Building Prediction Models for the E-Government Development Index (EGDI) in Iraq and KSA: A Comparative ARIMA - Based Approach

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Abstract

The E-Government Development Index (EGDI) represents the performance and reality of e-government. The importance of maintaining and planning for the enhancement of such an index enables the policymakers to understand, process, and develop the right plans and strategies for it. In this paper, the Auto Regressive Integrated Moving Average (ARIMA) has been utilized to build predictive models. The time-series data collected from the UN survey versions for the years 2003, 2005, 2008, 2010, 2012, 2014, 2016, 2018, 2020, 2022, and 2024 for the countries of Iraq and KSA. The necessary data maintenance was implemented, then analyzed, covering the inspection of their temporal behavior. Afterwards, two individual data sets were created for both countries under study, containing 253 months. The optimal values for the ARIMA models were determined by implementing the data transformation, including the autocorrelation function (ACF) and partial autocorrelation function (PACF). 80% of the dataset is used for training, and 20% is used for testing. The data residuals analyzed by ACF, PACF, and the Ljung-Box test were performed for the residuals independence check. Nine metrics were utilized for model evaluation and ruthlessness. By using ARIMA models, the e-government performance (EGDI) has been predicted for the next five years for Iraq and KSA. The ARIMA models for both Iraq and KSA showed high performance, where the RMSE value for the Iraq model was (0.0054) and the MAE value was (0.0031) compared to the RMSE value (0.0481) and the MAE value (0.0093) for the KSA model. The Iraq arima model has better quality of the prediction in absolute terms. On the other hand, the ARIMA model for KSA was better in terms of predicted trends with an accuracy of 98.44% compared to 97.39% for the Iraq model.

Keywords: ARIMA; E-Government; EGDI; Model Building; Time-Series

1. Introduction

The E-Government Development Index (EGDI) is the primary tool for measuring the performance of governments around the world. The United Nations Department of Economic and Social Affairs (UN-DESA) has adopted the index as an Integration of Digital Technologies in Governance. The index measures the extent to which government around the world is integrating digital technologies into the public service delivery [1]. Policymakers rely on the EGDI as a whole because it provides insights into areas that require improvement to enhance digital governance [3].

1.1 E-Government Index Components

E-Government Index Components are a multidimensional index consisting of three main sub-indices; each measures a different aspect of digital governance.

- Online Services Index (OSI) Measures the quality, availability and sophistication of e-government services provided through online platforms [2].

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- Telecommunications Infrastructure Index (TII)Measures the penetration and accessibility of digital infrastructure, including broadband subscriptions and mobile connectivity [3]
- Human Capital Index (HCI) Measures the level of digital literacy and educational levels of a country's population, reflecting its ability to deal with e-government services [5].

Together, these components determine the country's overall e-Government Index score, ranking governments based on their digital readiness. The e-Government Index is important for its value represents the ranking of e-government in the world. The e-Government Index consists of three indicators measure online services, the state of development of telecommunications infrastructure, and human capital with an emphasis on human status in education and other factors. After calculating each of these indicators, they are summed with the EGDI. The EGDI formula can be explained mathematically:

EGDI = (OSI+ TII+ HCI)/3

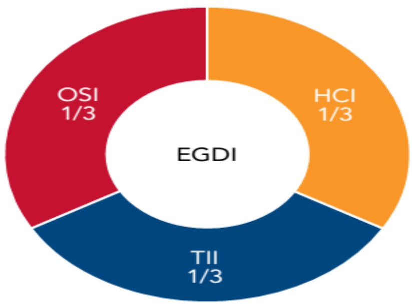

Figure 1. Three Components of the EGDI

The EGDI framework serves multiple purposes such as comparative analysis to recognize differences between countries identify leaders and laggards in digital governance [6] and align sustainable development through promoting inclusive digital governance [7]. This index helps governments formulate data-driven strategies to enhance e-government services [8]. EGDI scores have shown significant growth, reflecting the increasing global digital adoption. In 2018, the United Nations e-Government Survey showed that "EGDI has increased in many countries, very high" [9]. In 2020, the United Nations e-Government Survey showed that many developing countries continue to struggle with digital infrastructure [10]. In 2024, AI has been integrated into e-government services, improving efficiency and data analysis [1]. EGDI faces challenges hindering the progress of digital governance infrastructure shortcomings. Many developing countries lack adequate ICT infrastructure to support robust e-government platforms [3]. Digital Literacy Gaps is a large portion of the world's population is digitally illiterate, which limits the adoption of e-government services [5]. Moreover, cyber-security threats have led to growing concerns about data privacy and cyber-attacks [6]. EGDI remains an essential benchmarking tool for evaluating governmental digital transformation. While many nations have made remarkable progress, addressing infrastructural deficits, enhancing digital literacy, and bolstering cyber security remain critical challenges. Future advancements in AI and emerging technologies are expected to further refine EGDI measurements and accelerate the global shift toward digital governance [1].

1.2 ARIMA Model

Time series algorithms are indispensable for evaluating the future performance of any situation. They consist of time-indexed data to predict future performance based on past historical values. ARIMA models are commonly used in future forecasting and have proven their efficiency in this field. In the seventies, Box and Jenkins laid the scientific foundations for applying the ARIMA model (Auto Regressive Integrated Moving Average) and it was considered the cornerstone of time analysis and forecasting [12] [13]. The model is based on three main components: autoregressive (AR), integration (I), and moving averages (MA). ARIMA models are used in various fields such as economics, meteorology, finance, and engineering. The ARIMA model consists of three main components:

Auto Regressive (AR) Model Definition

(AR) Auto Regressive: The autoregressive part that depends on the past values of the time series. (I) Integrated: determines the number of differences required to make the time series stationary. An AR process is expressed as:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + e_t \ldots\ldots (1)$$

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Hence, (ϕ_1, ϕ_2…, ϕ_p) are the autoregressive coefficients, and e_t is a white noise term (independent, identically distributed random variable).

Moving Average (MA) Model Definition

(MA) Moving Average reflects the relationship between past values and random errors. An MA(q) model represents a time series as a linear combination of past white noise terms:

$$X_t = \mu_1 + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ldots + \theta_q e_{t-q} \ldots\ldots (2)$$

Hence, e_t: White noise (independent and identically distributed with zero mean and constant variance); θ_1, θ_2…, θ_q: Moving average coefficients.

Autoregressive integrated moving average process

The autoregressive integrated moving average process of orders (ARIMA(p,d,q)) is a process, Xt, whose differences satisfy an ARMA(p,q) model (that is, a stationary model) where d is a non-negative integer. An ARIMA (p, d, q) process X_t is defined by the equation: [12]

$$\theta(B)\Delta^d X_t = \theta(B) e_t \ldots\ldots (3)$$

Where θ(B) is an autoregressive polynomial of order p, θ(B) is a moving-average polynomial of order q, φ(B) and θ(B) have no common roots and e_t is a white noise sequence. Note that the differences process $\Delta^d X_t$ satisfies an ARMA (p, q) model.

The ARIMA model is represented in the form (p,d,q), where p is the number of time periods in the autoregressive; d is the number of differences required to make the series stationary; q is the number of time periods used in the moving averages. Building an ARIMA model requires several basic steps namely:

1. *Testing for stationarity*: using the extended Dickey-Fuller test (ADF) [14].
2. *Determining the parameters of (p, d, q)*: using the autocorrelation plot (ACF) and partial autocorrelation (PACF) [15].
3. *Estimating the model*: using methods such as maximum likelihood estimation (MLE) [16].
4. *Evaluation of the model*: using measures such as AIC, BIC, RMSE [17].
5. *Predicting the future*: using ARIMA equations and implementing them using programming languages such as Python (statsmodels library) (forecast library) [18] [19].

The ARIMA model has wide applications including: Economic forecasting: analysis of GDP, inflation rates [20] [21]; financial market analysis: forecasting stock and currency prices [22] [23]; meteorology: weather and precipitation forecasts [24] [25]; energy and transportation; analysis of electricity and fuel demand [26] [27]. Based on the success of the ARIMA model, models relied on it that have been developed, such as artificial neural networks (ANN) and seasonal and multi-decomposition models (SARIMA) [28] [23]. Hybrid ARIMA-ANN models have enhanced the accuracy of forecasts in some cases [29]. The ARIMA model is an effective technique for time series analysis and forecasting. In order to attain desired results, each dataset must be treated with special treatments from stability tests, residual analysis and selection of appropriate parameters.

