IRAQI Academic Scientific Journals

University of Kirkuk Journal For Administrative and Economic Science (2025) 15 (1): 269-279

UKJAES

University of Kirkuk Journal For Administrative and Economic Science

ISSN:2222-2995 E-ISSN:3079-3521

University of Kirkuk Journal For Administrative and Economic Science

Rasul Rahela Aziz, Taher Hindreen Abdullah & Ahmed Shaho Tahir. Optimizing the Exponential Trend Model by Flower Pollination Algorithm to Forecast the Carbon Dioxide (CO2) Gas in Iraq. ***University of Kirkuk Journal For Administrative and Economic Science*** **(2025) 15 (1):269-279.**

Optimizing the Exponential Trend Model by Flower Pollination Algorithm to Forecast the Carbon Dioxide (CO2) Gas in Iraq

Rahela Aziz Rasul [1], Hindreen Abdullah Taher [2,4], Shaho Tahir Ahmed[3]

[1] Department of Mathematics, University of Raparin- College of Basic Basic Education, Sulaimani, Iraq
[2] Department of Information Technology, University of Sulaimani - College of Commerce, Sulaimani, Iraq
[3] Department of Statistics and Informatics, University of Sulaimani - College of Administration and Economics
[4] Department of Software Engineering, Faculty of Engineering & Computer Science, Qaiwan International University Sulaymaniyah, Kurdistan Region-Iraq

rahella_amar@uor.edu.krd [1]
hindreen.taher@univsul.edu.iq [2,4]
shaho.ahmed@univsul.edu.iq [3]

Abstract: Air pollution due to carbon dioxide (CO2) emissions is a large environmental and public health issue in Iraq, driven by motor vehicle exhausts, industrial processes, and diesel generator usage. The current study proposes a new approach to forecast CO2 emissions using optimization of the Exponential Trend Model using the Flower Pollination Algorithm (FPA) to forecast the CO2 emissions. FPA-Exponential Trend Model form is applied to model nonlinear growth trends in CO2 concentrations, with FPA optimizing model parameters for optimal forecasting. Dickey-Fuller, Breusch-Pagan, and Durbin-Watson tests are employed to test the validity of the model and ensure randomness, homoscedasticity, and absence of residuals autocorrelation. Performance metrics such as Mean Squared Error (MSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) capture the strength and precision of the model. The final optimized results which achieved at iteration 80, when had the minimum values of evaluation measures. The results demonstrate the efficacy of the model as an effective tool for Iraq urban air quality management and policy-making.

Keywords: Carbon Dioxide CO2, Flower Pollination Algorithm (FPA), Optimization, and Exponential Trend Model.

تحسين نموذج الاتجاه الأسي باستخدام خوارزمية تلقيح الأزهار لتوقع غاز ثاني أكسيد الكربون (CO2) في العراق

م.م. راهيلا عزيز رسول [١]، أ.م.د. هندرين عبد الله طاهر [٢،٤]، م. شاهو طاهر أحمد [٣]

[١] قسم الرياضيات، جامعة رابرين - كلية التربية الأساسية، السليمانية، العراق
[٢] قسم تكنولوجيا المعلومات، جامعة السليمانية - كلية التجارة، السليمانية، العراق
[٣] قسم الإحصاء والمعلوماتية، جامعة السليمانية - كلية الإدارة والاقتصاد، السليمانية، العراق

IRAQI Academic Scientific Journals

University of Kirkuk Journal For Administrative and Economic Science (2025) 15 (1): 269-279

[4] قسم هندسة البرمجيات، كلية الهندسة وعلوم الحاسوب، جامعة قيوان الدولية، السليمانية، إقليم كردستان - العراق

المستخلص: يُعد تلوث الهواء الناتج عن انبعاثات غاز ثاني أكسيد الكربون (CO2) مشكلة بيئية وصحية عامة كبيرة في العراق، ناتجة عن عوادم المركبات، والعمليات الصناعية، واستخدام المولدات الكهربائية التي تعمل بالديزل. تقترح هذه الدراسة نهجًا جديدًا لتوقع انبعاثات ثاني أكسيد الكربون من خلال تحسين نموذج الاتجاه الأسي باستخدام خوارزمية تلقيح الأزهار (FPA). يُطبق نموذج الاتجاه الأسي المدعوم بـ خوارزمية تلقيح الأزهار لنمذجة الاتجاهات غير الخطية في تركيزات CO2، حيث تعمل FPA على تحسين معلمات النموذج لتحقيق توقعات مثلى. يتم إجراء اختبارات ديكي-فولر، بروش-باغان، ودوربين-واتسون لاختبار صلاحية النموذج وضمان العشوائية والتجانس وعدم وجود ارتباط ذاتي للمخلفات. يتم تقييم أداء النموذج باستخدام مقاييس مثل متوسط الخطأ التربيعي (MSE)، معيار معلومات أكايكي (AIC)، ومعيار معلومات بيزي (BIC) لقياس دقة النموذج وكفاءته. تم تحقيق أفضل النتائج عند التكرار ٨٠، حيث وصلت معايير التقييم إلى أدنى قيمها. تؤكد النتائج فعالية النموذج كأداة فعالة لإدارة جودة الهواء في المناطق الحضرية بالعراق وصياغة السياسات البيئية.

