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ANALYSIS OF OUTFLOW TIME SERIES FOR KUFA BARRAGE

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Abstract

Efficient management of water resources in barrage reservoirs requires a comprehensive understanding of future water availability. This paper focuses on the Kufa barrage, situated on the Euphrates River in the Najaf Governorate, specifically within the city of the Kufa. An annual time series of outflow discharge data for 31 years (1994–2024) was analyzed to assess short -term hydrological trends. A linear trend model was fitted to the historical data, and a synthetic sequence of future discharges was generated using classical time series modeling techniques. Minitab22 statistical software was employed for all time series analyses, including model fitting and forecasting. The paper presents the data, statistical outputs, and forecasts in both tabular and graphical formats, offering valuable insights for future water resource planning and reservoir operation strategies. The study concluded that the ARIMA (2,1,2) model is the most suitable among the evaluated alternatives for representing and forecasting the given time series data.

Keywords: Minitab22 Program, the Kufa barrage, Time Series, (ARIMA) model

1.Introduction

Time series modeling refers to the analysis of data that it chronologically ordered where time serves as an independent variable. This type of modeling is particularly important for hydrological applications, as it enables the examination and prediction of processes such as streamflow, precipitation, and reservoir inflow. Almost all statistical analyses of hydrologic time series rely on several foundational assumptions: the data series is homogeneous, stationary, Empty from trends and Transformations, non-periodic,, and exhibits no persistence. These assumptions are essential for ensuring the reliability of conventional time series models applied in typical water resources studies.

Naresh and Soorya (2016) [1].

Time series analysis is widely used for predicting future values and monitoring operational systems, because it allows us to identify the underlying structure and influencing factors within the data. Time series analysis encompasses a variety of statistical methods for identifying, analyzing, and forecasting temporal patterns in data. Key objectives of this analysis include highlighting the main characteristics of the time series pattern, understanding how historical

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data impacts future outcomes, and studying how multiple interrelated time series interact to predict future values. **Sara and Hanumanthappa (2017) [2].**

The ARIMA model developed by Box and Jenkins in the 1970, this is one of the most popular time series analysis models .This model can forecast future values by integrating three components: integration (I), moving average (MA) , and auto regression (AR), which takes into account data non stationarity. The Box and Jenkins model it still used today, despite the scientific advances we have achieved so far due to its flexibility in dealing with different types of data the seasonal component (SARIMA) was added to the model in later periods, which contributed to the widespread use of this model in analyzing seasonal fluctuations. **Ntebogang Dinah Moroke (2014) [3].**

2. Material And Method

2.1 Case Study

The Kufa barrage, one of the barrages in Iraq situated on the Euphrates River in the Najaf Governorate, and more especially within the city of Kufa . The barrage is the main reservoir for the Al-Kafeel-Al-Shanafiya Irrigation Project, with an initial storage capacity of 75 million cubic meters. Annual time series of outflow discharge data for 31 years (1994–2024) were analyzed to assess long-term hydrological trends**.**

2.2 Methodology

2.2.1 Time Series Structure

To analyze the variation in the outflow rate from the Kufa barrage, outflow rate data recorded for 31-year period (1994 to 2024) **[4]** was used to identify the correlation that reflects the trend behavior in these data.

3. Time Series Analysis.

A Time series plot of the average annual flow rates was created using Minitab 22 software, with the aim of Application of techniques used in time series analysis to study the water flow data of the Kufah barrage (Figure 1).This figure serves as a crucial initial step in highlighting trends, seasonal patterns, and anomalous behaviors. **(Dr. Nigel Lee Forrester 2013) [5]**

Then, the correlation between the outflow rate in a given year and its previous values was measured using the autocorrelation function (ACF). The resulting autocorrelation plot (Figure 2) clearly indicates how current outflows are statistically dependent on past lags a crucial step in identifying suitable autoregressive orders. **(SpyrosMakridakis at al 2018) [6].**