2. Methodology

The e-government indicators EGDI, HCI, OSI and TII are used to measure the performance and reality of e-government. Therefore, it is important that these indicators are easy to be understood and interpreted their performance behavior. The data were collected from two countries of Iraq and KSA through the UN survey versions for the years 2003, 2005, 2008, 2010, 2012, 2014, 2016, 2018, 2020, 2022 and 2024. Finally, two individual datasets were created for each of the countries under study. The main purpose is to reveal the performance expectations of e-government indicators according to periods, each dataset contained 253 instants. This research aims to build an ARIMA model to predict the e-government index (EGDI) data for Iraq and the KSA using Python language, as the time series-modelling methodology is one of the most important tools in analysing e-government data. The process starts with installing the basic libraries (such as pandas, stats models, and pmdarima) and configuring the necessary work environment, then the dataset is loaded from the Excel file and the required columns are checked (for example "year" and "EGDI"). The "year" column is then converted to date time format and used as an index for the data with a monthly frequency set to ensure the regularity of the time series.

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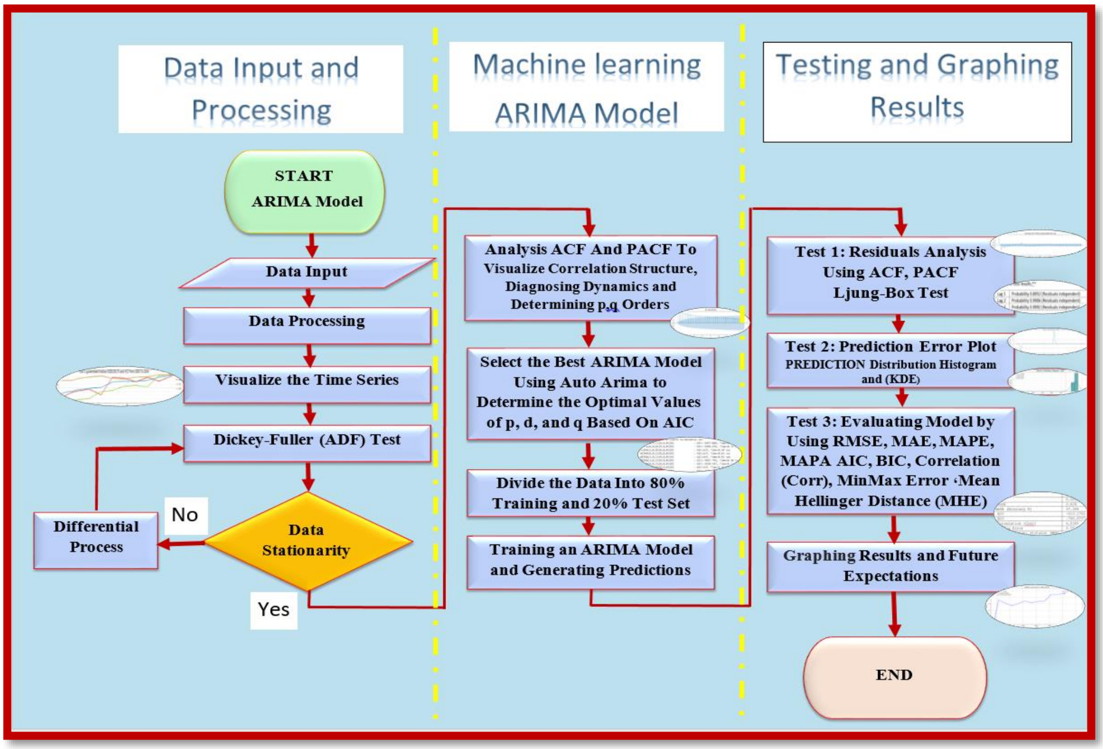

Figure 2. Methodology Flow Chart for Arima Model

The flow chart illustrates the construction of the ARIMA model. It begins by collecting data for the period 2003 to 2024. In first step, the data is cleaned by dealing with missing values using methods such as interpolating the mean, and removing outliers that may affect the accuracy of the model. Next, the data is tested for stationarity using the Advection Dickey-Fuller (ADF) test, which measures whether the time series is stationary, i.e. the mean and variance are constant over time, or non-stationary. If the data is non-stationary, a differentiation process is applied to convert it to stationary data by calculating the difference between successive values, and the ADF test is then repeated to check for stationarity. After the data is confirmed to be stationary, the autocorrelation function (ACF) and partial autocorrelation function (PACF) are analyzed to determine the initial values of the coefficients p and q. In second step, the ACF and PACF plots are examined to see how previous periods have influenced the current values. For example, if there is a slope in the ACF at a certain lag, it may indicate a moving average process, while if there is a strong effect in the PACF; it may indicate an AR (Autoregressive) process. The Auto ARIMA algorithm used to determine the optimal values for the model parameters p, d, q based on the Akaike Information Criterion (AIC), to select the optimal model from a set of different models based on the lowest AIC value. Once we found the settings to use for our analysis models parameters and split the data into 80 percent, for training and 20 percent for testing purposes. After training, the model residual analysis was carried out using ACF, PACf and Ljun Box test to ensure that residuals were independent and random. That confirmed that our model was a fit, for the time series data. The system computes the prediction error. Generates a plot to compare the values with the predicted ones to assess accuracy and identify any potential pattern errors present. Various statistical metrics are employed to assess model performance such, as root mean square error (RMSE) which gauges the extent to which predicted values diverge from values; mean error (MAe) which calculates the average variance between predicted and actual values; and mean absolute relative error (MAPE) which quantifies the error percentage in relation, to the true values. Additionally, assessing the models quality includes computing the correlation coefficient (Correlation). The Min-Max Error is also calculated to determine the error range, and the Mean Hellinger Distance (MHE) is calculated to assess the similarity between the actual and predicted distributions. After model performance is analyzed, the results and future forecasts are plotted via a graph showing historical values and future forecasts, with the last true value and the last predicted value indicated to illustrate the accuracy of the prediction.

2.1 Data Reprocessing

Box plot test analysis is a graphical tool used to test the statistical distribution of a set of data, and helps detect outliers and identify differences between groups. [14]

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2.1.1.1 IRAQ Box Plot Test

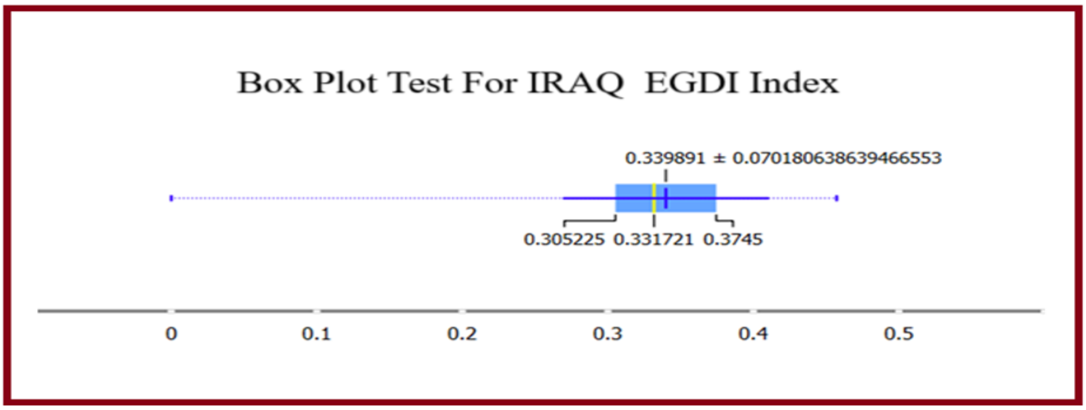

Figure 3. Box Plot Test for IRAQ EGDI Index

Box plot test results for EGDI Index for IRAQ show that the median value is (0.331721) which means that half of the values are below this number and the other half are above it. The inter quartile range (IQR) value is 0.305225 for the first quartile (Q1) and the value is 0.3745 for the third quartile (Q3). The inter quartile range is IQR = Q3 − Q1 = 0.3745 − 0.305225 = 0.069275. The value (± 0.07018063863946553) for the standard deviation shows the level of dispersion around the mean value. The horizontal boundaries of the data extend to the values of the minimum is 0.305225 and the maximum is 0.3745. There are no outliers, which is essential in the dataset and important for its performance. There are no points outside the expected limits, which indicates the stability of the data. By evaluating the quality of the Box Plot, the test is successful for the following reasons:

- The distribution of the data appears balanced around the median and the absence of outliers is a positive indicator.
- The standard deviation is relatively small, which indicates that the data is not dispersed.
- The Box Plot test is successful and shows a stable and reliable distribution of the data.
- The data is suitable for statistical analysis and forecasting if it represents part of a time series or a standard data set.

