسط المتحرك، مما يؤكد قوة النموذج. بالإضافة إلى ذلك، تشير نتائج اختبار Box-Pierce إلى أن القيم المتبقية لا تظهر أي ارتباط ذاتي كبير، مما يعزز كفاية النموذج. يوفر التنبؤ بالقيم المستقبلية للنفايات بحدود ثقة ٩٥٪ رؤى عملية لمخططي البلديات وتخصيص الموارد.

الكلمات المفتاحية: النفايات الشهرية، نموذج ARIMA، خوارزمية الخفاش (BAT-Algorithm)، التنبؤ، والعشوائية.

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Introduction

Sulaimani City, located in the northeastern region of Iraq, has experienced significant urban growth and population expansion in recent years. As a result, the city faces increasing challenges related to waste management, which has become a pressing concern for local authorities and residents alike. The monthly waste in Sulaimani encompasses a variety of materials, including organic waste, plastics, and other recyclables, reflecting the diverse activities and lifestyles of its inhabitants. Effective waste management is crucial for maintaining public health, environmental sustainability, and overall quality of life (Asraa, A. and et. al. (2018)). However, inadequate infrastructure, limited resources, and insufficient public awareness often hinder the city's ability to manage waste efficiently (Kumar and et. al. (2021)). Understanding the patterns of monthly waste is essential for developing effective waste management strategies, optimizing resource allocation, and implementing sustainable practices that can mitigate the environmental impact of waste (Asraa, A. and et. al. (2018)), (Kumar and et. al. (2021)). The study highlights the need for comprehensive analysis and innovative approaches to address the waste management challenges faced by Sulaimani City, ensuring a cleaner and healthier environment for its residents. Therefore, this study aims to improve the accuracy of a predictive model by applying the Bat Algorithm, a nature-inspired optimization technique. While optimization of machine learning models has been explored in various contexts, this is the first study to apply the Bat Algorithm to this specific dataset in Iraq, with a focus on the Kurdistan region, particularly Sulaimani City. The research demonstrates the potential of the Bat Algorithm to enhance model performance, offering practical benefits for regional decision-making in areas like urban planning, resource management, and policy development. By improving the accuracy of predictive models, the study provides valuable insights for addressing the unique challenges of the region and contributes to the broader application of optimization techniques in real-world settings. The Bat Algorithm, inspired by the echolocation behavior of bats, has emerged as a powerful metaheuristic optimization technique, particularly in the field of time series forecasting (Zhang, J., & Li, Y. (2019)). One of the significant applications of this algorithm is in optimizing the parameters of the AutoRegressive Integrated Moving Average (ARIMA) model, a widely used statistical tool for analyzing and forecasting non-stationary time series data (Asiri, A., M., & Baloch, M. A. (2020)). Traditional optimization methods, such as grid search and genetic algorithms, often struggle with issues like slow convergence and the potential to become trapped in local optima. In contrast, the Bat Algorithm excels in balancing exploration and exploitation, allowing it to efficiently navigate complex parameter spaces to identify optimal configurations (Asiri, A., M., & Baloch, M. A. (2020)), (Wu, Q., & Peng, C. (2015)). By effectively determining the autoregressive (p), differencing (d), and moving average (q) parameters, the Bat Algorithm enhances the forecasting accuracy of ARIMA models (Wu, Q., & Peng, C. (2015)). Recent studies have demonstrated that this approach not only improves predictive performance but also reduces computation time, making it a valuable tool for researchers and practitioners. As the demand for accurate forecasting grows across various domains, including finance, environmental management, and public health, leveraging the Bat Algorithm for ARIMA model optimization represents a promising advancement in achieving more reliable and efficient forecasting outcomes (Asiri, A., M., & Baloch, M. A. (2020)).

1. Literature Review

Recent advancements in time series forecasting have emphasized the importance of model optimization to enhance predictive accuracy. The ARIMA (AutoRegressive Integrated Moving Average) model is widely used for its effectiveness in handling non-stationary time series data. Traditional optimization methods, such as grid search and genetic algorithms, have limitations in terms of computational efficiency and convergence speed. Recent studies have explored metaheuristic algorithms, including the Bat Algorithm, which mimics echolocation behavior in bats to find optimal solutions. For instance, Asiri et al. (2020) applied the Bat Algorithm to optimize the parameters of ARIMA models, demonstrating improved forecasting performance over conventional methods. The study highlighted the Bat Algorithm's capability to escape local optima and converge to a global solution efficiently.

