Wasit Journal of Engineering Sciences
Journal homepage: https://ejuow.uowasit.edu.iq
Vol. 13 No. 1 March 2025, pp.39-49
https://doi.org/10.31185/ejuow.Vol13.Iss1.614

ISSN 2305-6932
Original Research

Predicting Annual Tigris River Streamflow at Kut Barrage using SAMS Program

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ABSTRACT

Forecasting synthetic hydrologic data is the primary goal of the Stochastic Analysis, Modeling, and Simulation (SAMS) program. This research examined yearly data on the streamflow of the Kut Barrage on the Tigris River spanning 21 years, from 2003 to 2023. The data were converted using the logarithm transformation method, and the skewness and Filliben tests were run to assess the data's normality. To calculate the parameters of the univariate autoregressive moving average (ARMA) model, historical data were examined and ACF and PACF were shown. From these two graphs, it was concluded that the values of the ARMA model orders must be greater than one, and therefore four types of ARMA models were chosen: ARMA (1,1), ARMA (1,2), ARMA (2,1), and ARMA (2,2). The four ARMA models were compared with two criteria corrected Aikaike information criterion (AICC) and the Schwarz information criterion (SIC), which had the lowest values for the ARMA (1,1) forecasting model, which were 15.753 and 14.431, respectively. The generated data's mean value of 377 is quite near to the historical data's mean value of 380.7 the same is true for the covariance and standard deviation, which for the historical and anticipated data are 177.3 and 0.4836, respectively, and 182.3 and 0.4836.The RMSE value which is 0.34 for the historical and forecast data was found to be an acceptable value indicating that the ARMA (1,1) model is a suitable model for generating data, and the generated data for another 21 years after 2023 is highly accurate and reliable.

Keywords: Tigris river, Kut barrage, SAMS, Predicting, Streamflow

1. Introduction

Because of the rapid expansion of the global economy and population, there is a growing need for easily accessible freshwater supplies to meet the rising demand. However, this has resulted in several issues, such as the global water crisis, the drought, and the scarcity of freshwater resources [1]. Water shortages are now a global problem due to the rapid increase in demand for residential, commercial, and agricultural applications as well as the growing need for water conservation to maintain ecosystem services [2]. When water needs outweigh available water in cities worldwide, water scarcity is made worse by socioeconomic factors including industry, urbanization, and population growth as well as climate change [3]. Thus, water scarcity, high energy demand, agricultural needs, and drinking reasons are the primary factors motivating scholars to accurately forecast streamflow for the best use of water resources [4] . Streamflow is a channelized form of surface and subsurface runoff that travels toward the ocean [5]. For all life on Earth to survive, water is one of the most vital resources. Earth's water supply is finite, thus as the population rises, so does the demand for water. Therefore, the proper planning and management of water resources is one of the most significant issues facing hydrology today [6]. Streamflow management is therefore crucial since it directly affects applications of water resources engineering, such as the demand and supply for drinking water, the demand for agricultural irrigation, reservoir management, water quality parameters, hydroelectric systems, extreme hydrological events, and other factors [7]. The study's challenge is that Iraq's water resources face a number of problems that can be summed up as follows:

1. Because of the scarcity of water resources and the policies of neighboring countries, the annual water harvest and the quantity of water imported have declined [8] .
2. The problem is exacerbated by Iraq's growing population, which implies that there will be a water shortage as demand rises and availability decreases. The Tigris and Euphrates Rivers are predicted to dry up entirely by 2040, yet supply and demand will be 17.61 and 77 billion cubic meters (BCM) in 2025, respectively [9] .
3. A decline in the quality of the entering water due to the large number of manufacturers [10] .
4. Global warming and climate change [11] .

