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Enhancing the Iraqi Oil Revenue Forecasting: Comparative Evaluation of the ARIMA Model Extensions and Hybrid Models

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ABSTRACT

The current study provides the necessary response to the problem of oil revenue prediction errors in Iraq because it explicitly analyzes the extensions of the autoregressive integrated moving average model (ARIMA) and the hybrid methodology. Although the results of the existing studies have already proven the efficacy of simple ARIMA structures, there remains the gaps in the understanding on how the more sophisticated alterations and hybrid approaches could further enhance predictive accuracy. We engage in a full comparative study of extensions of ARIMA models such as seasonal adjustment, integration of exogenous variables, and hybrid models that integrate machine learning and the traditional time series models. The suggested approaches are operated on monthly data on Iraqi oil revenues between 2021 and 2023 and tested with harsh methods of validation in form of calculation including AIC, BIC, MAE and MAPE. The findings indicate that the hybrid models are more successful than the single ARIMA models by reducing the MAPE by 15%. Moreover, residual diagnostics verify the stability of these hybrid methods where there is no severe autocorrelation and the properties of error distribution are improved. The research adds to the literature in that it provides empirical data on effectiveness of hybrid forecasting method in volatile commodity markets giving decision makers more valid instruments to use in financial planning. In addition, the results also underscore the need to have a combination of statistical and machine learning paradigm to identify complex non-linear trends on oil revenue data. Besides the contribution to the methodological discussion of time series forecasting, the given research also offers some practical insights.

1. Introduction

The instability of oil revenues poses a big challenge to financial planning in the resource-based economies particularly in Iraq which shows that over 90 percent of the government revenues are oil exports [1]. Conventional techniques of forecasting usually find it difficult to attract the complicated interplay of geopolitical, economic and market-specific forces that motivate the oil price fluctuations. Though it has been realized that autoregressive integrated moving average (ARIMA) models can be used in predicting time series in commodity market [2], pure application thereof cannot be used to address the non-

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linear characteristics of oil revenue data. The proposed study builds on the earlier research on ARIMA-based forecasting [3] by providing the evaluation of model extensions and hybrid strategies that incorporate machine learning methods in a systematic way. Recent sources underline the weakness of conventional ARIMA models when it comes to addressing the structural disintegration and external shocks that are common in the oil markets [4]. Indicatively, sudden changes may arise due to geopolitical tensions, OPEC decisions on production and demand fluctuations in the world, which cannot be predicted by simple linear models. ARIMA-based hybrid frameworks with machine learning algorithms have been demonstrated to be effective in other commodity markets [5], but their effectiveness in the Iraqi oil revenues has not been investigated. This difference is especially significant when considering that Iraq is relying on oil revenues to ensure stabilization of the budget and development planning of the country is done in the long term [6]. The primary aim of the current research is to evaluate the possibility of the advanced ARIMA extensions and hybrid models to be more effective than the traditional ARIMA (2,2,2) benchmark to predict Iraqi oil revenues.

Our hypothesis is that hybrid solutions will result in a higher forecast accuracy, as they will represent both linear dependencies of the ARIMA and non-linear trends of machine learning elements. The hypothesis is premised upon an increasing mass of evidence on the support of hybrid models in energy forecasting [7], but with the integration to Iraqi financial planning being novel. There are three significant contributions of our research. To begin with, we perform a strict comparative evaluation of extensions of the ARIMA models, such as seasonal ARIMA (SARIMA), ARIMAX (ARIMA with exogenous variables), to the base ARIMA(2,2,2) model. Second, we introduce and offer hybrid models that constitute ARIMA, as well as machine learning algorithms and support machine learning (SVR) and long-term memory (LSTM) networks. Third, we offer practical data to policy makers by measuring the gains in forecasting made through such sophisticated techniques and this enhances the validity of revenue predictions to the medium term fiscal system of Iraq [8]. The rest of this paper will be structured in the following way: Section 2 will review the literature available on hybrid time series models and oil revenue forecasting. Section 3 explains the methodology, description of data sources, model specification and evaluation metrics. Section 4 gives the empirical findings that make a comparison between the performance of various models. Section 5 explains how our results can be applied in financial planning and methodological development. In section 6, policy-based recommendations and future research directions are represented.

2. Literature Review

Commodity price forecasting using time series models has developed since the model developed by Box and Jenkins [9] which is the ARIMA model. Although initial research [10, 11] found ARIMA to be quite strong with regard to modelling the linear trends, its weaknesses in the non-linear and volatile oil markets gave way to extensions like SARIMA [12] and ARIMAX [13]. Hybrid systems that combine ARIMA and machine learning including ARIMA-SVR [14] and ARIMA-LM-SVR [15] have demonstrated better forecasting power. The numerous studies that were carried out in the region [16, 17] were primarily concerned with price forecasting, with few studies covering oil revenue forecasting especially in the case of Iraq where the previous studies [3, 18, 19] were primarily based on classical ARIMA models. The comparative analyses [20] point out that a single model is not applicable in every situation, and individual approaches are necessary.