2.1.1.2 KSA Box Plot Test

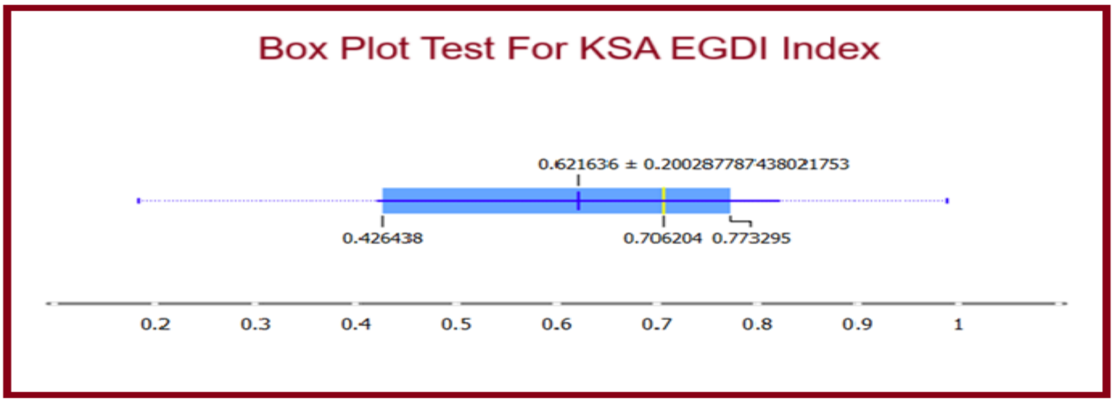

Figure 4. Box Plot Test for KSA EGDI Index

Figure 4 represents the EGDI index Box Plot test for the dataset of the Kingdom of KSA(KSA). Through the basic values shown in the figure, we notice that the dark blue line represents the median, which is 0. 0.706204. Half of the data is less than median and the other half is higher than it. The value of the first quartile (Q1) is 0.426438. The value of the third quartile (Q3) is 0.706204. The inter quartile range (IQR) is: $IQR = Q3 - Q1$ = 0.773295 − 0.426438 = 0.346857. The standard deviation is, ±0.200287787438021753. The dispersion is at a moderate level of the minimum value is 0.426438 and the maximum value is 0.773295. There are no outliers as there are no obvious outliers outside the normal limits. The box plot test is successful based on the following:

- The distribution of the data is balanced around the median, with a slight or medium dispersion.
- The values are distributed within a reasonable and acceptable range.

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- The absence of outliers, as there are no outliers, which enhances the quality of the data and indicates its stability.
- The inter quartile range (IQR) is relatively wide compared to other data, which may reflect a slight variation in the data but does not significantly affect the analysis.

In short, the data is ready for analysis and represents stability and balance. The graph reflects the success of the box plot test to represent the distribution of values without obvious anomalies. This data can be used for statistical analysis or predictive models easily.

2.2 Data visualization

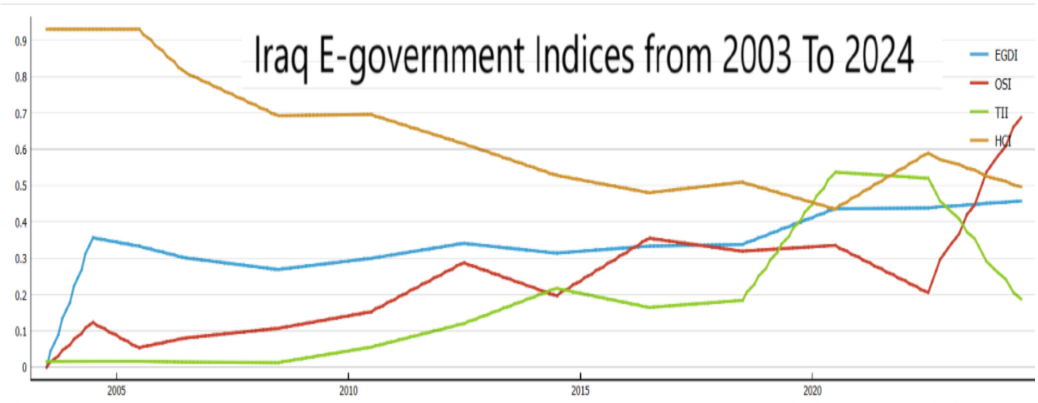

Figure 5. IRAQ e-government indices from 2003-2024

The figure above shows the IRAQ e-government indicators over the years, where HCI (Human Capital) shows a continuous decline, while EGDI (E-Government Development Index) gradually increases until it stabilizes. TII (Telecommunications Infrastructure) and OSI (Online e-Services) show fluctuating growth, but OSI has seen a significant jump in recent years, reflecting the expansion of digital services. The relationship between the indicators shows that the success of e-government depends on the development of digital infrastructure and services, while the decline in HCI may indicate the need to improve digital skills. Therefore, digital education should be promoted, infrastructure investment should be made, and a safe and efficient user experience for e-services should be ensured.

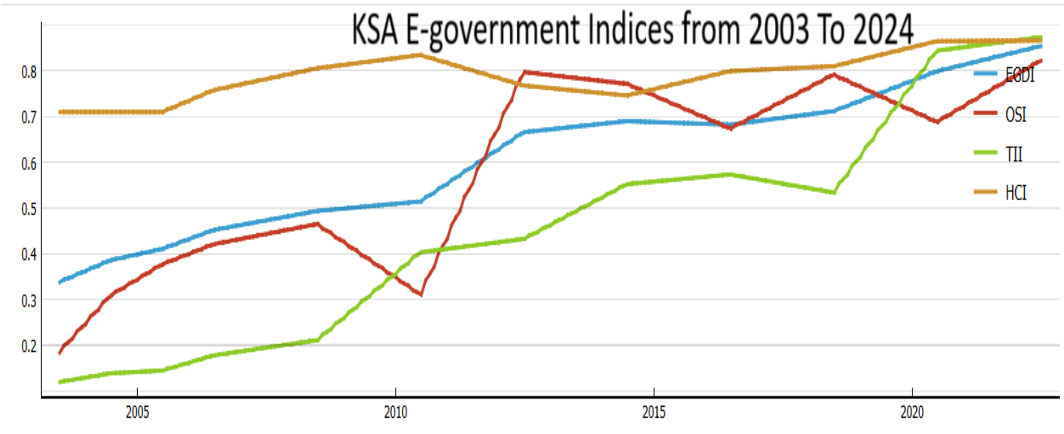

Figure 6. KSA e-government indices from 2003-2024

The data indicates a significant development in e-government indicators in KSA from 2003 to 2024, with EGDI witnessing steady growth to approach 1.0. OSI recorded significant leaps after 2008, while TII showed significant improvement after 2018. HCI (human capital) remained at high levels with gradual improvement, reflecting efforts to develop digital education.

2.3 Augmented Dickey-Fuller (ADF) Test Results for ARIMA Model

It is a statistical test used to test the presence of a unit root in a time series, to evaluate whether the series is stable around a constant mean or not, i.e. contains a unit root. It is written as follows: $\Delta y_t = \alpha + \gamma y_{t-1} + \varepsilon_t$ [14].

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Table 1: IRAQ Augmented Dickey-Fuller (ADF) Test

Augmented Dickey-Fuller (ADF) Test Results for IRAQ ARIMA Model								
Test Condition	ADF Statistic	p-value	Lags Used	Observations Used	Critical Values (1%)	Critical Values (5%)	Critical Values (10%)	Stationarity
Before Differencing	-1.6805	0.4412	1	251	-3.4567	-2.8731	-2.5729	Non-Stationary
After Differencing	-24.899	0	0	251	-3.4567	-2.8731	-2.5729	Stationary

2.3.1 IRAQ ADF Test Results for ARIMA Model

The initial test for IRAQ dataset before differencing resulted in an ADF statistic of -1.6805 with a p-value of 0.4412, which is greater than 0.05, indicating non-stationarity. After applying first-order differencing, the ADF statistic improved significantly to -24.8990, and the p-value dropped to 0.0000, which is less than 0.05, confirming that the time series is now stationary. The null hypothesis (presence of unit root) was rejected after differencing, making the data suitable for ARIMA modeling. Building Predictive Model by ARIMA.