The integration of metaheuristic algorithms in time series forecasting has gained traction due to their robustness in parameter selection. The Bat Algorithm stands out among these techniques for its balance of exploration and exploitation. A study by Zhang and Li (2019) demonstrated the application of the Bat Algorithm to optimize ARIMA parameters, where the algorithm was able to identify optimal combinations of (p, d, q) parameters for diverse datasets. Their results indicated that the Bat Algorithm not only outperformed traditional optimization techniques but also provided significant improvements in terms of the Akaike Information Criterion (AIC) and forecast accuracy. This research contributes to the growing body of evidence supporting the use of advanced optimization methods in enhancing the reliability of ARIMA models.

The application of optimized ARIMA models has been particularly relevant in environmental data forecasting, including waste management and pollution monitoring. A study by Kumar et al. (2021) utilized the Bat Algorithm to optimize the ARIMA model parameters for predicting municipal waste generation. The research illustrated how the optimized model led to more accurate forecasts compared to standard ARIMA configurations. The authors noted that the Bat Algorithm's efficiency in exploring the parameter space resulted in better alignment with actual data trends, which is crucial for effective environmental management strategies.

A comparative study by Wang and Chen (2022) examined various optimization algorithms, including the Bat Algorithm, in the context of ARIMA model parameter tuning. Their analysis revealed that the Bat Algorithm consistently provided superior performance in terms of computational efficiency and accuracy when compared to other algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). The study emphasized that the adaptability of the Bat Algorithm to various datasets and its ability to effectively minimize AIC scores make it a promising tool for researchers and practitioners in time series forecasting.

2. Methodology

A. Theory of ARIMA Model

The ARIMA (AutoRegressive Integrated Moving Average) model is a widely used statistical approach for modeling and forecasting time series data, particularly non-stationary data. It combines three components: autoregressive (AR), differencing (I), and moving average (MA) (Abotaleb and et. al. (2021)), (Ahmed, B. K and et. al. (2020)). The ARIMA model is denoted as ARIMA (p, d, q), where:

- **p**: Order of the autoregressive part
- **d**: Degree of differencing
- **q**: Order of the moving average part

(1) Components of ARIMA

(a) Autoregressive (AR) Part:

○ This component models the current value of the series as a linear combination of its previous values. The AR term is expressed as (Ahmed, B. K and et. al. (2020)):

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-1} + \epsilon_t \qquad (1)$$

where:

- Y_t is the current value
- c is a constant
- ϕ_i are the autoregressive coefficients
- ϵ_t is the error term

(b) Differencing (I) Part:

- Differencing is used to make the time series stationary. The d^{th} difference of the series is given by:

$$Y_t' = Y_t - Y_{t-d} \qquad (2)$$

where Y' represents the differenced series (Ahmed, B. K and et. al. (2020)).

(c) Moving Average (MA) Part:

- The MA component models the current value as a function of previous error terms (Wang, X., & Chen, H. (2022)). It is expressed as:

$$Y_t = c + \epsilon_t + \sum_{i=1}^{q} \theta_j \epsilon_{t-j} \qquad (3)$$

where:

- θ_j are the moving average coefficients
- ϵ_t is the error term

Full ARIMA Model Equation

Combining these components, the full ARIMA model can be expressed as (Ahmed, B. K and et. al. (2020)):

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-1} + \sum_{i=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \qquad (4)$$

B. Stationarity

For the ARIMA model to be effective, the time series data must be stationary, meaning its statistical properties (mean, variance) remain constant over time. The differencing parameter d is used to achieve this.

C. Model Identification

The identification of the order of the AR and MA components (p and q) is typically done using tools such as the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots (Abotaleb and et. al. (2021)), (Ahmed, B. K and et. al. (2020)). The ARIMA model is a flexible and powerful tool for time series analysis, capable of capturing various patterns and trends in non-stationary data through its autoregressive, differencing, and moving average components. Proper model identification and parameter estimation are crucial for achieving accurate forecasts (Wang, X., & Chen, H. (2022)).