الكلمات المفتاحية: ثاني أكسيد الكربون (CO2)، خوارزمية تلقيح الأزهار (FPA)، التحسين، نموذج الاتجاه الأسي.

Corresponding Author: E-mail: rahella_amar@uor.edu.krd

Introduction

One of the most troublesome environmental and public issues in Iraq is Air pollution due to carbon dioxide (CO_2) gas. The combination of inadequately maintained public infrastructure, swift urban growth, and continuous shutdowns of electricity have led to the extensive use of diesel-powered generators and low-quality cars, both of which are major contributors of CO_2 emissions. Cities like Baghdad, Basra, and Mosul are heavily impacted, and in most cases, CO_2 emissions are above level due to the high level of traffic, industrial Interventions, and using generators during the power outage (Al-Hassan, 2016). These shifts have resulted in CO_2 pollution becoming an acute problem for the nation with dire consequences to human health and the ecosystem. There are many reasons that the health consequences of CO_2 pollution are very disturbing. CO_2 binding with hemoglobin during inhalation results in formation of carboxyhemoglobin and reduces the blood's oxygen transport capacity. This often leads to chronic symptoms of headaches, fatigue, and dizziness as well as severe cardiovascular, neurological disorders, and death in extreme cases (World Health Organization, 2018). Children, elderly, and already sick people are more prone to deal with these issues. Cognitive function can also be inhibited and overall quality of life can decline from prolonged exposure to heightened emissions of CO_2. Besides, Carbon dioxide pollution does aggravate the impacts of other airborne pollutants and adds to the level of toxicity that can damage the environment and lessen agricultural output (Al-Delaimy, 2019). Iraq is also burdened with the problem of CO_2 pollution and attempts to mitigate it have not been successful because of the political turmoil, economic hardship, and general unawareness on the potential threats caused by air pollution. Nonetheless, some progress has been made to address the problem. For one, the Iraqi government has tried to make investments into renewable energy and, together with international organizations, improve public transport systems to cut down the use fossil fuels (Iraqi Ministry of Environment, 2020). Furthermore, there is more identification of the existence of a demand for more emission controls with strict compliance to the environmental law. There is also much more need for campaigns to inform the public on the health effects of CO_2 pollution and the need to control emissions. In a nutshell, the problem of CO_2 pollution in Iraq is multi-faceted, emanating from vehicle use, industrial operations, and the common use of generators, making it an important environmental and public health concern. Solving this problem requires a multi-faceted approach that implements tighter regulations, funds new, cleaner technologies, and boosts public awareness. The strides that have been made are minimal, but the prospect of cutting CO_2 emissions provides better health, a cleaner environment, and an overall improved quality of life (United Nations Environment Programme, 2017).