Table 2: KSA Augmented Dickey-Fuller (ADF) Test

Augmented Dickey-Fuller (ADF) Test Results for KSA ARIMA Model								
Test Condition	ADF Statistic	p-value	Lags Used	Observations Used	Critical Values (1%)	Critical Values (5%)	Critical Values (10%)	Stationarity
Before Differencing	-2.4152	0.1375	0	251	-3.4567	-2.8731	-2.5729	Non-Stationary
After Differencing	-15.748	0	0	250	-3.4568	-2.8732	-2.573	Stationary

2.3.2 KSA ADF Test Results for ARIMA Model

The initial test for KSA dataset before differencing resulted in an ADF statistic of -2.4152 and a p-value of 0.1375, which is greater than 0.05. Since we failed to reject the null hypothesis, differencing was applied. After the first-order differencing (d=1), the ADF Statistic dropped to -15.7481, and the p-value became 0.0000, which is significantly less than 0.05. This confirms that the series became stationary. Given these results, an ARIMA(p,1,q) model.

3. Machine Learning ARIMA Model Bullding

3.1 ACF and PACF TEST for ARIMA Model

The autocorrelation and partial correlation functions in ARIMA models provide us with visual tools that facilitate understanding the correlation structure of the time series, which helps in diagnosing its dynamic properties. In addition to determining the order of the autoregressive components, (AR) and the moving average (MA). ACF calculates the correlation coefficients between the time series and its values at multiple lags, while PACF evaluates the direct relationship between the series and its lagged values at a given lag after removing the effect of shorter lags.

3.1.1 IRAQ and KSA Autocorrelation Function (ACF) Test

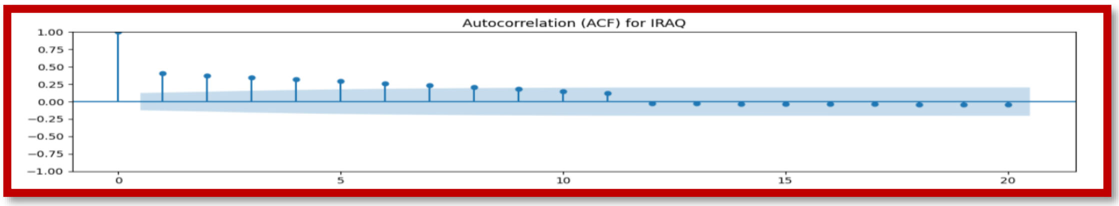

Figure 7. IRAQ Autocorrelation Function (ACF) Test

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Based on the figure 7, it is clear that the autocorrelation value at the first lag (Lag = 0) is$r$ = 1.0, which reflects the complete correlation between the values and themselves, which is normal and expected. In addition, the values at other lags (Lags from 1 to 40) gradually decrease as the lag increases, indicating a strong correlation between the current values and the previous values. On the other hand, the graph shows the shaded confidence region that represents the expected limits of random correlation. It can be seen that many of the autocorrelation values fall outside these limits, indicating that the series is not just white noise, but rather contains a strong temporal pattern. In addition, the slow decrease in autocorrelation values reflects the presence of a trend or non-stationarity in the time series. For statistical analysis, this behavior indicates that the time series is not stationary.

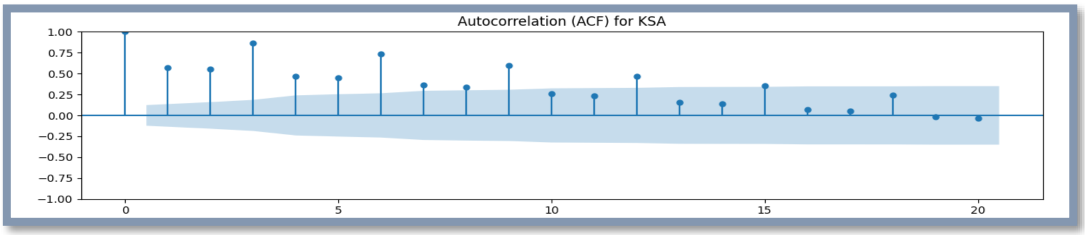

Figure 8. KSA Autocorrelation Function (ACF) Test

The autocorrelation figure 8 for the KSA dataset shows that the autocorrelation at the first lag is high and then gradually decreases as the lag increases, indicating a strong temporal relationship between the current values and the past values. The shaded area in the graph represents the confidence limits for the statistical confidence level. Besides, it is noted that some values fall outside these limits, indicating that the time series is not white noise but rather has a clear temporal pattern. The slow decline in values indicates the possibility of a trend or non-stationarity in the time series, which calls for additional tests to verify its stationarity. This can be confirmed using the extended Dickey-Fuller test to determine whether the series needs a differentiation process to achieve stability. Since there is autocorrelation in the early periods, the ARIMA model is likely to be suitable for analyzing and forecasting this time series, with the need to determine the optimal values for the model coefficients by analyzing the partial autocorrelation function.

3.1.2 IRAQ and KSA Partial Autocorrelation Function (PACF) Test for ARIMA Model

The partial autocorrelation function (PACF) reflects the extent to which past values in a time series influence current values after removing the influence of intermediate values between them, which helps in determining the optimal order of AR models:

The partial autocorrelation function (PACF) graph is a tool for analysing time series by assessing how well current values correlate with past values while removing the effects of intermediate lags. According to the graph, it can be seen that the partial correlation value at the first lag (Lag = 1) is very high, at around. r=1.0r=1.0, indicating a strong influence of the first value on the time series. At subsequent lags, the partial correlation values drop significantly, with most of them returning to within the shaded confidence limits (blue area). This suggests that the significant influences on current values stop at the first or second lag, supporting the hypothesis that the time series may follow a model with a first- or second-order autoregressive (AR) component. Based on this behavior, it appears that values outside the confidence limits at early lags indicate that there is a strong pattern in the series, while values within the confidence limits at higher lags indicate that there is no additional influence from these lags. The Akaike Information Criterion (AIC) test will be used to select the most appropriate predictive model. Hence, to determine its suitability for the time series. We will perform additional analysis of the residuals to ensure that the proposed model is able to explain all the temporal patterns in the data.

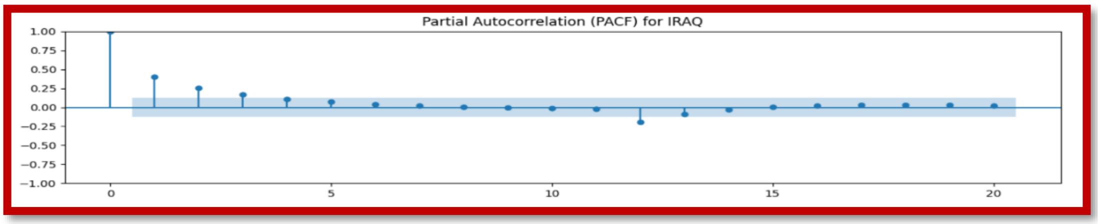

Figure 9. IRAQ partial autocorrelation function (PACF)Test

The graph in figure 9 shows that the value at the first lag is high, indicating a strong influence of past observations on current values. There are also positive values at certain lags, but most of the values after the third lag are within the confidence limits, indicating that the influence of past values quickly fades away after several lags. The

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presence of prominent values at the first lags indicates the suitability of a low-order AR model such as AR (2) or AR (3), as the rapid fading of partial correlation after these lags indicates that the influence of past values becomes weak. If the goal is to build an ARIMA model, the PACF analysis helps in determining the optimal p. p value for the autoregressive component, which can be chosen based on the lags at which the PACF function values appear outside the confidence limits. Based on this analysis, a time series model can be adopted that takes into account only the first lags, ensuring the stability of the time series through additional tests, and selecting the final model based on its forecasting performance and residual error analysis.