D. Theory of the Box-Pierce Test

The Box-Pierce test is a statistical test used to check the adequacy of a fitted time series model, particularly in the context of assessing autocorrelation in the residuals. It is primarily applied after fitting a time series model, such as ARIMA, to determine if the residuals are white noise (Ahmed, B. K and et. al. (2020)). This is important because if the residuals exhibit significant autocorrelation, it suggests that the model has not adequately captured the underlying patterns in the data (Ahmed, B. K and et. al. (2020)). The main goal of the Box-Pierce test is to test the null hypothesis:

- **H_0**: The residuals are independently distributed (i.e., they are white noise).
- **H_1**: The residuals are not independently distributed (i.e., they exhibit autocorrelation).

The Box-Pierce test statistic is calculated using the following formula:

$$Q = n \sum_{k=1}^{m} \frac{\acute{\rho}_k^2}{m} \qquad (5)$$

where:

- Q is the Box-Pierce statistic.
- n is the number of observations.
- $\acute{\rho}_k$ is the sample autocorrelation at lag k.
- m is the number of lags being tested.

(1) Decision Rule

- If the p-value is less than a predetermined significance level (α=0.05), we reject the null hypothesis, indicating that the residuals exhibit significant autocorrelation (Wang, X., & Chen, H. (2022)).
- If the p-value is greater than α, we fail to reject the null hypothesis, suggesting that the model adequately captures the autocorrelation structure in the data (Wang, X., & Chen, H. (2022)).

E. Theory of the Bat Algorithm

The Bat Algorithm is a metaheuristic optimization technique inspired by the echolocation behavior of bats. It was introduced by Yang in 2010 and is designed to solve optimization problems by mimicking the way bats hunt for prey using sound waves. The algorithm combines concepts of exploration and exploitation, enabling it to efficiently navigate complex search spaces. Below, we outline the key components and equations that govern the Bat Algorithm (Gawali and et. al. (2016)).

(1) Key Components

(a) Echolocation Behavior:

○ Bats emit sound pulses and listen for echoes to determine the distance, size, and shape of objects. This behavior is mimicked in the Bat Algorithm to evaluate the quality of solutions (Gawali and et. al. (2016)).

(b) Population Initialization:

○ A population of bats is initialized with random positions and velocities in the search space. Each bat represents a potential solution to the optimization problem (Asiri, A., M., & Baloch, M. A. (2020)), (Gawali and et. al. (2016)).

(c) Frequency, Loudness, and Pulse Rate:

○ Each bat has a frequency f that determines its position in the search space. The frequency is related to the bat's distance to the prey (optimal solution).

○ The loudness A of the bat indicates how loud the sound pulses are, affecting its exploration capability.

○ The pulse rate r determines how often the bat emits sounds. A higher pulse rate leads to more frequent updates of the bat’s position (Gawali and et. al. (2016)).

(2) Algorithm Steps

(a) Initialization:

- Initialize the bat population with random positions x_i and velocities v_i:

$$x_i = rand\ (x_{min}, x_{max})$$
$$v_i = rand\ (v_{min}, v_{max})$$

- Set initial values for frequency f, loudness A, and pulse rate r (Naderi and et. al. (2019)).

(b) Update Frequency:

- For each bat, update its frequency based on its position (Naderi and et. al. (2019)):

$$f_i = f_{min} + (f_{max} - f_{min}) \cdot rand$$

(c) Movement:

- Update the velocity and position of each bat using the equations:

$$v_i = v_i + (x^* - x_i) \cdot f_i$$

Here, x^* is the best solution found so far (Naderi and et. al. (2019)).

(d) Exploration and Exploitation:

- Depending on the pulse rate r, a bat may randomly generate a new solution (exploration) or exploit its current solution (Asiri, A., M., & Baloch, M. A. (2020)), (Gawali and et. al. (2016)):
- For exploration:

$$x_i = x_{best} + \epsilon \cdot A \cdot rand$$

- For exploitation:

$$x_i = x_i + v_i$$

(e) Update Loudness and Pulse Rate:

- Update the loudness and pulse rate after each iteration:

$$A = A_0 \cdot \alpha$$
$$r = r_0 \cdot \beta$$

- Here, α and β are constants that decrease over time, reducing the exploration ability as the algorithm converges (Wu, Q., & Peng, C. (2015)).