The annual outflow rate data were analyzed using an autoregressive (AR) model to estimate future outflow values based on historical data. To overcome random fluctuations in outflow rates and achieve accurate predictions. the AR model was applied using an order determined by the partial autocorrelation function (PACF) and autocorrelation function (ACF) **(Juan Frausto-Solis and Esmeralda Pita 2008) [7]**

If the (Y) values are normally distributed, the partial autocorrelation between(Y_{t-u}) and (Y_t) can be defined as

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$Ø (u) = cor(Y_t , Y_{t-u} | Y_{t-1} , . . . , Y_{t-u+1})$.

A broader methodology using regression theory.

Y_t based on Y_{t-1}….., Y_{t-u+1} . The prediction is

$\acute{Y}_t = β_1 Y_{t-1} + β_2 Y_{t-2} \cdot \cdot \cdot , β_{u-1} Y_{t-u+1}$

In the case of thinking back and predicting Y_{t-u}, we can use the same set of predictors. While originally proposed in **Bras & Rodríguez-Iturbe (1985)**, this concept was later formalized in a time-symmetric moving-average representation by **Koutsoyiannis (2000)**, which provides a general stochastic framework suitable for both backward and forward forecasting in hydrologic time series. **(Demetris Koutsoyiannis 2000) [8].** the best predictor will be

$\acute{Y}_{i-u} = β_1 Y_{t-u+1} + β_2 Y_{t-u+2} \cdot \cdot \cdot , β_{u-1} Y_{t-1}$.

A resulting formula was applied to all data using Minitab22 built-in functions. The results are explained in Table (1) and are also presented in the solid and dashed graphs in Figure (4).