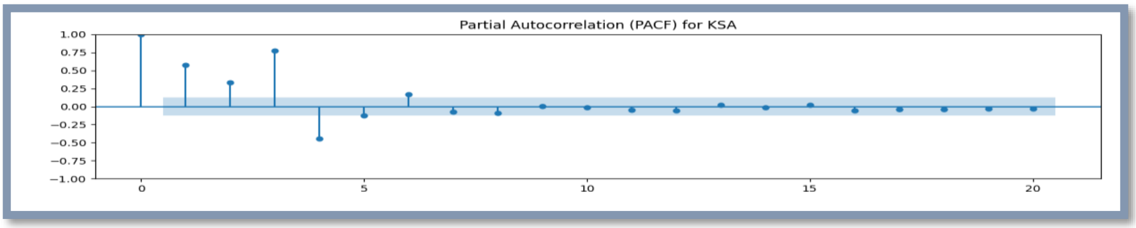

Figure 10. KSA partial autocorrelation function (PACF) Test

3.1.3 Training and Validation for ARIMA

Arima model split the data series into 80% training data and 20% testing and validation data. The order for Iraq model has been taken as (1,0,1), while The order for KSA model as (3,1,2). The ARIMA model was trained using a "rolling forecast" approach; where the data set is updated gradually after each prediction to ensure a dynamic simulation of the series. The predictions are then restored to their original range. After applying differentiation, the original values are restored and using cumulative aggregation

4. Testing and Graphing Results

We relied on three main tests to verify our work to build the ARIMA model: Test 1: Residuals Analysis, Test 2: Prediction Error Plot and Test 3: Evaluating Model by Using RMSE, MAE, MAPE, MAPA AIC, BIC, Correlation (Corr), MinMax Error, Mean Hellinger Distance (MHE). These stages demonstrate the integration between visual and statistical analysis to evaluate the model, ensuring that we provide an ARIMA model that performs well in predicting time series.

4.1 TEST 1: Residuals Analysis by ACF, PACF and Ljung-Box

The model residuals calculate the difference between the actual and predicted values to reveal the presence of a temporal correlation the white noise and the fit of the model. The Ljung–Box test checks the independence of the residuals and whether the hypothesis of no correlation is rejected if the probability values are low, indicating the presence of untreated residual effects in the model.

4.1.1 Residuals Analysis by ACF and PACF

The autocorrelation function (ACF) plot of the residuals shows that the vast majority of the correlation values fall within the confidence limits.

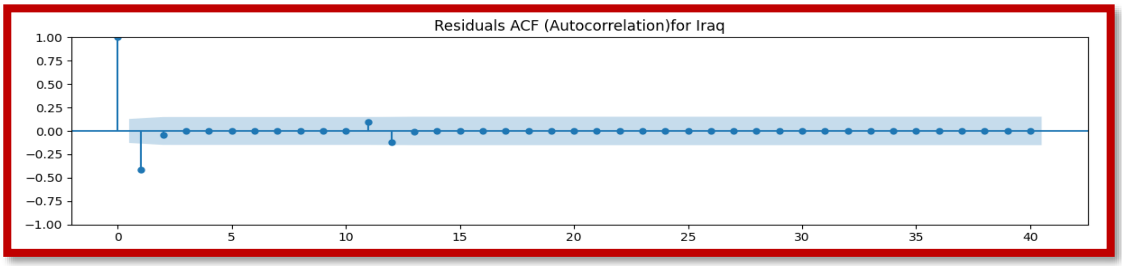

Figure 11. IRAQ Residuals Autocorrelation Function (ACF) Test

Indicating that the residuals are random and do not contain temporal patterns or correlations. This can be interpreted as an indication that the estimated model has successfully explained the temporal patterns in the original data. A few values are also observed outside the confidence limits at the first and second lags, but they do not form a clear pattern, suggesting that these correlations may be due to chance rather than an unexplained temporal pattern. This supports the hypothesis that the residuals represent white noise, meaning that the model has captured the dynamics of the time series well.

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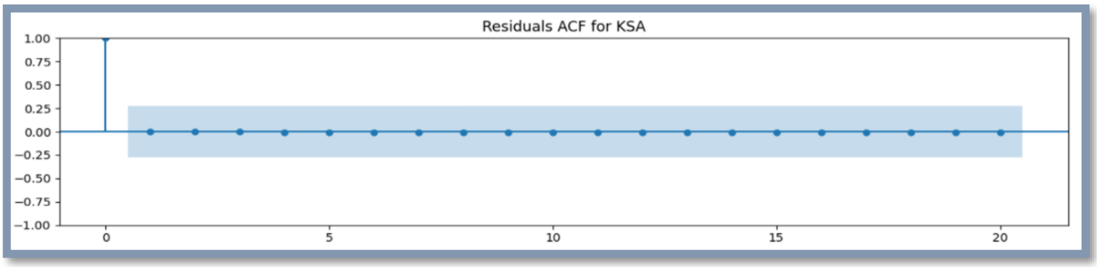

Figure 12. KSA Residuals Autocorrelation Function (ACF) Test

Examining the ACF plot of the residuals, we find that all values fall within the confidence limits shaded in blue, indicating that the residuals do not contain significant autocorrelation. This means that the model has successfully captured the temporal relationships between the data, and that the predictions are not biased by unaccounted time correlations.

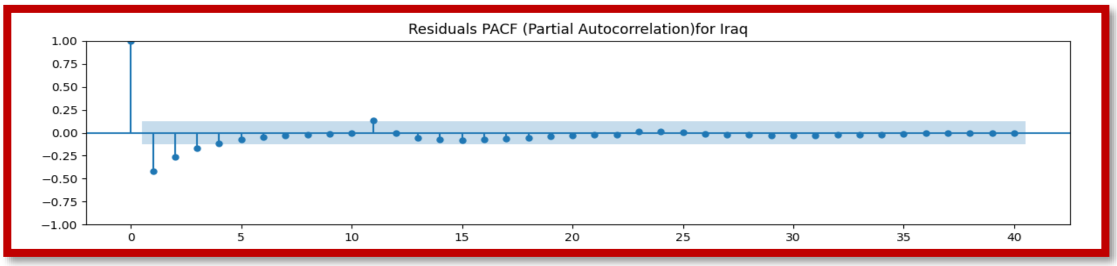

Figure 13. IRAQ Residuals Partial Autocorrelation Function (PACF) Test

The partial autocorrelation function (PACF) plot of the residuals shows that the vast majority of values fall within the confidence limits, indicating that the model has successfully captured the temporal patterns of the original series. This means that the resulting residuals are white noise and do not contain significant temporal correlations. A high value at the first lag may be due to an initial effect and does not necessarily indicate an unexplained long-run correlation. Other values, which fall within the confidence limits, indicate that there is no partial temporal correlation between the residuals over different lags. These results indicate that the model is suitable for representing the time series under study, as the residuals exhibit random properties and are consistent with the assumptions of statistical models.

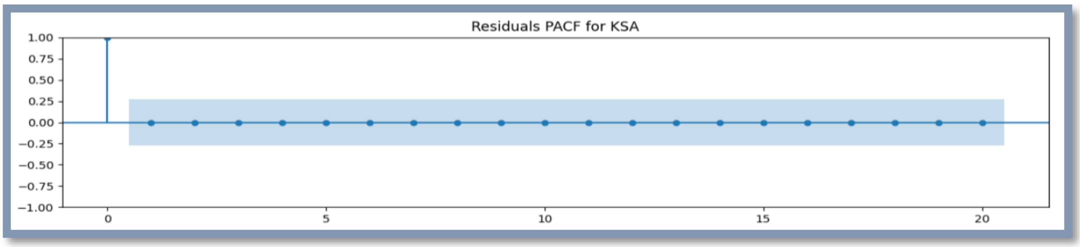

Figure 14. KSA Residuals Partial Autocorrelation Function (PACF) Test

We can say that ARIMA Model is Efficiency Based on the previous analysis; the model captured all the temporal patterns in the data. Because there is no significant autocorrelation in the ACF/PACF, the residuals are like "white noise". The absence of a clear pattern in the residuals indicates that the forecasts are unbiased, which is an indication that the model is appropriate for the time series used. Since the values are within the confidence limits, there is no evidence that additional variables need to be added or the model improved. The absence of outliers or recurring trends in the residuals means that the model does not leave any information untapped, which support the reliability of the predictions. Analysis of the residuals using ACF and PACF, it is clear that the ARIMA model used in this research appears to be appropriate for the data due to the absence of autocorrelation in the residuals. This result is a strong indication that the model is able to produce relatively accurate forecasts without bias.