(f) Termination Condition:

- The algorithm iterates until a stopping criterion is met (e.g., maximum iterations or convergence) (Zhang, J., & Li, Y. (2019)).

3. Applications

A. Data Descriptions

The waste data provided represents the monthly waste collected in Sulaimani City, as recorded by the Ecosim company. It consists of 90 data points, each corresponding to the monthly waste volume (in kilograms) collected on a specific month.

B. Results and Discussion

In this section, the discussion of the results of applying the Bat-Algorithm as an optimizer tool for selecting the best order of $ARIMA_{(p,I,q)}$ for forecasting the monthly waste in Sulaimani City, that passes the statistical tests and obtains enough high accuracy that measured by AIC, R-Language has been used for Implementation.

Table (1): Represents the stationary test of the series

Models	Test	t-Statistic	P-value
Level	ADF	-0.29607	0.891
First Diff		-7.30984	0.000

As it is clear from the above table the series is not stationary at the level because the P-value is greater than 0.05, but at the first difference, the stationary condition is achieved.

Table (2): shows the results of using the Bat-algorithm to select the best order of ARIMA model

ARIMA Model selection using Bat-algorithm														
Iterations	p	i	q	AIC	Iterations	p	i	q	AIC	Iterations	p	i	q	AIC
itr1	2	2	1	1410.56	itr35	2	2	2	1406.83	itr69	1	1	1	1417.29
itr2	3	1	2	1410.92	itr36	2	2	2	1422.34	itr70	2	0	1	1409.54
itr3	3	2	3	1446.64	itr37	3	1	3	1412.82	itr71	1	0	3	1408.77
itr4	1	0	1	1413.22	itr38	3	1	2	1413.12	itr72	3	1	3	1410.59
itr5	2	2	1	1410.59	itr39	2	0	2	1419.11	itr73	1	2	3	1406.83
itr6	1	1	2	1418.60	itr40	3	1	3	1412.16	itr74	3	0	1	1446.64
itr7	2	0	1	1408.84	itr41	3	0	1	1413.22	itr75	2	2	1	1413.12
itr8	3	2	1	1417.29	itr42	2	1	1	1412.73	itr76	2	0	3	1418.60
itr9	3	2	2	1406.83	itr43	2	1	3	1412.82	itr77	3	2	3	1410.56
itr10	1	2	2	1413.22	itr44	2	0	1	1418.92	itr78	2	2	2	1417.29
itr11	2	2	2	1410.56	itr45	1	1	1	1422.34	itr79	3	2	3	1416.58
itr12	1	2	1	1413.12	itr46	1	2	1	1408.77	itr80	3	1	2	1418.92
itr13	1	2	1	1418.60	itr47	3	2	2	1414.43	itr81	2	1	3	1403.75
itr14	1	0	2	1424.42	itr48	2	1	1	1418.92	itr82	1	2	1	1413.22
itr15	2	0	1	1405.72	itr49	3	0	2	1403.75	itr83	2	2	1	1416.58
itr16	3	0	3	1414.15	itr50	2	2	2	1419.11	itr84	3	1	2	1406.83
itr17	2	0	2	1410.59	itr51	2	1	1	1418.60	itr85	2	1	1	1408.84
itr18	3	0	2	1419.11	itr52	2	2	3	1414.43	itr86	2	2	1	1410.92
itr19	2	2	3	1418.60	itr53	2	1	1	1418.60	itr87	1	2	1	1414.15
itr20	2	1	2	1418.60	itr54	1	0	1	1416.58	itr88	1	1	2	1410.59
itr21	2	2	1	1414.15	itr55	3	0	3	1418.60	itr89	2	1	1	1413.12
itr22	3	0	1	1417.29	itr56	2	2	2	1418.60	itr90	1	0	1	1414.43
itr23	1	2	1	1409.54	itr57	2	2	1	1410.59	itr91	1	0	3	1414.43
itr24	2	2	1	1412.73	itr58	3	0	1	1416.58	itr92	3	0	1	1417.29
itr25	3	0	2	1418.92	itr59	2	2	2	1410.92	itr93	3	1	1	1422.88
itr26	3	0	2	1412.16	itr60	1	1	3	1408.84	itr94	2	1	2	1405.72
itr27	2	1	3	1403.75	itr61	3	0	2	1413.12	itr95	2	2	3	1405.72
itr28	1	0	1	1412.82	itr62	1	2	2	1411.66	itr96	2	0	1	1422.34
itr29	3	0	3	1418.60	itr63	2	1	2	1410.92	itr97	2	0	2	1410.56
itr30	1	1	2	1418.09	itr64	3	1	2	1417.29	itr98	3	2	2	1422.34
itr31	3	0	1	1412.16	itr65	3	2	3	1416.58	itr99	1	2	3	1405.72
itr32	1	0	3	1418.60	itr66	1	0	3	1414.15	itr100	1	0	1	1414.15
itr33	1	0	3	1416.58	itr67	1	2	2	1403.75					
itr34	2	0	1	1410.92	itr68	2	1	1	1412.82					