Figure (1), a graph of the total outflows data for cofa barrage

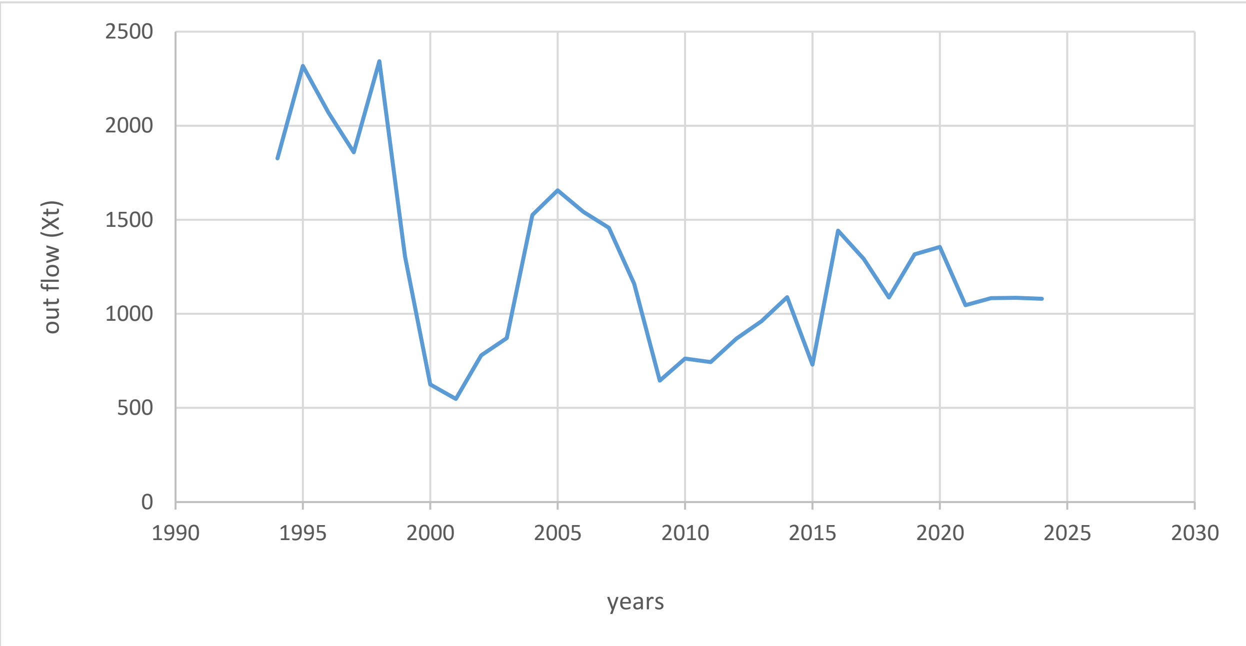

Table (1): Data on the outflow from the Kufa barrage for the period (1994-2024)

	T	year	outflow (Xt)	Xt*T	T^2
	1	1994	1827	1827	1
	2	1995	2318	4636	4
	3	1996	2070	6210	9
	4	1997	1859	7436	16
	5	1998	2343	11715	25
	6	1999	1307	7842	36

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	7	2000	625	4375	49
	8	2001	548	4384	64
	9	2002	779	7011	81
	10	2003	872	8720	100
	11	2004	1525	16775	121
	12	2005	1657	19884	144
	13	2006	1543	20059	169
	14	2007	1458	20412	196
	15	2008	1159.76	17396.4	225
	16	2009	645.17	10322.72	256
	17	2010	761.99	12953.83	289
	18	2011	743.78	13388.04	324
	19	2012	867.25	16477.75	361
	20	2013	960.71	19214.2	400
	21	2014	1089.06	22870.26	441
	22	2015	729.95	16058.9	484
	23	2016	1442.82	33184.86	529
	24	2017	1293.35	31040.4	576
	25	2018	1086.35	27158.75	625
	26	2019	1315.8	34210.8	676
	27	2020	1355.6	36601.2	729
	28	2021	1045.47	29273.16	784
	29	2022	1083.66	31426.14	841
	30	2023	1085	32550	900
	31	2024	1080	33480	961