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4.1.2 Ljung-Box test for ARIMA Model

Table 3: IRAQ Ljung-Box TEST

IRAQ Ljung-Box Test Results			
Lag 1	Probability 0.8952 (Residuals independent)	Lag 11	Probability 1.0000 (Residuals are independent)
Lag 2	Probability 0.9906 (Residuals independent)	Lag 12	Probability 1.0000 (Residuals are independent)
Lag 3	Probability 0.9992 (Residuals independent)	Lag 13	Probability 1.0000 (Residuals are independent)
Lag 4	Probability 0.9999 (Residuals independent)	Lag 14	Probability 1.0000 (Residuals are independent)
Lag 5	Probability 1.0000 (Residuals independent)	Lag 15	Probability 1.0000 (Residuals are independent)
Lag 6	Probability 1.0000 (Residuals independent)	Lag 16	Probability 1.0000 (Residuals are independent)
Lag 7	Probability 1.0000 (Residuals independent)	Lag 17	Probability 1.0000 (Residuals are independent)
Lag 8	Probability 1.0000 (Residuals independent)	Lag 18	Probability 1.0000 (Residuals are independent)
Lag 9	Probability 1.0000 (Residuals independent)	Lag 19	Probability 1.0000 (Residuals are independent)
Lag 10	Probability 1.0000 (Residuals are independent)	Lag 20	Probability 1.0000 (residuals are independent)

The results of table 3 Ljung-Box test indicate that the residuals are independent at all lags tested. At the first lag, the p-value was 0.8952, indicating that there is no temporal correlation in the residuals. As the lags increase, the values increase steadily until they reach 1.0000 at the 15th lag and beyond, meaning that the residuals show no significant autocorrelation. All p-values are very high, indicating that the residuals have no temporal correlation, and therefore the ARIMA model used is appropriate, producing random and uncorrelated residuals.

Table 4: KSA Ljung-Box TEST

KSA Ljung-Box Test Results			
Lag 1	Probability 0.9884 (Residuals are independent)	Lag 11	Probability 1.0000 (Residuals are independent)
Lag 2	Probability 0.9998 (Residuals are independent)	Lag 12	Probability 1.0000 (Residuals are independent)
Lag 3	Probability 1.0000 (Residuals are independent)	Lag 13	Probability 1.0000 (Residuals are independent)
Lag 4	Probability 1.0000 (Residuals are independent)	Lag 14	Probability 1.0000 (Residuals are independent)
Lag 5	Probability 1.0000 (Residuals are independent)	Lag 15	Probability 1.0000 (Residuals are independent)
Lag 6	Probability 1.0000 (Residuals are independent)	Lag 16	Probability 1.0000 (Residuals are independent)
Lag 7	Probability 1.0000 (Residuals are independent)	Lag 17	Probability 1.0000 (Residuals are independent)
Lag 8	Probability 1.0000 (Residuals are independent)	Lag 18	Probability 1.0000 (Residuals are independent)
Lag 9	Probability 1.0000 (Residuals are independent)	Lag 19	Probability 1.0000 (Residuals are independent)
Lag 10	Probability 1.0000 (Residuals are independent)	Lag 20	Probability 1.0000 (residuals are independent)

Based on table 4 Ljung-Box test on the residuals of the ARIMA model to check whether they are independent or not, by measuring the autocorrelation of the residuals across a range of times. The probability values show a clear increase, which means that the residuals are independent and confirms the efficiency of the model. All the probability values resulting from the test range between 0.9884 and 1.0000, which is greater than the traditional significance level of 0.05, which means that the residuals do not show any autocorrelation among themselves during the time periods tested. The ARIMA model captured all the important time patterns in the data and does

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not have the problem of autocorrelation, which reflects its accuracy and efficiency in representing the original data. Since the residuals do not have any autocorrelation, the errors do not follow a specific pattern, and there is no bias in the model. The model does not need further improvement or parameter adjustment, and can be used with high confidence to make future predictions. The Ljung-Box test shows the independence of the residuals and that the ARIMA model is suitable and reliable for future predictions.

4.2 TEST 2: Prediction Error Plot, Distribution Histogram and (KDE)

A prediction error plot is an analytical tool used to evaluate the performance of a forecasting model by displaying the differences between actual and predicted values over time. Errors are represented on the vertical axis (Actual - Predicted) while time intervals are represented on the horizontal axis (Time Steps). Beside, Prediction Error Distribution Analysis using a Histogram and Kernel Density Estimation (KDE) used to evaluate how well a forecasting model aligns with actual values by analysing mean error, standard deviation of Errors, probability distribution and (KDE) - Kernel Density Estimation:

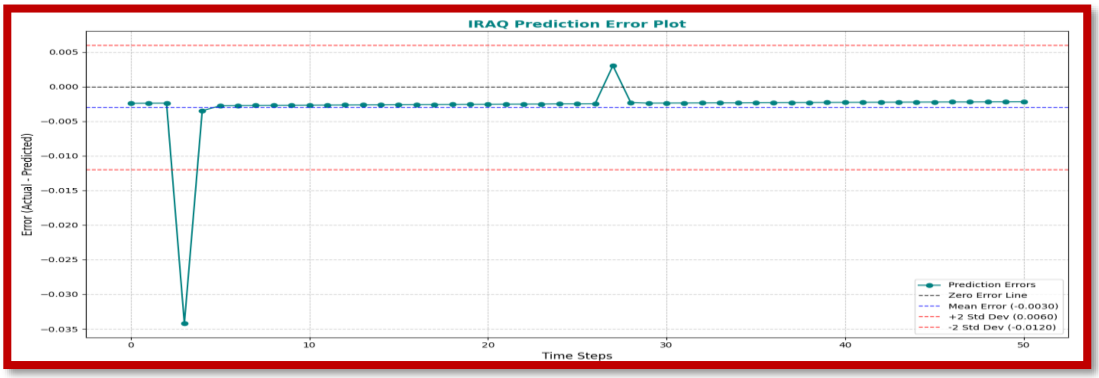

Figure 15. IRAQ prediction error plot

The dashed blue line Mean Error = -0.0030 is very low, indicating that the model is neither positively nor negatively biased. The dashed red lines (+2 Std Dev = 0.0060, -2 Std Dev = -0.0120) represent the second standard deviation range of errors. Most errors are very small and fall within ±2 standard deviations, indicating that the model is stable. The mean error is very close to zero (-0.0030), indicating that there is no obvious bias in the forecasts. On the other hand, the upper value of the standard deviation is low (0.0060), indicating that the model produces consistent results. The forecast error plot shows the differences between the actual and predicted values of the ARIMA model for Iraq. The blue dashed line Mean Error = -0.0030 is a very low mean error, indicating that the model is neither positively nor negatively biased. The red dashed lines (+2 Std Dev = 0.0060, -2 Std Dev = -0.0120) represent the second standard deviation range of errors. Most of the errors are very small and fall within ±2 standard deviations, indicating that the model is stable. The mean error is very close to zero (-0.0030), indicating that there is no obvious bias in the forecasts. On the other hand, the upper value of the standard deviation is low (0.0060), indicating that the model provides consistent results. There are two extreme values, the, which indicates a slight deviation at some points, as most of the errors remain within a very narrow range, making it suitable for future forecasts of the EGDI in Iraq.

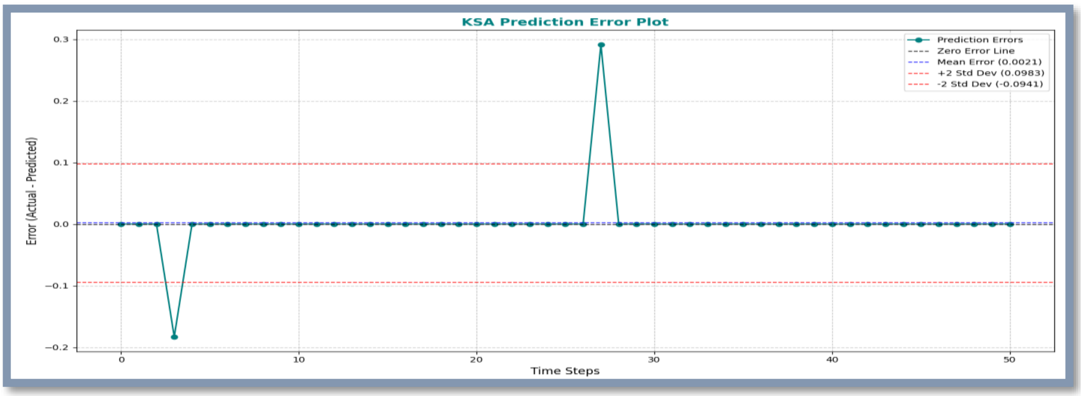

Figure 16. KSA prediction error plot

The Figure 16 shows the EGDI for KSA prediction error, most of the errors are very small and centered around zero with a mean error of 0.0021. Indicating no obvious bias in the forecasts, most of the values are within ±2

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standard deviations reflecting the stability of the forecasts, but there are two extreme values at the beginning and end of the time period which may indicate sudden changes or an atypical pattern in the data, the standard deviation range (+0.0983, -0.0941) indicates that the errors are within an acceptable range, the model performs very efficiently with good stability. The ARIMA model is considered successful, as the forecasts are accurate most of the time, the errors are small and fluctuate around zero, with no obvious bias towards positive or negative values.