1. Literature Reviews

The literature review section explores the application of the Flower Pollination Algorithm (FPA) combined with an exponential trend model in air pollution forecasting, highlighting its effectiveness in addressing complex environmental challenges and improving prediction accuracy.
The Flower Pollination Algorithm (FPA) combined with an exponential trend model has been increasingly applied in environmental studies, particularly for air pollution forecasting. One notable study by Zhang et al. (2019) utilized this hybrid approach to predict PM2.5 concentrations in urban areas. The exponential trend model captured the nonlinear growth patterns of pollution levels, while FPA optimized the model parameters to minimize forecasting errors. The results demonstrated that the FPA-Exponential trend model outperformed traditional statistical methods, providing more accurate and reliable predictions. This study highlighted the potential of bio-inspired optimization algorithms in addressing complex environmental challenges.
In a study conducted by Li and Chen (2020), the FPA-Exponential trend model was employed to analyze carbon monoxide (CO) pollution trends in industrial cities. The exponential trend model effectively captured the rapid increase in CO levels during peak industrial activity periods, while FPA fine-tuned the model parameters to enhance accuracy. The study found that the hybrid model significantly reduced prediction errors compared to conventional methods. The authors emphasized the importance of integrating optimization algorithms like FPA with statistical models to improve the precision of air quality forecasts, particularly in regions with high industrial emissions.
Research by Wang et al. (2021) explored the application of the FPA-Exponential trend model for urban air quality management. The study focused on predicting nitrogen dioxide (NO2) levels in metropolitan areas, where traffic emissions are a major contributor to air pollution. The exponential trend model provided a robust framework for capturing the temporal dynamics of NO2 concentrations, while FPA optimized the model parameters to ensure high forecasting accuracy. The findings indicated that the FPA-Exponential trend model could serve as a valuable tool for urban planners and policymakers in designing effective air pollution control strategies.
A comparative study by Kumar and Singh (2022) evaluated the performance of the FPA-Exponential trend model against other machine learning and statistical models in forecasting sulfur dioxide (SO2) levels. The exponential trend model was used to capture the underlying growth patterns of SO2 emissions, while FPA optimized the model parameters to minimize errors. The study concluded that the FPA-Exponential trend model consistently outperformed other methods in terms of accuracy and reliability. The authors recommended the use of this hybrid approach for air pollution forecasting, particularly in regions with complex emission sources and varying pollution trends.
The reviewed studies highlight the effectiveness of the FPA-Exponential trend model in air pollution forecasting, demonstrating its ability to capture complex, nonlinear trends with high accuracy. By optimizing model parameters, FPA enhances the precision of predictions for pollutants like PM2.5, CO, and NO2, making it a valuable tool for urban air quality management. While the results are promising, further research could explore broader applications and integration with other optimization techniques to maximize its potential in diverse environmental contexts.

2 Methodology

A. Methodology of FPA-Exponential Trend Model

The Flower Pollination Algorithm (FPA) combined with an Exponential Trend Model offers a powerful approach for optimizing and forecasting time series data. Inspired by the natural pollination process of flowering plants, FPA excels in global optimization by balancing exploration and exploitation. When integrated with an exponential trend model, it effectively estimates parameters to capture exponential growth or decay patterns in data. This hybrid framework is particularly useful for improving forecast accuracy in various domains, such as finance, environmental modeling, and resource management.

(1) Exponential Trend Model

The Exponential Trend Model is widely used for time series forecasting due to its simplicity and effectiveness in capturing the growth or decay patterns in data. The general form of the Exponential Trend Model is:

$$y_t = \ . e^{(b\,.\,t)} \qquad (1)$$

Where:

y_t is the value of the time series at time t.
 is the initial value or the intercept parameter.
b is the rate of growth or decay (trend parameter).
t is the time step $(1, 2, 3, ..., n)$.
e is the base of the natural logarithm.

This model assumes that the time series grows or decays exponentially over time, and the values of and b need to be estimated based on historical data. The goal is to find the best-fitting values of and b that minimize the error between the predicted and actual values of the time series.

(2) FPA-Exponential Trend Model Framework

The Flower Pollination Algorithm (FPA) combined with an Exponential Trend Model Framework involves several steps. Below are the detailed steps with equations:

Step 1: Initialize Parameters

- Define the number of flowers solutions N.
- Set the maximum number of iterations T.
- Define the switch probability p for global and local pollination.
- Initialize the population of flowers X_i (where $i = 1, 2, ..., N$) with random values for parameters and b of the exponential trend model:

$y_{(t)} = \ . e^{bt}$.

Step 2: Evaluate Initial Solutions

- For each flower X_i, calculate the forecasted values using the exponential trend model:

$$y_{(t)} = {}_i \,.\, e^{bit}. \qquad (2)$$

- Compute the fitness for each flower.

Step 3: Flower Pollination Process

- For each iteration, update the positions of the flowers using the following rules:

Global Pollination (with probability *p*):

$$X_i^{t+1} = X_i^t + L\,.\,(X_{best} - X_i^t) \qquad (3)$$

where X_{best} is the current best solution, and L is a Lévy flight step size.

Local Pollination (with probability *1 - p*):

$$X_i^{t+1} = X_i^t + \epsilon\,.\,(X_j^t - X_k^t) \qquad (4)$$

where ϵ is a random number between 0 and 1, and X_j^t , X_k^t are randomly selected flowers.