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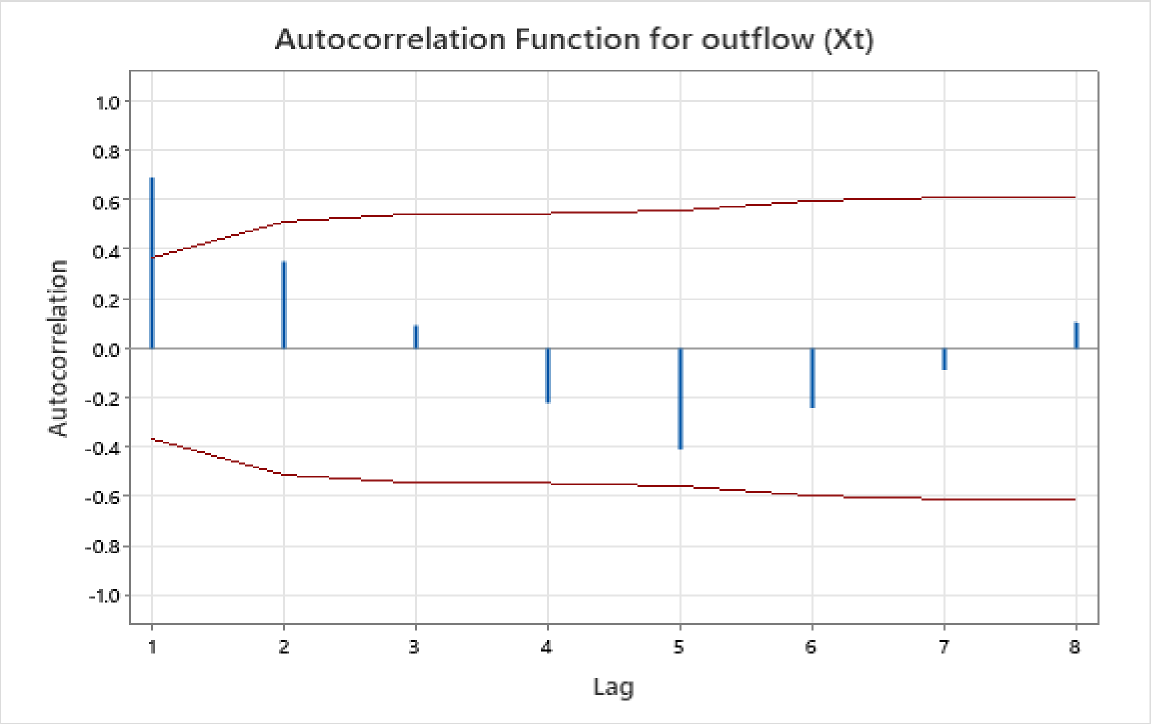
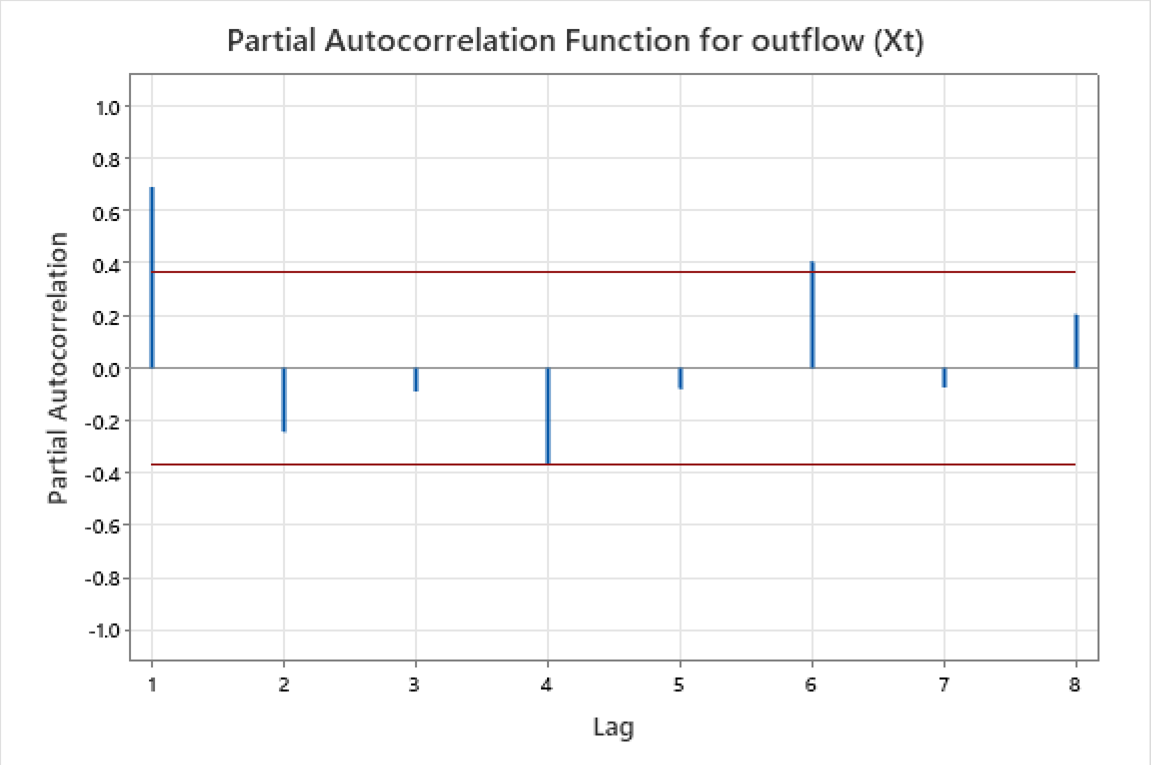