Forecasting hydrological processes is one of the primary focuses of hydrology research [12,13]. Hydrological forecasting is essential for analyzing physical systems and the causes of their changes [14] . The outcomes of forecasting can also be used for hydraulic structure design and management, flood warning, agricultural irrigation management, and water resource management [15,16]. Thus, it is not surprising that hydrological forecasting techniques, model development and improvement, and real-world model implementation have drawn a lot of interest, e.g. [17,18]. Forecasting changes in streamflow requires using streamflow series alone, with a certain degree of time delays, when streamflow data is all that is available [19] . Streamflow forecasting models can be broadly classified into three categories: conceptual, physical-based, and data-driven. Models based on data offer a nonlinear input-output relationship without requiring physical catchment knowledge or minimum data demands. As a result of improvements in computing power and data set accessibility, the usage of data-driven models is becoming more and more prevalent [20]. Data-driven modeling techniques, like univariate models, use streamflow data alone as input and output [21]. Stochastic modeling of hydrologic time series, such as streamflow, is frequently facilitated by mathematical models [22] . Since the streamflow flow series is frequently handled as a univariate time series and can usually be represented with ARMA type models, we choose a univariate time series based approach [23] to determine the degree of predictability of the univariate streamflow time series used in this investigation. In this paper, autoregressive moving average models (ARMA) are proposed. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to analyze correlation coefficients between the streamflow with lags and the current streamflow [24] . The parameters of the ARMA model are determined by using the Stochastic Analysis, Modeling, and Simulation (SAMS) program to chart these coefficients for the observed time series. Therefore, the purpose of the study is to clarify how to use the SAMS algorithm to analyze the observed streamflows of the Tigris River at Kut Barrage and deduce future streamflow from them. The following are the goals of the study:

1. Plot annual historical streamflows and plot ACF and PACF of original streamflows.
2. Check the normality of historical streamflows and transform the observed streamflows using one of the transformation methods if it does not follow a normal distribution
3. Finding the best ARIMA model for prediction and check the forecasting model.
4. Forecasting future data for Tigris River at Kut Barrage station.
5. Compare the basic statistics of historical data with the basic statistics of forecast streamflows.

By forecasting future streamflow, the study helps determine the maximum future streamflow that will be used as the design discharge for building any hydraulic construction, including dams and water reservoirs.

2. Literature review

The idea of creating water discharges was first introduced in 1914 when researcher Hazen combined 14 years of monitoring data into a single record, creating and installing a 300-year sequence of discharges. After further work, researcher Barnes used random integers to create the first streamflow values in 1954. The limitation of these methods is that they were unable to use monthly conjugation series since they did not consider the serial correlation between the conjugation values. Additionally, they restricted the statistical distribution that was employed as well as the ranges of these series that were created. Following these tests, Thomas and Fiering, two scientists, developed a model for producing monthly streamflows, which allowed them to overcome the drawbacks of previous converters [25]. Consequently, stochastic models that offer monthly and annual streamflow continued to emerge. In this section, some previous studies that utilized and exploited the ARIMA model are described. The three most popular classical data-driven models are MLR, ARIMA, and ARMAX. These models have been in use since 1970 [14]. Researcher Ledolter [26] looked at the Carpathian River's monthly streamflow time record in the Austrian state of Luxembourg. After determining that the streamflow variation was unstable, the researcher transformed the data by taking the time series' logarithm in order to stabilize it. The researcher determined that seasonality needed to be taken into account after diagnosing the model using autocorrelation and partial autocorrelation functions. When developing a statistical model to predict the monthly discharge and explain the variation in the Tigris River's streamflow entering the Mosul Dam, the ARIMA model was employed by scholar Al-Rizzo [27]. According to the researcher's study using general trend analysis, the time series of monthly streamflows exhibits a general trend. By calibrating the model with the observed data, the researcher demonstrated a discernible convergence between the two, which led him to the conclusion that this model is a valuable tool for identifying the type of changes in the streamflows of the Tigris River and forecasting future streamflows. The first difference of the time series must be taken in order to remove it from the series and produce a stable series. Researchers Yu and Tseng [28] used the autoregressive integrative model (ARI), where the autocorrelation and partial autocorrelation functions were used to estimate the model coefficients, to predict flow using the maximum discharge values at the measuring stations on the Shan Hu and Chang Pan bridges in China. The model's accuracy was verified using the autocorrelation function of the residual values (RACF) for various time shifts. All of the residual values' autocorrelation values were not significant, suggesting that the model is appropriate for prediction. To forecast six flood discharge values at measuring stations, a model with rank ARI (5,1) was chosen. The Yellow River's daily flow in China was analyzed as a time series by researchers Wang et al. [29]. Analysis was done to determine the series' general trend. The researchers then used the autocorrelation function to measure the unpredictability of the series. The results showed that no overarching trend could be identified. Additionally, it was shown that the impacts of seasonality become visible when the autocorrelation function is displayed. Additionally, the ARIMA model was used to predict daily discharge, and the results showed a significant correlation between predictability and the values of the autoregressive coefficients.