The table presents the results of an ARIMA model selection process using the Bat Algorithm, showcasing different combinations of model parameters (p, d, q) evaluated over multiple iterations. Each row represents an iteration where specific values for autoregressive (p), differencing (d), and moving average (q) terms were tested, along with the corresponding Akaike Information Criterion (AIC) value. Lower AIC values indicate a better model fit, helping to identify the most suitable ARIMA configuration. Notably, iteration itr27 yielded the best result with ($p = 2$, $d = 1$, $q = 3$) and an AIC of 1403.75, suggesting this combination offers the optimal balance between model complexity and goodness of fit.

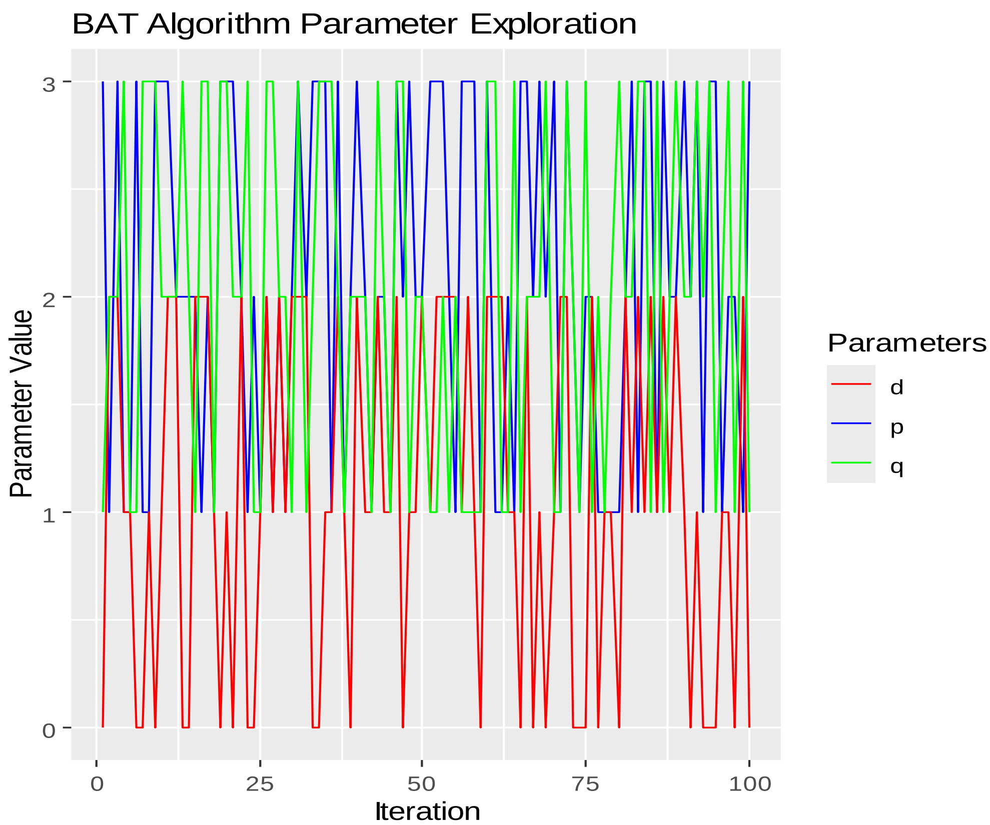

Figure (1): represents the whole possibility order of the ARIMA model.