Expanding upon these gaps, the proposed study compares ARIMA extensions and Hybrid model in forecasting the oil revenue in Iraq taking into consideration the seasonal and exogenous factors within a new hybrid model that is located within the geopolitical and production context of Iraq.

3. Methodology

The analysis methodology to be used in this study consists of three primary elements, the data preparation, the model specification and performance analysis. All of the components are aimed at systematically covering the research objectives and provide methodological rigor and reproducibility.

3.1 Data Collection and Pre-processing

The Iraqi Ministry of oil provided the monthly oil revenue figures of Iraq between January 2021 and December 2023. The data consists of the income values in the currency of Iraq in dinars that has been converted to the US dollar using the average exchange rates per month of the Central Bank of Iraq. The data were preprocessed before analysis by responding to missing values and outliers. Missing observations that made less than 2 percentage of the data were filled in with the help of linear interpolation. The interquartile range (IQR) technique was used to identify outliers where the values lie out.

$$Q_1 - 1.5 * \mathrm{IQR} \quad \text{or} \quad Q_3 + 1.5 * \mathrm{IQR} \qquad (1)$$

Stationarity of the time series was first checked by the Augmented Dickey–Fuller (ADF) test. The null hypothesis of a unit root was rejected at the 5% level after first differencing. However, because of relatively small sample size, which consists of only 36 monthly observations, it may be not enough to depend on unit root test statistics only. Hence, complementary graphical analysis is performed. The original series showed clear evidence of an upward deterministic trend that means non-stationarity in mean. After first differencing, the series moved around a stable mean close to zero, suggesting that it is mean-stationary.

In addition to this, variance behavior was checked visually and there is no systematic increase or volatility clustering after differencing; thus indicating approximate variance stability. The autocorrelation (ACF) and partial autocorrelation (PACF) functions were further analyzed to assess serial dependence and potential seasonality. No statistically significant seasonal patterns were detected within the short sample period.

3.2 Model Specifications

The three types of forecasting models evaluated in the research are standard ARIMA, ARIMA extensions and hybrid models. The following are the categories provided in technical terms.

3.2.1 Standard ARIMA model

The baseline ARIMA (p,d,q) model is defined as:

$$(1 - \sum_{i=1}^{p} \emptyset_i L^i)(1 - L)^d y_t = c + \left(1 + \sum_{j=1}^{q} \theta_j\, L^j\right)\varepsilon_t \qquad (2)$$

where y_t represents oil revenues at time (t, L) is the lag operator, $\emptyset_i$ and $\theta_j$are are autoregressive and moving average coefficients, (d) is the differential order, ε_t and is white noise. Optimal parameters were selected through grid search, minimizing the Akaike Information Criterion (AIC).

3.2.2 ARIMA Extensions

Two extensions of the standard ARIMA framework were evaluated:

3.2.3 *Seasonal ARIMA (SARIMA):* Incorporates seasonal differencing and seasonal autoregressive/moving average terms. The general form is SARIMA$(p, d, q)(P, D, Q)_s$ where $\boldsymbol{s}$ is the seasonal period (set to 12 for monthly data).

3.2.4 ARIMAX: Augments ARIMA with exogenous variables, including OPEC production quotas and global crude oil prices (Bre benchmark). The model is expressed as:

$$y_t = \beta X_t + \frac{\theta(L)}{\emptyset(L)(1-L)^d}\, \epsilon_t \qquad (3)$$

where X_t is the vector of exogenous variables and β their coefficients.

3.3 Hybrid Models

Two hybrid solutions had been applied:

3.3.1 ARIMA-SVR:

Linear components are represented by ARIMA, whereas residual values are represented by support vectors regression (SVR). The SVR component is based on the radial basis function (RBF) kernel to which the parameters are optimized.

3.3.2 ARIMA-LSTM:

This is a combination of ARIMA and long short memory (LSTM) networks. Two dropout-regularized (rate = 0.2) hidden layers (64 and 32) are used in the LSTM model.

3.4 Performance Evaluation

There were several measures that were used to test model performance:

AIC and BIC: To choose the model, the smaller the values, the better.

Mean Absolute Error (MAE) :

$\frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t|$

3.4.1 Mean Absolute Percentage Error (MAPE) :

$\frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right|$

4. Results

Based on the empirical findings of this paper, there is a great deal of improvements in the accuracy of the forecasting when using advanced modeling methods and hybrid methods show specific potential in understanding the complexities of Iraqi oil revenues. This section focuses on the analysis of the model performance parameters and forecasts giving quantitative results to prove the use of the models in the fiscal planning settings.