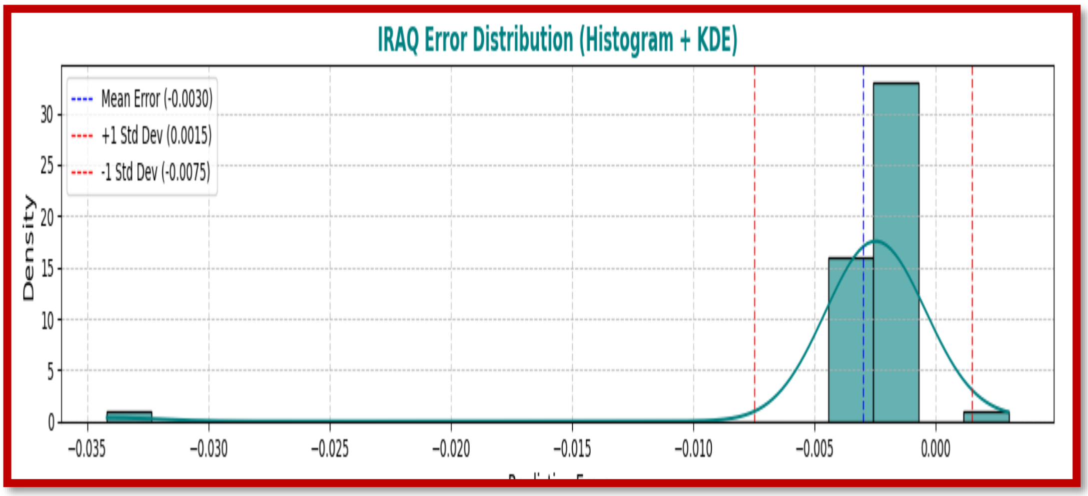

Figure 17. IRAQ Error Distribution using a Histogram (KDE) Test

The plot in figure 17 shows that the prediction errors are centred on zero with a mean error of -0.0030 indicating no obvious bias in the predictions. Most of the errors fall within ±1 standard deviation (0.0015 and -0.0075) reflecting the stability of the model, but there are some outliers on the left-hand side that may indicate atypical data or unexpected changes. The distribution of errors is not quite symmetrical with a greater concentration of negative errors, which may indicate a slight tendency of the model to predict values higher than the actual values. The model performs very efficiently with good stability.

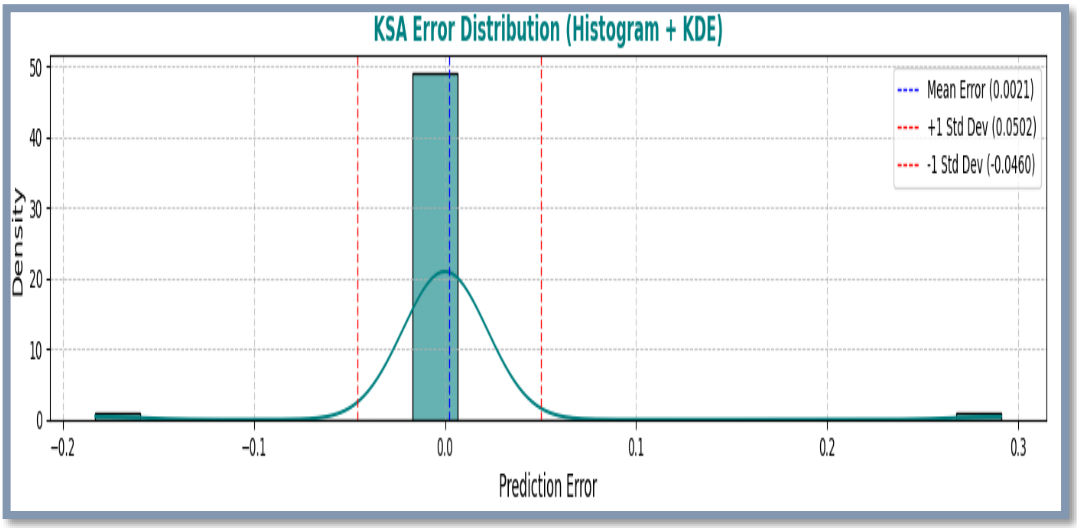

Figure 18. KSA Error Distribution using a Histogram (KDE) Test

The Figure 18 shows that most of the prediction errors are centred on zero, indicating a high accuracy of the model. The average error is 0.0021, which is very close to zero, meaning there is no significant bias. Most of the errors are within ±1 standard deviation (0.0502 and -0.0460), reflecting the stability of the forecasts. However, there are some extreme values on the edges that do not affect the model's performance. Overall, the model provides strong performance and good stability.

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4.3 TEST 3: Model evaluation metrics TEST

Model evaluation metrics are statistical criteria used to measure the accuracy and performance of forecasting models and analyze how well they match actual values. These metrics help in comparing different models and choosing the best one based on the accuracy of predictions.

Table 5: IRAQ and KSA Model Evaluation Metrics Test

Model Evaluation Metrics EGDI ARIMA Model IRAQ and KSA			
Metric	**IRAQ**	**KSA**	**Model Performance Comparison**
RMSE (Root Mean Square Error)	**0.0054**	0.0481	Iraq - Lower Error
MAE (Mean Absolute Error)	**0.0031**	0.0093	Iraq -Lower Error
MAPE (Mean Absolute Percentage Error)	**2.61%**	1.56%	KSA -Lower Relative Error
MAPA (Prediction Accuracy %)	97.39%	**98.44%**	KSA -Higher Accuracy
AIC (Akaike Information Criterion)	**-813.176**	-561.714	Iraq -Better Model Complexity & Accuracy Tradeoff
BIC (Bayesian Information Criterion)	**-799.074**	-540.585	Iraq -Better Model Complexity & Accuracy Tradeoff
Correlation (Corr)	**0.8388**	0.9417	KSA -Higher Correlation Between Actual & Predicted Values
MinMax Error	**9.78%**	3.19%	KSA -Lower Error Variability
MHE (Mean Hellinger Distance)	2.43%	**5.91%**	Iraq -Better Similarity Between Actual & Predicted Distribution

From table 5 IRAQ arima model has a very high accuracy (97.39%) according to MAPA. The RMSE and MAE values are very low because the differences between the actual values and the predictions are very small. The MAPE is less than 5%, indicating a low error in the predictions. The AIC and BIC are low and negative, indicating that the model is effective and not complicated. The Corr coefficient is strong (0.8388), reflecting the accuracy of the predictions. The MinMax Error is low (0.0978), indicating that the model performs well with the maximum and minimum values. The MHE is very close to zero (0.0243), meaning that the distribution of the predicted values is almost identical to the actual values. The ARIMA model performs perfectly, and it is a very accurate model for predicting EGDI with a very low error rate. KSA arima model has a very high accuracy (98.44%) according to MAPA, indicating an excellent performance in forecasting. The RMSE and MAE values are very low, reflecting small differences between the actual values and the forecasts. The mean forecast error (MAPE) is less than 2%, indicating high accuracy in forecasting. The low and negative values of both AIC and BIC confirm the efficiency of the model and the absence of over complication. The Corr coefficient is very high (0.9417), indicating a strong agreement between the predicted and actual values. The low MinMax Error value (0.0319) reflects the stability of the model with the maximum and minimum values. In addition, the MHE (0.0591) is very close to zero, confirming that the distribution of predicted values matches the actual values. The ARIMA model performs very efficiently, and is an ideal choice for EGDI forecasting with a very low error rate, making it reliable for use in future forecasting. IRAQ ARIMA model shows higher accuracy in absolute errors RMSE and MAE, which means that the model is more stable and less biased. While KSA model achieves higher relative accuracy MAPA = 98.44%, which reflects more consistent predictions. Iraq has lower AIC and BIC values, which means that the model is more efficient in terms of balance between accuracy and complexity. KSA has higher correlation (0.9417) because the predicted values follow the actual trend better. Mean Hellinger distance (MHE) is lower in Iraq (0.0243), the distribution of actual and predicted values is more convergent. Both ARIMA models for Iraq and KSA are successful and efficient, and both reflect successful and different performance due to the different nature of the data.