In their study of the Cekerek River in Turkey, Kadri et al. [30] used the ARIMA and Thomas-Fiering models to calculate the maximum daily flows for a specific month. Three sites throughout the river basin provided the discharge data. When the general trend test using the Mann-Kendall technique was conducted, it was found that the data lacked a general trend at the 5% significant level. In order to assess the degree of correspondence between the generated series and the observed series, the researchers also employed the absolute error mean and root mean square error tests. They came to the following conclusions: The ARIMA model is marginally superior to the Thomas-Fiering model, and the researchers advised using both models to produce the maximum daily discharges per month. Adhikary et al.'s seasonal ARIMA model was used to model the groundwater table [31]. Using weekly time series, they concluded that SARIMA stochastic models might be utilized to predict changes in ground water levels. The SAMS program was not used for prediction in any of the previous studies. The SAMS program was utilized in this study to forecast the Tigris River's future streamflows near the Al-Kut Barrage.

3. Study area and data description

The Al-Kut barrage is considered one of the most important irrigation facilities on the Tigris River in Iraq because it controls the distribution of water among the governorates of Wasit, Maysan, and Dhi Qar and provides irrigation for projects on the Gharraf River, the Dujaila Irrigation Project, and the Dalmaj, Jihad, and Al-Battar projects. This Barrage is located at Lat. 32° 29'N, Long. 45°50'E . The data is annual, and the record period spans 21 years (2003–2023). The SAMS methodology uses a strategy that preserves the general mean and variance of each record while making use of all available data [32].

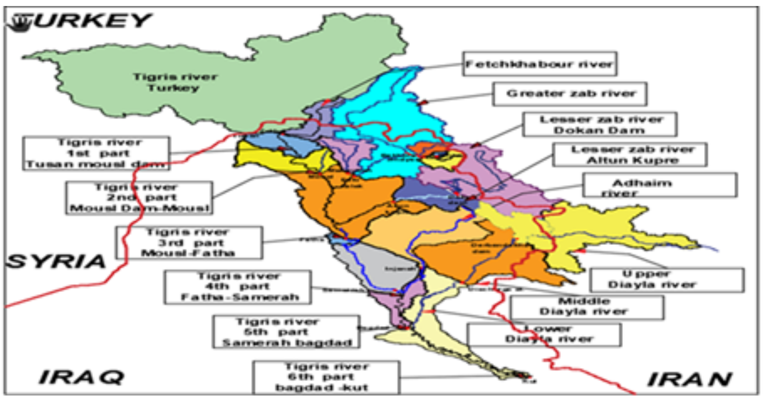


Figure 1. GIS Map Showing the Path of the Tigris River from Turkey to the Kut Barrage

4. SAMS Software

The most recent version, SAMS 2007, comes with further capabilities for modeling and data analysis. SAMS 2007 analyses the seasonal and annual data's stochastic features [32].

5. Methodology

5.1 Statistical Analysis of Data

5.1.1 Plot Data

Plotting the data can help identify trends, changes, outliers, and errors (in the data). A yearly data time series graphic is displayed in Figure 2.