Step 4: Evaluate New Solutions

- For each updated flower X_i^{t+1}, calculate the new forecasted values:

$$y_t^{t+1} = {}_i^{t+1}\,.\,e^{b_i^{t+1} t} \qquad (5)$$

- Compute the new fitness for each updated flower.

Step 5: Update Best Solution

- Identify the flower with the best minimum fitness and update X_{best} if a better solution is found.

Step 6: Check Stopping Criterion

● Repeat Steps 3 to 5 until the maximum number of iterations T is reached or a convergence criterion is met.

Step 7: Final Forecast

● Use the parameters and b from the best solution X_{best} to make final forecasts using the exponential trend model:

$$y_{forecast(t)} = {}_{best} \cdot e^{b_{best} t} \qquad (6)$$

B. Dickey-Fuller Test

The **Dickey-Fuller test** (or **Augmented Dickey-Fuller test**) is a statistical test used to determine whether a time series is **random** or not. The basic form of the Dickey-Fuller test involves estimating the following regression:

$$\Delta y_t = + \beta_t + \gamma y_t - 1 + \sum_{i=1}^{p} \delta_j \Delta y_{t-1} + \epsilon_t \qquad (7)$$

Where:

- Δy_t is the first difference of the time series.
- is a constant (intercept).
- β_t is a time trend.
- y_{t-1} is the lagged value of the series.
- γ is the coefficient of the lagged dependent variable.
- Δy_{t-i} are the lags of the differenced series.
- ϵ_t is the error term.

C. Breusch-Pagan Test

The Breusch-Pagan test can also be adapted for use with time series models to check for heteroscedasticity in the residuals. In the context of time series, heteroscedasticity often manifests as changing volatility over time, which can affect the reliability of forecasts and inferences, it tests the hypothiesiss:

● **Null Hypothesis (H_0):** The errors are homoscedastic (constant variance).
● **Alternative Hypothesis (H_1):** The errors are heteroscedastic (non-constant variance).

The below steps are showing the implementation of the breusch pagan test:

1. Fit the Model: Estimate the exponential trend model.
2. Auxiliary Regression: Regress the squared residuals $e_{(t)}^2$ on time t:

$$e_{(t)}^2 = \gamma_0 + \gamma_{1t} + u_{(t)} \qquad (8)$$

3. Test Statistic: Compute $LM = n \cdot R^2$, where n is the number of observations and R^2 is from the auxiliary regression.
4. Decision: Compare the LM statistic to a chi-squared distribution. If the p-$value < 0.05$, reject the null hypothesis, indicating heteroscedasticity.

This test ensures the model's reliability. If heteroscedasticity is found, consider transformations or alternative modeling approaches.

D. Durbin-Watson Test

The Durbin-Watson test is used to detect autocorrelation in the residuals of the model, which is crucial for ensuring the reliability of the model's predictions.

Null Hypothesis (H_0): **There is no autocorrelation in the residuals.**

Alternative Hypothesis (H_1): **There is autocorrelation in the residuals.**

The test statistic is named by (Durbin-Watson test statistic (DW).

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \qquad (9)$$

If the calculated (d_L < DW < 4-d_L) the Null Hypothesis will be accepted, otherwise it will be rejected. Where critical value from Durbin-Watson table.

E. Evaluate Precision of Forecasting Models

Evaluating the precision of forecasting models is a critical step in determining how well a model predicts future values. The precision of a forecasting model refers to its ability to generate accurate, reliable, and consistent predictions. There are various statistical measures and methods used to assess the precision of forecasting models, depending on the type of model being used. Below is an overview of some common methods and metrics used to evaluate the precision of forecasting models:

(1) Mean Squared Error (MSE)

MSE is a metric that is used to evaluate how well a model's predictions match the actual data. It calculates the average of the squared differences between the predicted values and the actual values.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \qquad (10)$$

where:

- n is the number of observations.
- y_t is the actual value.
- $\hat{y}_t$ is the predicted value.

(2) Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is another commonly used metric to evaluate forecasting accuracy. RMSE penalizes large errors more heavily than MAE because it squares the differences between actual and forecasted values before averaging them. This makes RMSE particularly sensitive to outliers and large deviations in forecasts.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \qquad (11)$$

(3) Akaike Information Criterion (AIC)

AIC is a model selection criterion that helps evaluate how well a statistical model fits the data while penalizing the model for having too many parameters (complexity). It is widely used to compare different models.

$$AIC = 2\,k - 2\,\ln(\mathscr{L}) \qquad (12)$$

Where:

- n: is the number of observations.
- $\mathscr{L}$: is the log-likelyhood.