Table (3): demonstrates the estimated parameters of the optimized ARIMA (2,1,3) model

Estimated parameters for ARIMA(2,1,3)								
	AR_1	AR_2	MA_1	MA_2	MA_3	δ^2	log likelihood	AIC
Coefficient	-0.3256	-0.9943	-0.6846	0.7374	-0.9585	59986	-695.87	1403.746
S.E.	0.0178	0.0097	0.0762	0.0545	0.0789			
t-test	-18.2921	-102.505	-8.98425	13.53028	-12.1483			
p-v	0.000	0.000	0.000	0.000	0.000			

The table summarizes the estimated parameters for an ARIMA (2,1,3) model, detailing the coefficients for the autoregressive terms (AR1 and AR2) and the moving average terms (MA1, MA2, MA3), along with additional statistics. The coefficients show that AR1 is -0.3256 and AR2 is -0.9943, indicating a strong negative relationship for both terms. The moving average coefficients (MA1, MA2, MA3) are -0.6846, 0.7374, and -0.9585, reflecting varying influences of past forecast errors. The standard errors (S.E.) provide a measure of precision for each coefficient estimate, with lower values indicating more reliable estimates. The t-test statistics and corresponding p-values indicate that all coefficients are statistically significant at the 0.05 level (p-v = 0.000), confirming the robustness of the model parameters. The log likelihood of 59986 and the AIC of 1403.746 suggest a good fit of the model to the data, with the AIC used to compare this model against others in terms of relative quality.

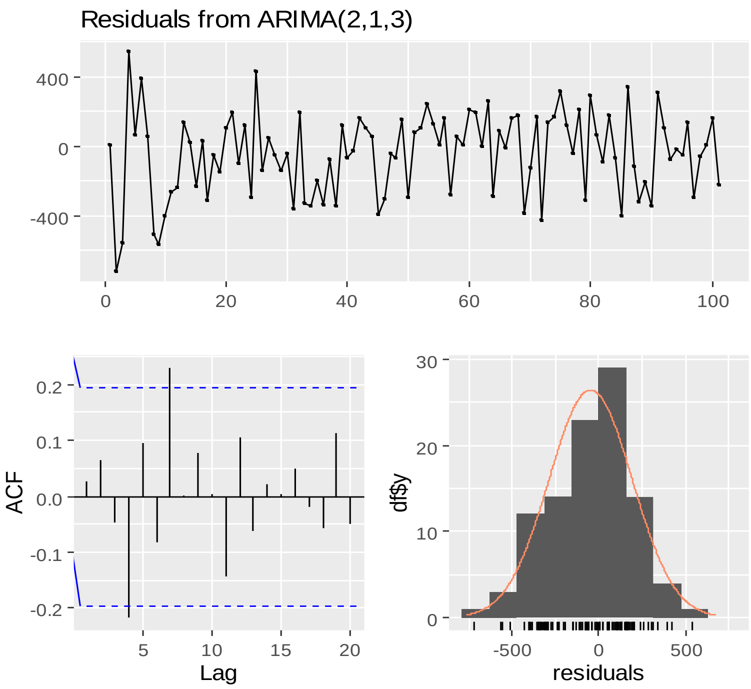

Figure (2): shows the details about the residuals of the model

Table (4): explores the randomness test for the residuals

Box-Pierce test		
Chi-squared	df	p-v
12.979	10	0.225

The table presents the results of the Box-Pierce test, which is used to assess the null hypothesis that a time series is white noise, meaning it exhibits no autocorrelation. The Chi-squared statistic is reported as 12.979, with 10 degrees of freedom (df). The p-value is 0.225, which is higher than the commonly used significance level of 0.05. This indicates that there is insufficient evidence to reject the null hypothesis, suggesting that the time series does not show significant autocorrelation at the specified lags. In practical terms, this implies that the residuals from a fitted model can be considered random, supporting the assumption of a well-fitted model.