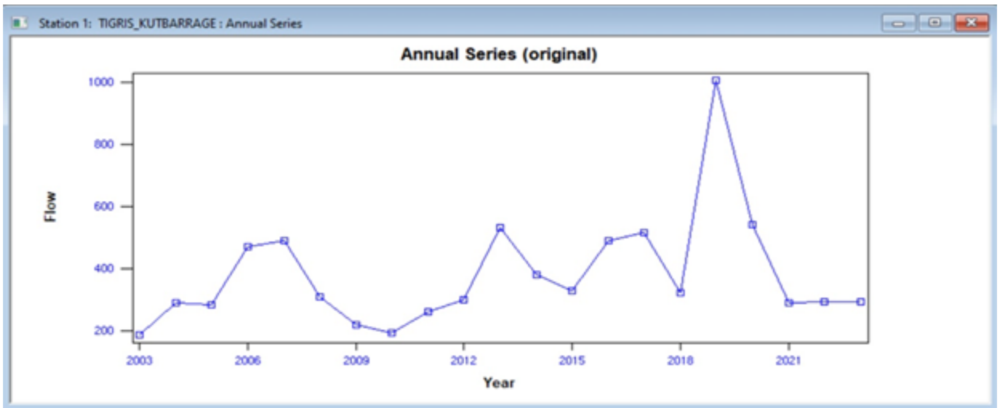


Figure 2. Plot of Original Time Series

5.1.2 Transform time series

The original data was transformed using the logarithmic transformation, one of the transformation techniques, after normality checks revealed that it was not normal. The distribution plot of the original data prior to transformation and the outcomes of the normality tests are displayed in Figure 3, and the distribution plot of the transformed data following transformation, along with the outcomes of the Filliben and skewness tests, are accepted as shown in Figure 4.

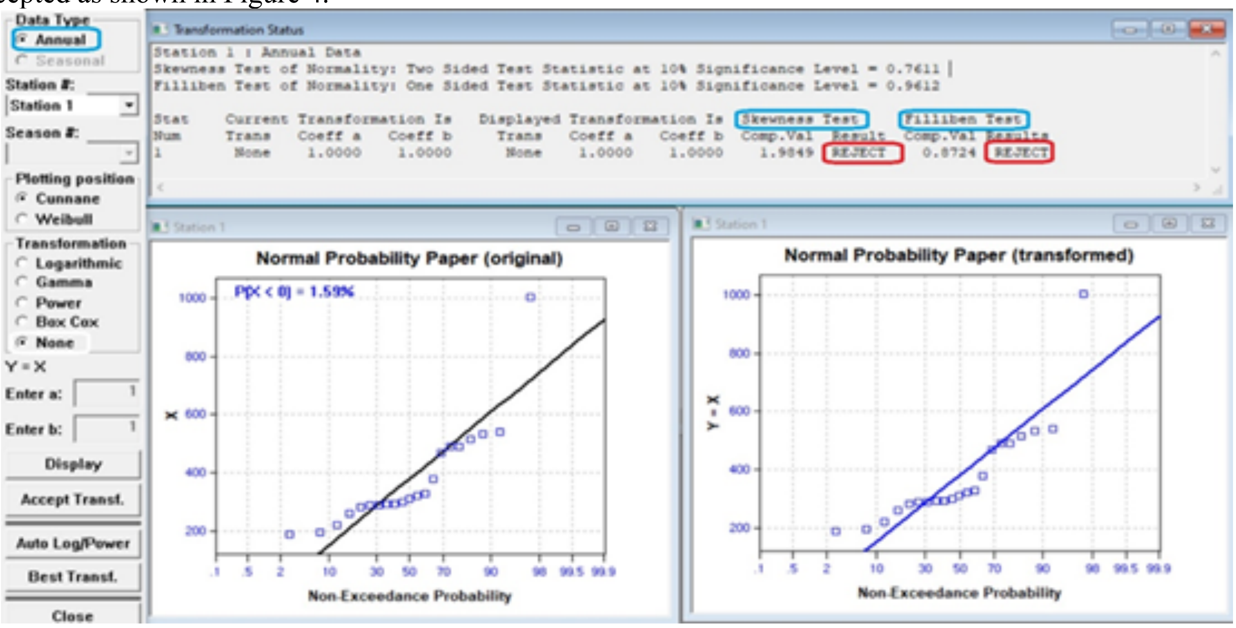


Figure 3. Plot of the Original Data on Normal Probability Paper and Test of Normality