Figures (2). The autocorrelation coefficient for the outflow data



Figures (3).Partial autocorrelation coefficient for the outflow data

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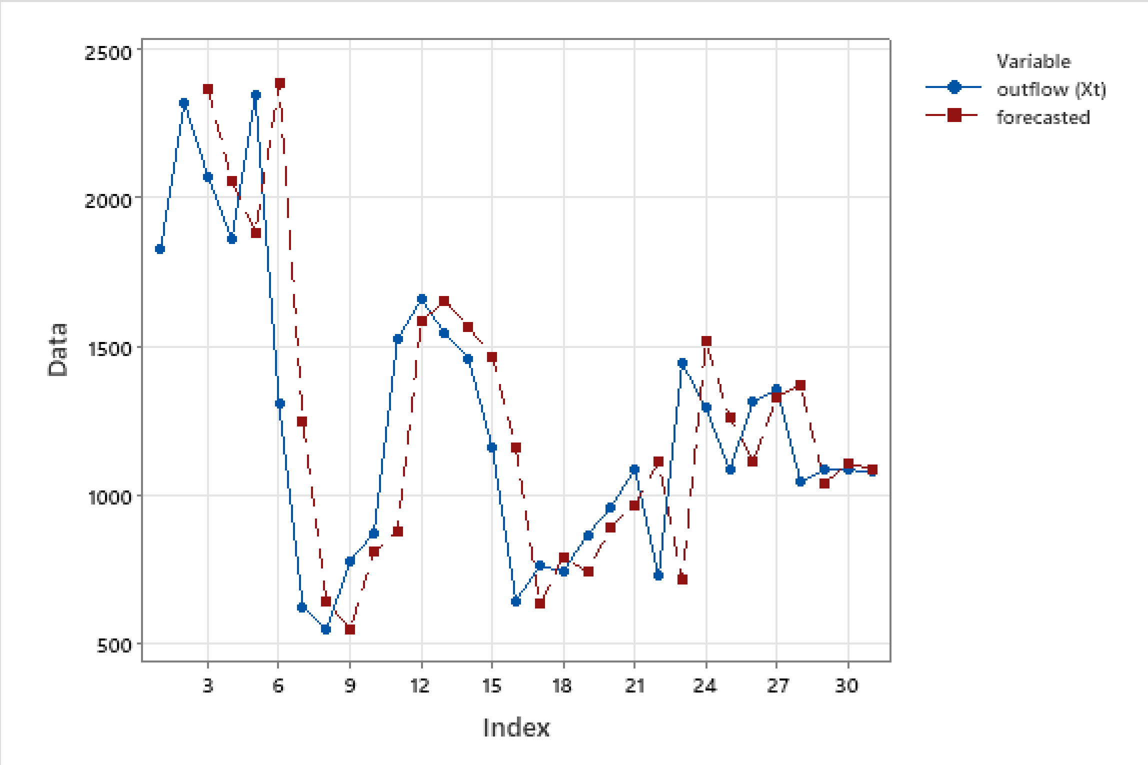

Figure (4), Time series plot for outflow kufa barrage (actual and forecasted) (1994-2024)