(4) Bayesian Information Criterion (BIC)

BIC is very similar to AIC in that it also balances model fit with model complexity, but it applies a stronger penalty for complexity. It is based on Bayesian principles and is often used in statistical model selection.

$$BIC = k \,.\, \ln(n) - 2\,\ln(\mathscr{L}) \qquad (13)$$

Where:

- n: is the number of observations.
- $\mathscr{L}$: is the log-likelyhood.
- k: is the number of explanatory variables in the model.

3. Applications

A. Data Description

the dataset provides annual CO_2 emissions data for Iraq from 1988 to 2023, measured in metric tons. Over this period, emissions generally increased, with notable fluctuations, such as a sharp decline in 2007 followed by a recovery and steady rise until 2019, before a dip in 2020 likely due to global economic impacts. The highest emissions were recorded in 2019 (190,233,920 metric tons), reflecting Iraq's growing industrial and energy-related activities.

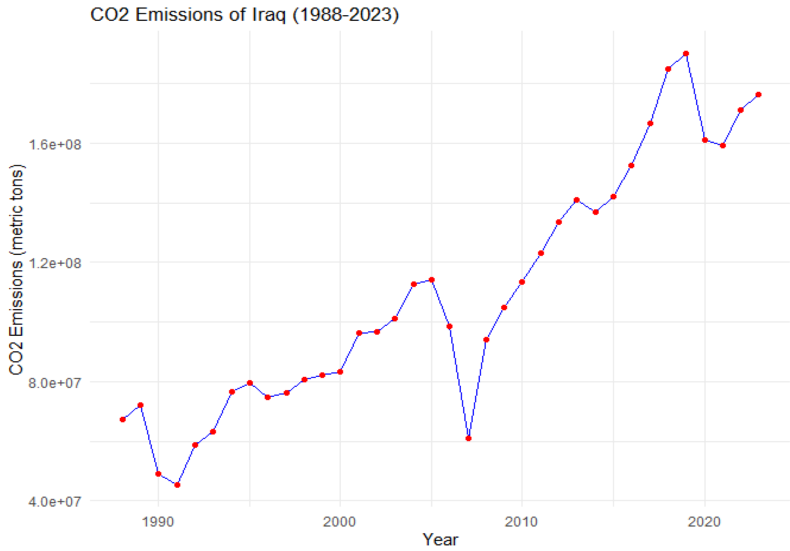

Figure (1)

Table (1) Represents the stationary test of the series

Models	Test	t-Statistic	P-value
Level	ADF	-0.74002	0.506
First Diff		-6.04496	0.000

From the above table, 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.

B. Results and Discussions

After manipulating the dataset, the aforementioned model was implemented, then the researchers reached the below results:

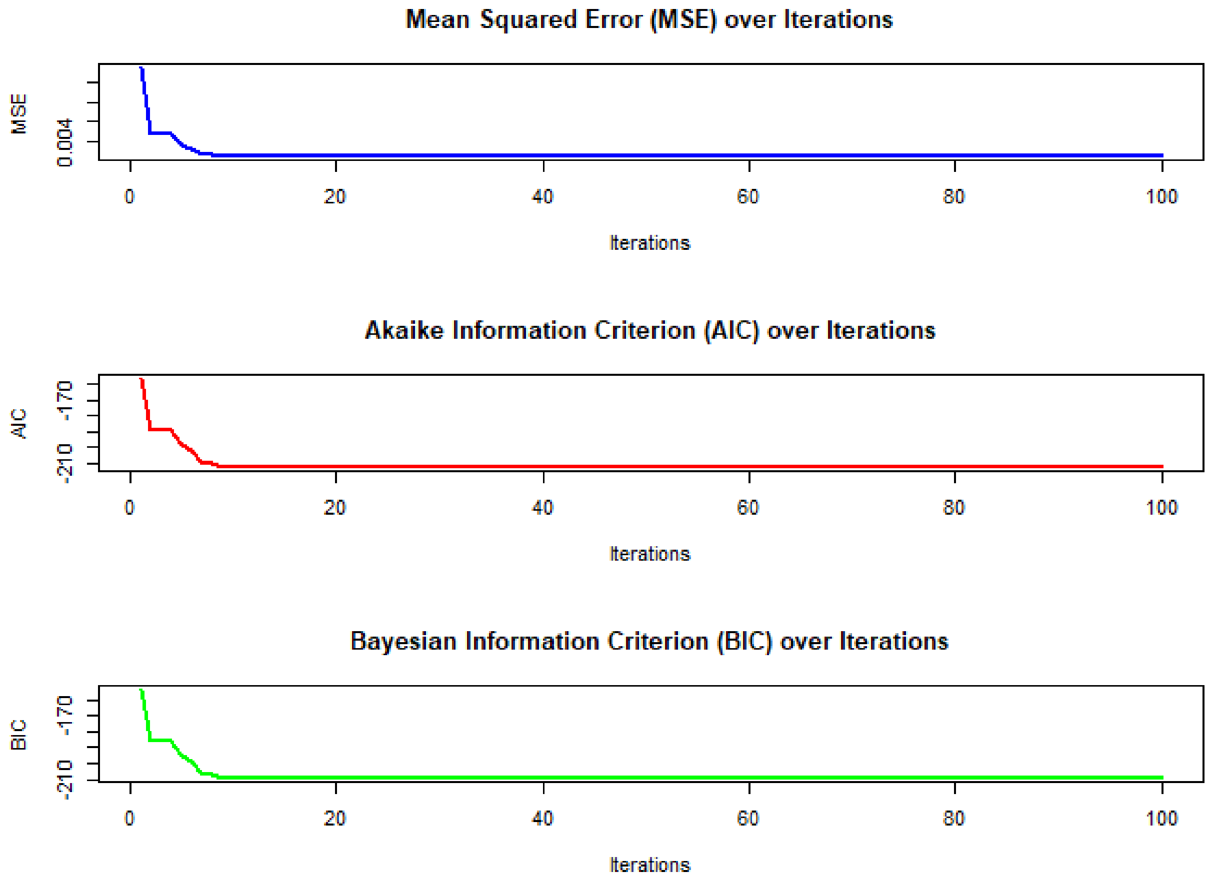

Figure (2)

Sum to up figure contains three graphs depicting the performance metrics of FPA-Exponential trend model over iterations. The first graph shows the Mean Squared Error (MSE), which decreases over iterations, indicating that the model's predictions are becoming more accurate. The second graph displays the Akaike Information Criterion (AIC), which also decreases, suggesting that the model is improving in terms of balancing goodness of fit and complexity. The third graph illustrates the Bayesian Information Criterion (BIC), which similarly decreases, reinforcing that the model is becoming more statistically robust.

Table (2) shows the performance metrics over the iterations of FPA

Iterations	Best		
	MSE	**AIC**	**BIC**
10	0.002456	-212.333	-209.166
20	0.002448	-212.447	-209.28
30	0.002445	-212.489	-209.322
40	0.002445	-212.489	-209.322
50	0.002445	-212.49	-209.323
60	0.002445	-212.49	-209.323
70	0.002445	-212.49	-209.323
80	**0.002442**	**-212.43**	**-209.320**
90	0.002445	-212.49	-209.323
100	0.002445	-212.49	-209.323

The above table represents the results of the FPA-Exponential trend model, which are the Best values of Mean Squared Error (MSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) for different iteration counts, from 10 to 100. Initially, the MSE decreases slightly, with the lowest value occurring at iteration 80 (0.002443), the AIC and BIC values also are minimum at the same iteration. The best optimized values of the estimated values for the model is ($\alpha = 0.4889074$, and $\beta = 0.0189963$)