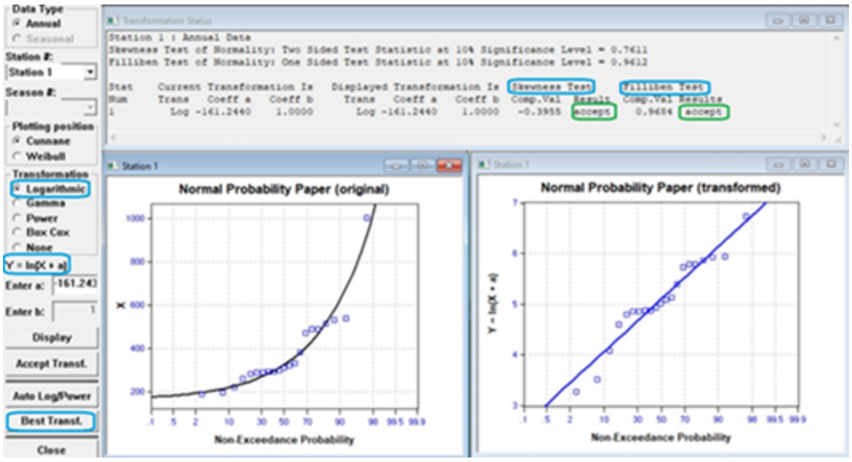


Figure 4. Plot of the Transformed Data on Normal Probability Paper and Test of Normality

5.2. Fitting a stochastic model

After transforming the data, the transformed data was plotted as shown in Figure 5, and the ACF and PACF were plotted for that transformed data as in Figure 6 and Figure 7, respectively, which will be adopted in building the model.

Figure 5. Plot of Transformed Time Series for Tigris River at Kut Barrage Station

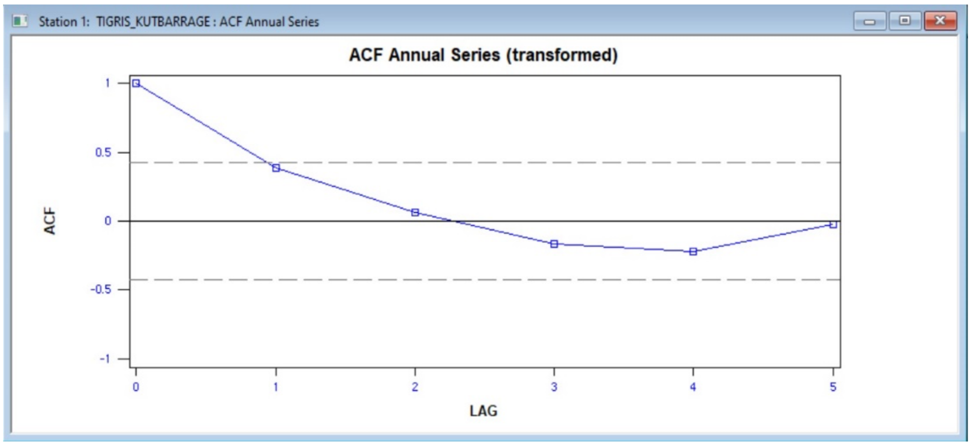


Figure 6. Plot ACF of Transformed Time Series for Tigris River at Kut Barrage Station

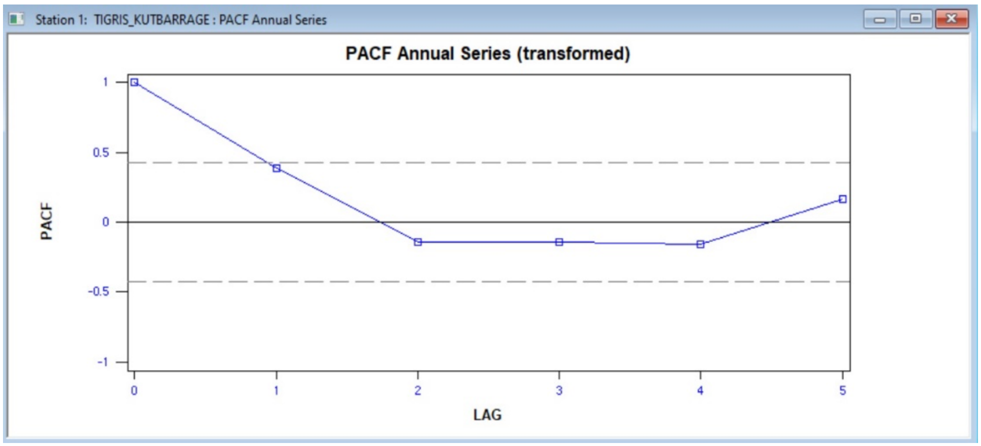


Figure 7. Plot PACF of Transformed Time Series for Tigris River at Kut Barrage Station