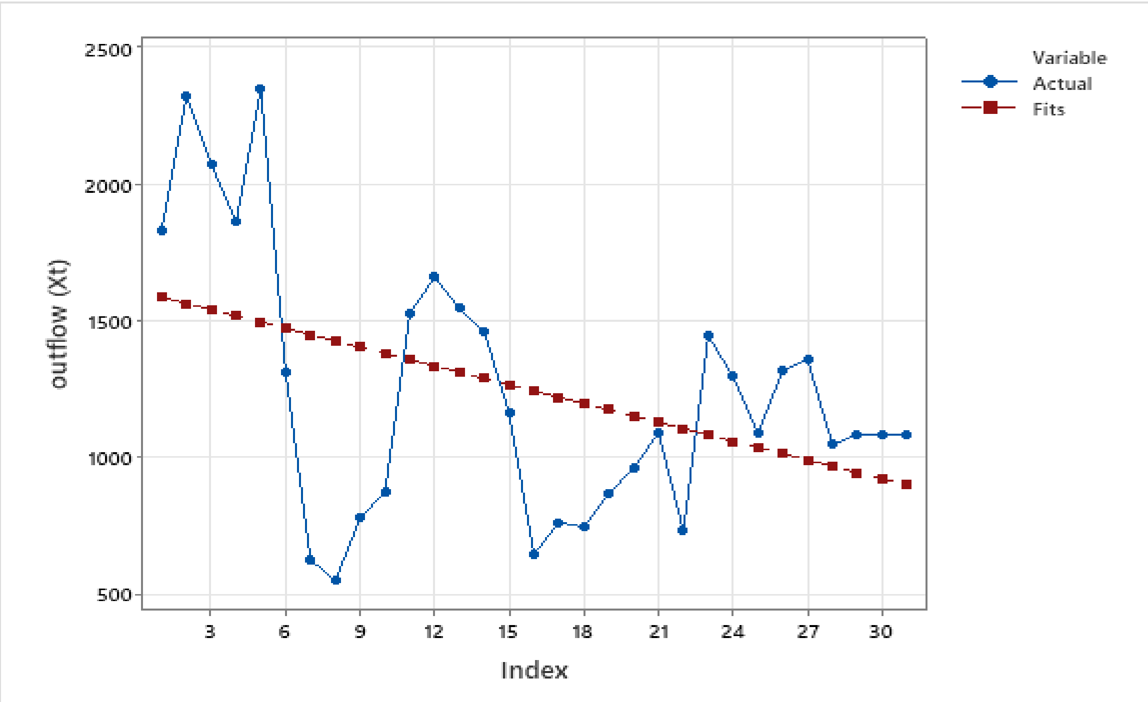

Figure (5), Trend Analysis Plot for outflow (Xt)

Table (2), the outflow rates for kufa barrage (actual and forecasted) (1994-2024)

year	outflow (Xt)	Forecasted	e
1994	1827		

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1995	2318		
1996	2070	2364.484253	**-294.4842529**
1997	1859	2057.584083	**-198.5840825**
1998	2343	1883.408079	**459.591921**
1999	1307	2385.946936	**-1078.946936**
2000	625	1247.515586	**-622.5155859**
2001	548	642.9698639	**-94.9698639**
2002	779	550.0056983	**228.9943017**
2003	872	809.3971993	**62.60280073**
2004	1525	877.8794194	**647.1205806**
2005	1657	1581.585183	**75.41481684**
2006	1543	1654.654729	**-111.6547293**
2007	1458	1562.898075	**-104.898075**
2008	1159.76	1464.855298	**-305.0952975**
2009	645.17	1160.67421	**-515.5042102**
2010	761.99	633.8737109	**128.1162891**
2011	743.78	793.4348088	**-49.65480876**
2012	867.25	741.0797655	**126.1702345**
2013	960.71	894.3581834	**66.35181662**
2014	1089.06	968.2946236	**120.7653764**
2015	729.95	1111.589057	**-381.6390572**
2016	1442.82	713.7736384	**729.0463616**
2017	1293.35	1514.47958	**-221.1295802**
2018	1086.35	1262.243031	**-175.893031**
2019	1315.8	1114.274276	**201.5257241**
2020	1355.6	1332.448035	**23.15196464**
2021	1045.47	1369.154794	**-323.6847939**
2022	1083.66	1039.385671	**44.27432909**
2023	1085	1108.921421	**-23.9214211**
2024	1080	1088.684093	**-8.684092728**