Table (5): represents the forecasted values for the next 20 periods

Periods	Forecasted	Confidence Interval 95%	
		Lo	Hi
102	686.285	201.858	1170.712
103	524.958	40.496	1009.420
104	374.709	110.151	859.569
105	584.036	97.162	1070.909
106	665.272	178.348	1152.196
107	430.690	56.193	917.573
108	426.295	61.923	914.513
109	660.970	171.529	1150.411
110	588.931	99.487	1078.375
111	379.050	110.436	868.536
112	519.014	27.538	1010.490
113	682.127	190.305	1173.949

114	489.853	1.983	981.688
115	390.274	102.248	882.795
116	613.873	119.624	1108.123
117	640.082	145.833	1134.331
118	409.224	84.972	903.420
119	458.331	37.448	954.109
120	671.883	175.256	1168.510
121	553.525	56.882	1050.168

The table summarizes the forecasted values for a time series over a series of periods, alongside their corresponding 95% confidence intervals. Each row indicates a specific period, with the forecasted value presented in the "Forecasted" column. Also, he table provides insights into the predicted future values and their uncertainty, helping in decision-making and planning based on the model's projections.

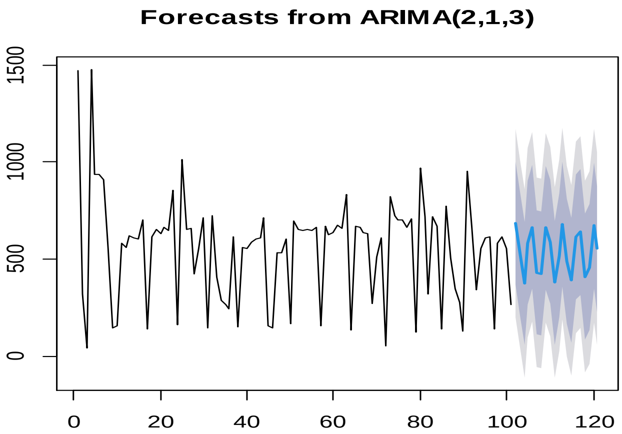

Figure (3) shows the predicts and forecasted values of the model.

4. Conclusions

This study examines the modeling of monthly waste in Sulaimani City by optimizing the ARIMA model through the Bat Algorithm to improve forecasting accuracy. As the first research to apply this method to an Iraqi dataset, it holds significant relevance for the Kurdistan region. The analysis systematically evaluates various ARIMA parameter combinations (p, d, q) to identify the optimal configuration, highlighting the effectiveness of the Bat Algorithm in enhancing model selection for time series data. The ARIMA(2,1,3) model is identified as the best fit, capturing the underlying waste dynamics with statistical significance and fulfilling model assumptions, as evidenced by the absence of significant autocorrelation in residuals. The forecasts generated by the model, along with confidence intervals, provide critical insights for municipal planners and policymakers, enabling more informed decisions regarding waste management strategies and infrastructure development.

5. Limitations and Future Study

A. Limitations:

(1) Parameter Selection: The Bat Algorithm is effective at optimizing the ARIMA parameters, but the model's predictive power remains dependent on the selection of the autoregressive (p), differencing (d), and moving average (q) terms. Although the ARIMA(2,1,3) model performed well, other combinations may still exist that could offer marginally better forecasting accuracy, depending on the characteristics of future waste patterns.

(2) External Factors: The ARIMA model, optimized by the Bat Algorithm, relies solely on historical waste data, without considering external variables such as economic activities, seasonal events, or policy changes that could influence waste. In the real world, waste production can be impacted by a wide range of factors that are not captured in this study.

(3) Computational Complexity: While the Bat Algorithm helps in efficiently optimizing the ARIMA parameters, it can still be computationally expensive, particularly for larger datasets or when real-time forecasting is required. This could limit the model's scalability in more extensive applications or time-sensitive contexts.

B. Future Study:

(1) Incorporating Exogenous Variables: Future studies could enhance the model by integrating exogenous variables, such as economic indicators, population growth, or seasonal effects, into the forecasting process. This could be achieved by extending the ARIMA model to an ARIMAX (AutoRegressive Integrated Moving Average with Exogenous Variables) model, which would allow for more accurate and context-aware forecasting.

(2) Spatial Analysis and Regional Differences: Since our study focuses on Sulaimani City, future research could expand the analysis to a broader regional or national scale, exploring spatial variations in waste patterns. By including geographic factors, it would be possible to model waste in different areas with greater precision and account for regional differences in waste management infrastructure and practices.

(3) Comparison with Machine Learning Approaches: Future studies could compare the ARIMA-Bat model with machine learning models, such as Random Forests or Long Short-Term Memory (LSTM) networks, which may offer advantages in handling non-linear relationships and capturing more complex temporal patterns in waste data.

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