Following data transformation, Table 1 was compared to the modified data's ACF and PACF plots. It was discovered that p and q ought to be greater than one [32].

Table 1. Properties of the ACF and PACF of ARMA (p, q) Processes

	AR(1)	AR(p)	MA(q)	ARMA(p,q)
ACF	Decays geometrically	Tails off	Zero at lag > q	Tails off
PACF	Zero at lag > 1	Zero at lag > p	Tails off	Tails off

After determining the values of the ARMA model p and q are greater than zero, four types of the ARMA model were chosen based on the ACF and PACF plots for transformed time series, ARMA (1,1), ARMA (1,2) and ARMA (2,1).

5.3 Model Testing

5.3.1 Testing the Criteria

Two information criteria are included in SAMS: the corrected Aikaike information criterion (AICC) and the Schwarz information criterion (SIC), also referred to as the Bayesian information criterion. According to [33,34], the AICC is:

$$AICC = n\, ln\hat{\sigma}^2(\epsilon) + n + \frac{2(k+1)n}{n-k-2} \quad (1)$$

where k is the number of parameters (k = p + q for the ARMA (p, q) model) omitting constant terms, n is the sample size used for fitting, and σ^2 (ϵ) is the maximum probability estimate (biased) of the residual variance. The AICC statistic is useful but inconsistent for small samples, and it tends to overfit when samples are big and k is large. The SIC is given by[35,36]:

$$SIC = n \ln \hat{\sigma}^2 (\epsilon) + n + k \ln n \quad (2)$$

where σ^2 (ϵ), n, and k are defined similarly to the AICC statistic. The SIC generally performs well on large samples but underfits on small ones. Since the actual model order for real-world data is unknown, efficiency is typically more significant than consistency.
Four types of ARMA models were selected with different orders and the best model was chosen based on AICC and SIC criteria as shown in Table 2.

Table 2. Comparison of AICC and SIC Criterions for ARMA Model with Different Orders

ARMA(p,q)	ARMA(1,1)	ARMA(1,2)	ARMA(2,1)	ARMA(2,2)
AICC	15.753	19.261	18.847	21.419
SIC	14.431	17.894	17.481	19.597

We observe from table 2 that the ARMA (1,1) model is the most appropriate forecasting model for Kut Barrage yearly data since it has the lowest AICC and SIC values. Consequently, the ARMA (1,1) was selected for forecasting.

5.3.2 Testing the properties of the process

The forecast list demonstrates that the length of the time series to be generated is equal to the length of the historical data, demonstrating the application of the ARMA model for forecasting in Figure 8. Following data generation, a comparison was made between the historical record, time series plots, and the basic statistics of the generated data. Figure 9 shows the option for the comparison of basic statistics. Figure 10 shows the comparison of the time series.