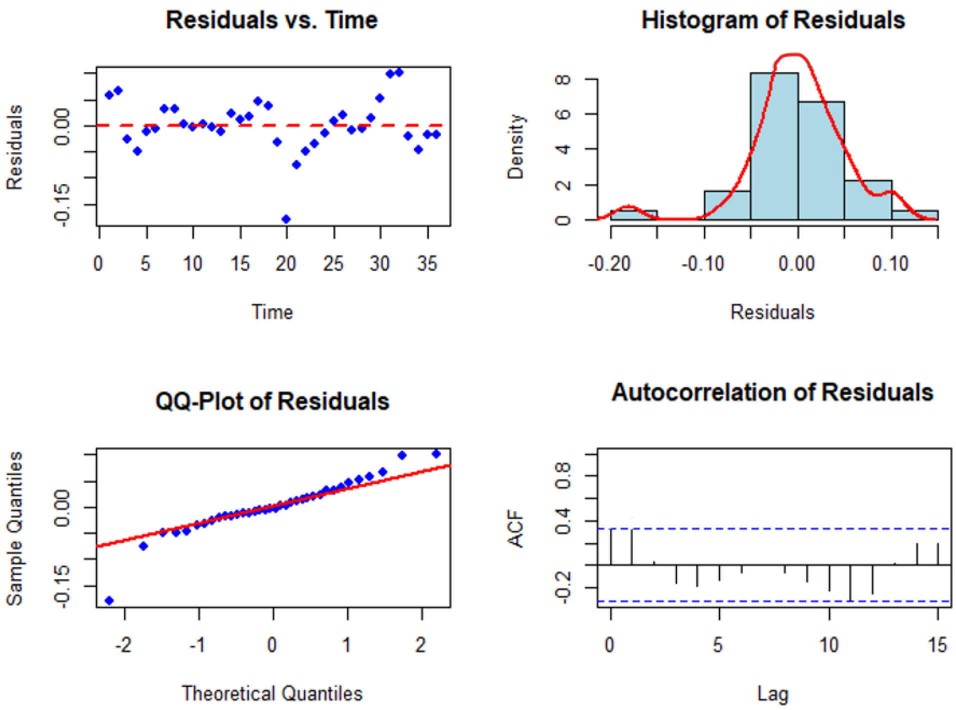

Figure (3) shows the diagnostic graphs of the residuals.

Table (3) represents the diagnostic tests of residuals

Residuals Tests		
Tests	**Statistic**	**p-value**
ADF	-6.68	0.008
BP	0.421	0.516
D-W	1.94	0.708

The results of the diagnostic tests suggest that the model is well-specified in terms of stationarity, autocorrelation, and heteroscedasticity. The Augmented Dickey-Fuller (ADF) test has a test statistic of -6.680816 with a p-value of 0.008, indicating that the time series is stationary at the 5% significance level, as we reject the null hypothesis of a unit root. The Durbin-Watson (DW) test result of 1.9401 with a p-value of 0.708 shows no significant autocorrelation in the residuals, as the p-value is above 0.05 and the DW statistic is close to the optimal value of 2. Finally, the Breusch-Pagan (BP) test yields a test statistic of 0.421 with a p-value of 0.516, suggesting that the residuals do not exhibit heteroscedasticity, as we fail to reject the null hypothesis of homoscedasticity. These findings imply that the model's residuals are stationary, uncorrelated, and homoscedastic, which are desirable properties in a well-fitting model.

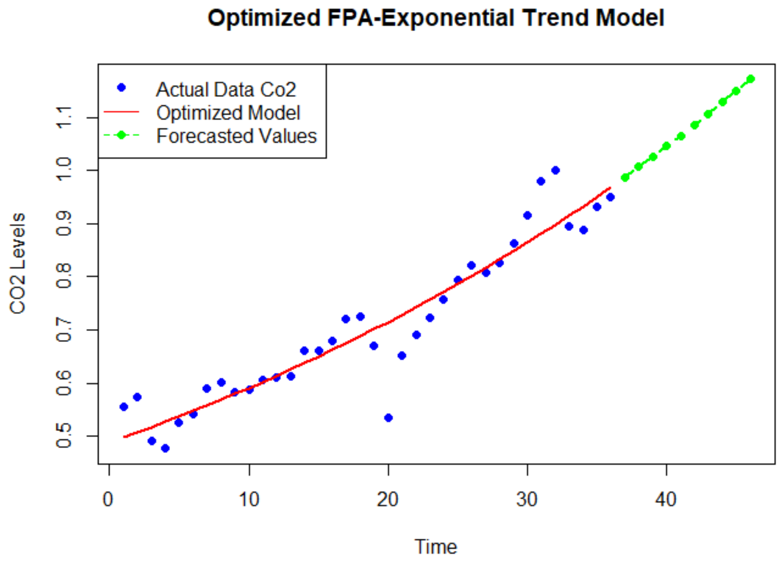

Figure (4) represents the line of the optimized model and the forecasted values.

Table (4) demonstrates the forecasted values.

Years	Forecasted	Confidence Interval 95%	
		Low	High
2024	987361	937361	1012361
2025	1006297	918797	1018797
2026	1025595	975595	1088095
2027	1045264	1007764	1120264
2028	1065310	1052810	1152810
2029	1085740	998240	1173240
2030	1106562	1031562	1194062
2031	1127784	1065284	1177784
2032	1149412	1099412	1174412
2033	1171455	1133955	1246455

This table presents forecasted values along with their corresponding 95% confidence intervals, indicating the range within which the true value is expected to lie with 95% confidence. The first column shows the forecasted values, while the Low and High columns represent the lower and upper bounds of the confidence interval, respectively.