4.4 ARIMA Forecasting results

Forecasting results using the ARIMA model are values produced by the model after it has been trained on a specific time series, based on past data to predict future values based on the temporal relationships present in the data.

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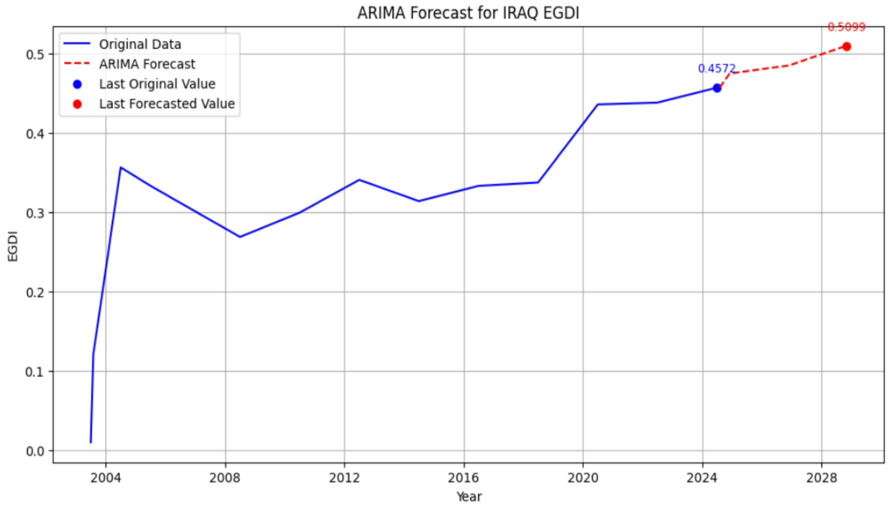

Figure 19. IRAQ ARIMA FORECASTING RESULTS

The Figure 19 shows the time series of the original data for the EGDI index for Iraq with a blue line reflecting a general trend of gradual increase with relative stability in recent years. The blue dot represents the last value of the original data at 2024, with a numerical value of 0.4572. Future forecasts are shown with a red dashed line starting from the last point in the original data and extending until 2029, reflecting relative stability in a increase in the index. The red dot represents the last forecast value at 2029, with a numerical value of 0.5099, highlighting the continuation of the slight upward trend. The red dashed transition line connects the last point of the original data and the first point of the forecast, showing the smooth integration between historical data and future forecasts. The horizontal axis displays the times from 2003 to 2029, while the vertical axis displays the EGDI values ranging from 0.1 to 0.5. The model shows relative stability in future forecasts with the index remaining within the range of the original values, indicating the effectiveness of the ARIMA model used in forecasting. These forecasts can be used in planning and developing e-government strategies in Iraq.

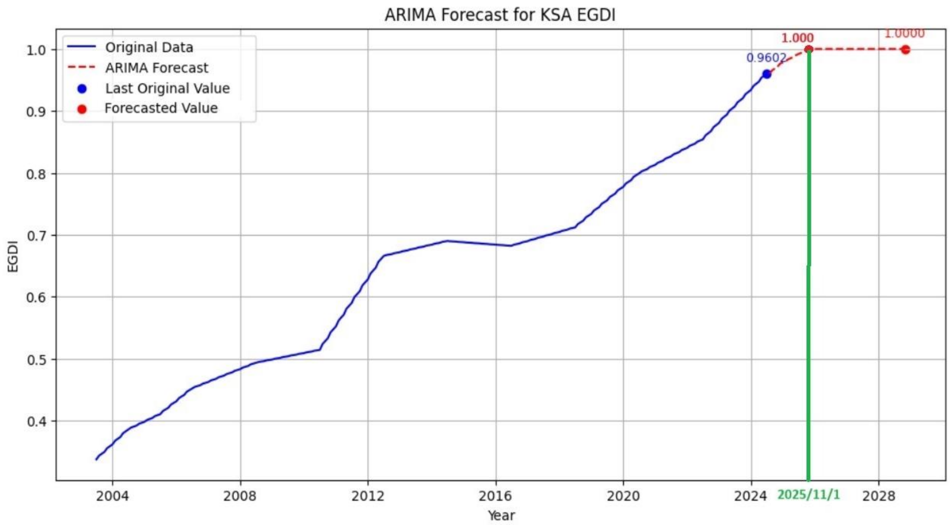

Figure 20. KSA ARIMA Forecasting Results

Figure 20 shows the ARIMA model is forecast for the EGDI in KSA based on historical data. The blue line shows the original data, while the red dashed line represents the model-based forecast. The graph shows that the last value of the original data is represented in blue at 0.9602, and the forecast starts to rise until it reaches the maximum value of 1.0000 by November 2025. This trend indicates a gradual improvement in the index, reflecting a positive long-term trend. The graph indicates that the model used is able to capture past trends and extrapolate them with relative accuracy into the future. The absence of sharp fluctuations in errors shows that the model has a high degree of reliability. However, the accuracy of the forecasts depends on the stability of the economic, political and technological conditions that affect the index. The analysis reflects the positive trend of the EGDI and provides a forward-looking framework to support decision-makers in assessing the future path of the Digital Development Index in KSA.

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4.5 Results and Discussion

The three main tests used to evaluate ARIMA results illustrate the integration of visual and statistical analysis to evaluate the model, ensuring that we provide an ARIMA model that performs well in forecasting time series. Test 1: Residuals Analysis Using ACF, PACF, Ljung-Box Test, and both models were successful as they showed that the residuals are independent. Test 2: PREDICTION ERROR PLOT and PREDICTION Distribution Histogram and (KDE), the plots of the prediction errors indicate that the differences between the predicted and actual values cluster around zero, indicating that there is no systematic bias in the model. The plots of the Histogram and KDE also show that the distribution of errors tends to be normal with moderate variance. The results reflected the high ability of the ARIMA model to capture the general trend of the data and that the random errors do not carry a pattern that can be significantly improved. Test 3: Model evaluation using RMSE, MAE, MAPE, MAPA AIC, BIC, Correlation (Corr), MinMax Error, and Mean Hellinger Distance (MHE). The results of the basic Metrics evaluation model for Iraq model were RMSE of 0.0054 versus 0.0481 for KSA model. Iraq model shows a decrease in absolute errors better than KSA model, although the KSA model has excellent results. In addition, Iraq model outperformed the absolute error reduction measure, as the MAE value (0.0031) in the Iraq model was lower than the KSA (0.0093). On the other hand, the accuracy MAPA measure in the KSA model was 98.44% versus 97.39% for the Iraq model. The KSA model is better in terms of relative accuracy of the expected trends, although the absolute errors were lower in the Iraq model. The evaluation model measures show successful and different behavior for each arima model, as the Iraq model outperforms in terms of reducing the error size (RMSE and MAE). The KSA model provides a higher relative predictive accuracy (MAPA). This discrepancy indicates the need to consider both aspects; while low RMSE and MAE show the quality of the prediction in absolute terms, high MAPA reflects the ability of the model to capture the overall trend of the data more accurately. Both models are successful with their own characteristics and provide high accuracy results.

4.6 Conclusion

The two ARIMA models differ in their behavior in trends and growth patterns. KSA has a strong and stable upward trend, the last actual value of the index is 0.9602, and the final forecast value is 1.0000, reflecting that the EGDI will reach its maximum. On the other hand, the EGDI for Iraq shows a volatile growth pattern, with the last actual value being 0.4572, and the final forecast value being 0.5099, reflecting a continuous but irregular progress. The performance of the EGDI for KSA is fast and stable, while the growth of Iraq is gradual with noticeable fluctuations. Confidence in the performance forecast for KSAis higher, as the trend is smoother and more predictable, while the forecast for Iraq is more uncertain due to the apparent fluctuations. KSAshows a more stable and predictable digital transformation. Iraq is witnessing continuous digital progress but with some fluctuations. Botha IRAQ and KSA arima models have good results Iraq model RMSE value (0.0054) and MAE value (0.0031) versus RMSE value (0.0481) and MAE value (0.0093) for KSA model, Iraq model better than KSA .On other hand KSA arima model is better in terms the expected trends with accuracies of 98.44% versus 97.39% for the Iraq model.

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