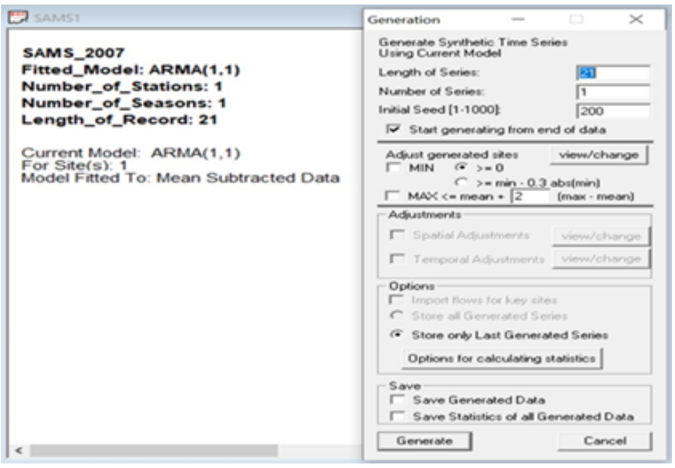
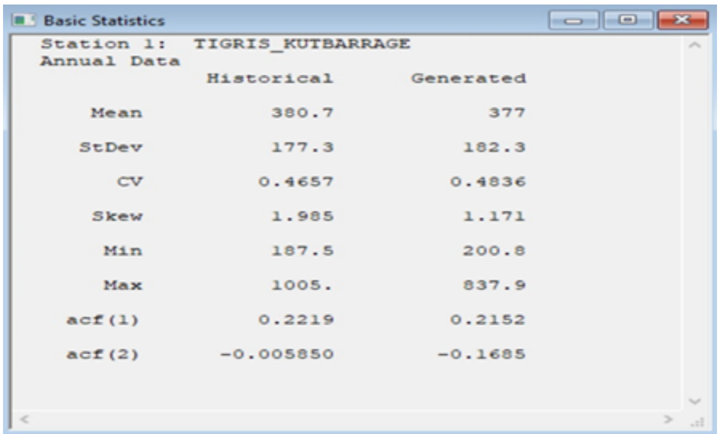


Figure 8. Fitting an ARMA (1,1) Model and Menu for Generate Data



	Historical	Generated
Mean	380.7	377
StDev	177.3	182.3
CV	0.4657	0.4836
Skew	1.985	1.171
Min	187.5	200.8
Max	1005.	837.9
acf(1)	0.2219	0.2152
acf(2)	-0.005850	-0.1685

Figure 9. Comparison of the Basic Statistics of the Generated Data and the Historical Record

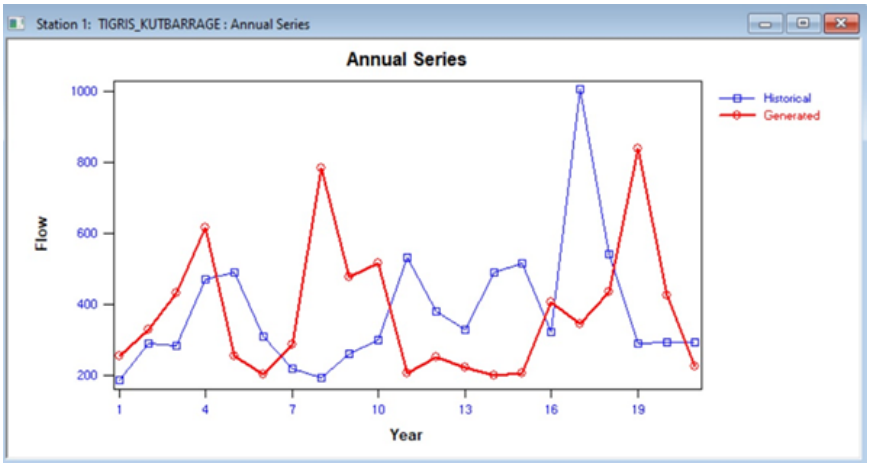


Figure 10. The Comparison of the Time Series

5.3.2 Root Mean Square Error (RMSE) Test

The average difference between the predicted and actual values of an estimation model is measured by the root mean square error, or RMSE. Low RMSE values show that the model has more accurate predictions and matches the data well.

$$RMSE = \sqrt{\frac{\Sigma(h-g)^2}{n}} \quad (3)$$

Where:
h = historical data, g = generated data and n = number of data
The equation above was used to determine the RMSE value, which came out to be 0.34. This is a very satisfactory outcome for the Tigris River yearly data at the Kut Barrage station for the years 2003–2023. This value indicates that the ARMA (1,1) model generates data with good precision and that the generated data is accurate and dependable.