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4. Results and Discussions

4.1 In this paper, two approaches were applied, visual inspection through graphical representation of the data and the Augmented Dickey–Fuller (ADF) statistical test. The results revealed a discrepancy between the two methods. While the visual inspection suggested that the series was non-stationary due to the presence of An Downward trend, the ADF test indicated that the series is stationary. Specifically, the test produced a p-value of (0.010), which is lower than the 0.05 significance level, Which led to the rejection of the null hypothesis and acceptance of the alternative hypothesis of stationarity. Accordingly, reliance it placed on the statistical test, as it provides a more objective and rigorous criterion compared to visual inspection, which serves only as a preliminary indicator. Thus, the time series under study can be considered stationary based on statistical evidence. This confirms that the time series is stationary. Three models were identified using (PACF) and (ACF). Of the three selected models, $ARIMA$ (2, 1, 2) was selected based on information criteria and standard error estimates. The model passed all diagnostic tests and was subsequently used to produce time-series forecasts of outflow from kufa barrage.

4.2 the model coefficients were estimated using Minitab 22 and its suitability was evaluated using the Akaike Information Criterion (AIC) as shown in Table 3.

Table (3) ARIMA Model Comparison Table

MODLE	**AICc**	**P-value (Lag 12)**	**P-value (Lag 24)**	**Overall Rating**
ARIMA(1,1,2)	448.02	0.013 ⛔	0.012 ⛔	**Weak – Highest AICc and significant autocorrelation in residuals**
ARIMA(2,1,2)	437.679	0.106 ✅	0.132 ✅	**Best in terms of AICc and independence of residuals**
ARIMA(2,2,2)	440.341	0.068 ✅	0.209 ✅	**Acceptable balance; residuals are uncorrelated but AICc is higher than (2,1,2)**

Conclusion.

The ARIMA (2,1,2) model outperforms the others in terms of residual independence and model fit, according to Table 3's results of the comparison of the models. As a result of its optimal complexity-fit ratio, the model produces the lowest corrected Akaike Information Criterion (AICc = 437.679). No statistically significant autocorrelation was found in the residuals according to the Ljung-Box test (with probability values of 0.106 for a lag 12 and 0.132 for a lag 24), indicating that the model is suitable. On the other hand. Given the high residual

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autocorrelation at both lags (p-values < 0.05) and the highest AICc value (448.020), it seems that the ARIMA (1,1,2) model fails to adequately represent the time series dynamics. However, despite demonstrating decent residual independence (p-values = 0.068 and 0.209), the ARIMA (2,2,2) model outperforms ARIMA(2,1,2) in terms of AICc (440.341). Consequently, out of all the options considered, the ARIMA (2,1,2) model best represents and predicts the provided time series data.

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تحليل سلسلة زمنية للتدفقات الخارجة من سد الكوفة

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ملخص

تتطلب الإدارة الفعالة للموارد المائية في خزانات السدود فهمًا شاملاً لتوافر المياه في المستقبل. تركز هذه الورقة على سد الكوفة الواقع على نهر الفرات في محافظة النجف، وتحديدًا داخل مدينة الكوفة. تم تحليل سلسلة زمنية سنوية لبيانات تصريف التدفق لمدة 31 عامًا (1994-2024) لتقييم الاتجاهات الهيدرولوجية قصيرة المدى. تم تركيب نموذج اتجاه خطي

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على البيانات التاريخية، وتم إنشاء تسلسل اصطناعي للتصريفات المستقبلية باستخدام تقنيات نمذجة السلاسل الزمنية الكلاسيكية. تم استخدام برنامج Minitab22 الإحصائي لجميع تحليلات السلاسل الزمنية، بما في ذلك ملاءمة النموذج والتنبؤ. تعرض الورقة البيانات والمخرجات الإحصائية والتنبؤات في كل من التنسيقات الجدولية والرسومية، مما يوفر رؤى قيّمة لتخطيط موارد المياه في المستقبل واستراتيجيات تشغيل الخزان. خلصت الدراسة إلى أن نموذج ARIMA (2،1،2) هو الأنسب بين البدائل المقيمة لتمثيل بيانات السلسلة الزمنية المعطاة والتنبؤ بها.

الكلمات المفتاحية: برنامج Minitab22، سد الكوفة، السلاسل الزمنية، نموذج (ARIMA)