4. Conclusions

The study demonstrates the effectiveness of the FPA-Exponential Trend Model in forecasting CO_2 emissions in Iraq, providing accurate and reliable predictions. By integrating bio-inspired optimization techniques with statistical modeling, the hybrid approach outperforms traditional methods, offering a robust framework for addressing complex environmental challenges. The model's ability to capture exponential growth patterns in CO_2 emissions, coupled with its diagnostic validity, makes it a promising tool for policymakers and urban planners. The findings underscore the importance of adopting advanced forecasting models to mitigate air pollution and its associated health risks in Iraq.

5. Limitations and Future Study

Despite its promising results, the study has limitations, including reliance on historical data, which may not fully account for sudden changes in emission sources or policy interventions. Additionally, the model's performance in regions with highly variable pollution trends requires further validation. Future research could explore integrating additional optimization algorithms, incorporating real-time data, and expanding the model's application to other pollutants and regions. Collaborative efforts with environmental agencies and policymakers could enhance the model's practical implementation, contributing to more effective air quality management strategies.

References

1- Ahmed, B. K., Rahim, S. A., Maaroof, B. B., & Taher, H. A. (2020). Comparison Between ARIMA And Fourier ARIMA Model To Forecast The Demand Of Electricity In Sulaimani Governorate. *Qalaai Zanist Journal*, *5*(3), 908-940.
2- Al-Delaimy, W. K. (2019). Air pollution in the Middle East: Sources, health effects, and mitigation strategies. Environmental Research Letters, 14(7), 074025.
3- Al-Hassan, J. M. (2016). Air pollution in Iraq: Causes, consequences, and solutions. Journal of Environmental Protection, 7(8), 1094-1103.
4- Asraa, A., Rodeen, W., & Tahir, H. (2018). Forecasting the Impact of Waste on Environmental Pollution. *International Journal of Sustainable Development and Science*, *1*(1), 1-12.
5- Aziz, A. A., Shafeeq, B. M., Ahmed, R. A., & Taher, H. A. (2023). Employing Recurrent Neural Networks to Forecast the Dollar Exchange Rate in the Parallel Market of Iraq. *Tikrit Journal of Administrative and Economic Sciences*, *19*(62), 2.
6- Iraqi Ministry of Environment. (2020). National report on the state of the environment in Iraq. Retrieved from http://www.moen.gov.iq
7- Karim, A. J. M., & Ahmed, N. M. (2023). Vector Autoregressive Integrating Moving Average (Varima) Model of COVID-19 Pandemic and Oil Price. *International Journal of Professional Business Review: Int. J. Prof. Bus. Rev.*, *8*(1), 13.
8- Kumar, R., & Singh, S. (2022). Comparative analysis of air pollution forecasting models: The role of FPA-Exponential trend model. Environmental Science and Pollution Research, 29(15), 22045-22058.
9- Li, J., & Chen, Y. (2020). Optimizing CO pollution predictions using FPA-Exponential trend model. Journal of Environmental Management, 260, 110123.
10- Mohammed, A. O., Ismael, K. A., Ahmed, H. G., & Taher, H. A. (2024). Forecasting the Iraqi Exchange Rate for the Years (2024 to 2026) by Using BAT-Exponential Trend Model. *University of Kirkuk Journal For Administrative and Economic Science*, *14*(4).
11- Taher, H. A., Mohammed, S. O., Yadgar, A. S., & Musa, O. R. (2024). Employing the ARDL Model to Predict the GDP of Iraq Through the Years (2005 to 2023). *University of Kirkuk Journal For Administrative and Economic Science*, *14*(4).
12- Taher, H. A., Salih, K. K., & Alwan, A. S. (2024). Forecasting For Silver Closing Price and Modifying Predictions by Using GARCH (1, 1) Wavelet Transformation. *University of Kirkuk Journal For Administrative and Economic Science*, *14*(2).
13- United Nations Environment Programme (UNEP). (2017). Iraq: Post-conflict environmental assessment. Retrieved from https://www.unenvironment.org/resources/report/iraq-post-conflict-environmental-assessment.
14- Wang, L., Zhang, Q., & Liu, Y. (2021). Urban air quality management using FPA-Exponential trend model: A case study of NO2 prediction. Atmospheric Environment, 245, 118023.
15- World Health Organization (WHO). (2018). Ambient (outdoor) air pollution. Retrieved from https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health
16- Zhang, Y., Li, X., & Wang, H. (2019). A hybrid FPA-Exponential trend model for PM2.5 concentration forecasting. Environmental Modelling & Software, 112, 1-10.