6. Results

Figure 2 plotted annual data for 21 years, from 2003 to 2023. Figure 6 and 7 plotted ACF and PACF for transformed data to provide a sense of the parameters (p, q) that can be employed in the ARMA (p, q) model After comparing it with Table 1, it was found that the values of p and q are greater than zero. The data was then analysed using the skewness and Filliben tests of normality to determine whether or not it followed the normal distribution. Figure 3 illustrates this, with the Filliben test written REJECT below. As a result, we used the logarithmic transformation method to change the data. Consequently, as seen in Figure 4, the optimal transformation was selected by setting the value to zero. Then, using AICC and SIC criteria, four different types of ARMA models were chosen with varying orders: ARMA (1,2), ARMA (2,1), ARMA (1,1), and ARMA (2,2). The results showed that the ARMA (1,1) model has the lowest AICC and SIC value, which is equal to (15.753) and (14.431), respectively, as shown in Table 2, indicating that ARMA (1,1) is the best model. In the prediction list displayed in Figure 8, the length of the time series to be forecasted was selected to be 21 years the length of the historical data because in SAMS, the length of the projected time series is equal to the length of the historical data. Following another 21 years of streamflow forecasting, the mean, standard deviation, and covariance (basic statistics between the historical and forecast data) were compared, as illustrated in Figure 9. As we can see, the mean value of 377 for the generated data is fairly close to the mean value of 380.7 for the historical data. The same is true for the standard deviation and covariance, which are 177.3 and 0.4836, 182.3 and 0.4836 for the historical and predicted data, respectively. The RMSE value was found to be 0.34, which is an acceptable value and indicates that the ARMA (1,1) model is a good model for prediction and that the predicted discharge values are values with good accuracy and can be relied upon and the maximum streamflow that the Tigris River can reach at Al-Kut Barrage within 21 years after 2023 is 837.9 m3/s, as shown in Figure 9 by comparing the maximum discharge of historical data during the first 21 years after 2003, which is equal to

1005 m3\sec, we conclude that the discharge of the Tigris River at the Kut Barrage will continue to decrease during the next 21 years. Figure 10 shows the comparison of the predicted and historical time series.

7. Conclusions

1- The original annual data of the Tigris River at Kut Barrage were plotted. The ACF and PACF were plotted for these data, which indicated that the ARMA model orders, p and q should be greater than one.
2- The normality of the original data was examined by two tests: The Filliben and Skewness tests. The result of the two tests was found to be rejection. The data was transformed using the logarithm method, so the result of the two tests became acceptance.
3- ARMA (1,1), ARMA (1,2), ARMA (2,1), and ARMA (2,2) were the four ARMA model types that were selected. The ARMA (1,1) forecasting model had the lowest results when the four ARMA models were examined using the Schwarz information criterion (SIC) and the corrected Aikaike information criterion (AICC).
4- ARMA (1,1) was used to predict the future streamflows of the Tigris River at Kut Barrage for another 21 years after 2023. The RMSE of the generated data was found to be 0.34, which is very acceptable and gives high reliability to the generated data.
5- After comparing the main statistical characteristics of the historical and generated data, their values showed a great convergence, which indicates that the ARMA (1,1) model is a suitable model for generating future data for the Tigris River in the Kut Dam for another 21 years after 2023.

Declaration of Competing Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

Funding Information

No funding was received from any financial organization to conduct this research.

Author Contributions

Author Laith B. AL-Badranee proposed the research problem. In addition to author Ghufran R. AL-Youdawi collected recent articles and organized them in simple shapes. Authors Laith B. AL-Badranee and Ghufran R. AL-Youdawi discussed the proposed design, the results, and the final version of this paper.

Acknowledgments

The authors express their gratitude to Wasit University/ College of Engineering/Civil Engineering department in Alkut-Wasit-Iraq for supporting this study. In addition, many thanks to the Directorate of Water Resources in Wasit and Kut Barrage District for its assistance in providing the necessary data for the Kut Barrage station.

Notation list

Abbreviations	Meaning
SAMS	Stochastic Analysis, Modeling, and Simulation program
ARMA	autoregressive moving average model
AICC	criteria corrected Aikaike information criterion
SIC	Schwarz information criterion
ACF	Autocorrelation function
PACF	Partial autocorrelation function
k	number of parameters
n	sample size
σ^^2 (ϵ)	maximum probability

$RMSE$	root mean square error
h	historical data
g	generated data

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