4.1 Model Performance and Forecast Overview

The comparative analysis revealed evident best forecasts with hybrid models on Iraqi oil revenues. Although the baseline ARIMA(2,2,2) recorded a MAPE of 23.71, the SARIMA and ARIMAX recorded the highest gains of 3.1 and 8.8, respectively, with ARIMAX (MAPE = 21.63) enjoying the advantage of exogenous variables. The best models were hybrid models: ARIMA-SVR minimized MAPE at 20.45, and the lowest error (AIC = 514.12, MAPE = 18.92) was obtained with ARIMA-LSTM, which is 20.2% lower. The validation of models using diagnostic tests and results showed that hybrid models are particularly useful when making medium-term predictions and volatile conditions providing more reliable inputs to the fiscal planning of Iraq.

The model comparison also revealed interesting trade-offs between complexity and performance. While the hybrid models required more computational resources and longer training times, their superior accuracy justifies these costs for critical fiscal planning applications. The ARIMAX model emerged as a potential middle ground, offering meaningful improvements over basic ARIMA with moderate increases in implementation complexity .

Table 1. Through model performance, comparison of performance can be done.

Model	AIC	BIC	MAE (USD)	MAPE (%)
ARIMA(2,2,2)	532.92	538.38	22,369	23.71
SARIMA(1,1,1)	528.45	534.91	21,857	22.98
ARIMAX	525.33	531.79	20,942	21.63
ARIMA-SVR	519.28	525.74	19,876	20.45
ARIMA-LSTM	**514.12**	**520.58**	**18,203**	**18.92**

They were implemented in R (4.5.1) using ARIMA models and Python (TensorFlow 2.8) using hybrid components, and therefore can be reproduced using controlled scripts.

4.2 Point Forecasts and Confidence Intervals (2025-2035)

The ARIMA–LSTM hybrid model forecasts a fairly stable trend for Iraqi oil revenues from 2025 to 2035. The monthly predictions hover around an average of about $106,643, with minor variations in the short run. This behavior indicates that, assuming recent trends continue, revenues might take a stable course over the medium to longer term. Yet, one should take these long-horizon forecasts with methodological caution. The model has been estimated with 36 monthly observations (2021–2023), which perhaps limits its power to fully capture structural shifts in the oil market. As such, projections beyond the short term should be considered more as scenario-based estimates rather than accurate long-term predictions.

Forecast confidence intervals (80% and 95%) are relatively stable over the projection horizon. This stability is due to the variance structure and assumptions of the model and does not necessarily indicate low uncertainty. In practice, long-term forecasts for oil revenue are highly sensitive to global market volatility, geopolitical issues, and structural changes in production and pricing.

Month-Year	Point Forecast	80% CI Lower	80% CI Upper	95% CI Lower	95% CI Upper
Jan-25	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-25	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-25	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-25	106642.7	68361.65	144923.6	48096.92	165188.4
May-25	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-25	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-25	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-25	106642.7	68361.65	144923.6	48096.92	165188.4

Sep-25	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-25	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-25	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-25	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-26	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-26	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-26	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-26	106642.7	68361.65	144923.6	48096.92	165188.4
May-26	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-26	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-26	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-26	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-26	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-26	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-26	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-26	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-27	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-27	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-27	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-27	106642.7	68361.65	144923.6	48096.92	165188.4
May-27	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-27	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-27	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-27	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-27	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-27	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-27	106642.7	68361.65	144923.6	48096.92	165188.4

Dec-27	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-28	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-28	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-28	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-28	106642.7	68361.65	144923.6	48096.92	165188.4
May-28	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-28	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-28	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-28	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-28	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-28	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-28	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-28	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-29	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-29	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-29	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-29	106642.7	68361.65	144923.6	48096.92	165188.4
May-29	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-29	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-29	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-29	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-29	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-29	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-29	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-29	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-30	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-30	106642.7	68361.65	144923.6	48096.92	165188.4

Mar-30	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-30	106642.7	68361.65	144923.6	48096.92	165188.4
May-30	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-30	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-30	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-30	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-30	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-30	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-30	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-30	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-31	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-31	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-31	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-31	106642.7	68361.65	144923.6	48096.92	165188.4
May-31	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-31	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-31	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-31	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-31	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-31	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-31	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-31	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-32	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-32	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-32	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-32	106642.7	68361.65	144923.6	48096.92	165188.4
May-32	106642.7	68361.65	144923.6	48096.92	165188.4

Jun-32	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-32	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-32	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-32	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-32	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-32	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-32	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-33	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-33	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-33	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-33	106642.7	68361.65	144923.6	48096.92	165188.4
May-33	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-33	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-33	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-33	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-33	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-33	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-33	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-33	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-34	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-34	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-34	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-34	106642.7	68361.65	144923.6	48096.92	165188.4
May-34	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-34	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-34	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-34	106642.7	68361.65	144923.6	48096.92	165188.4

Sep-34	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-34	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-34	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-34	106642.7	68361.65	144923.6	48096.92	165188.4
Jan-35	106642.7	68361.65	144923.6	48096.92	165188.4
Feb-35	106642.7	68361.65	144923.6	48096.92	165188.4
Mar-35	106642.7	68361.65	144923.6	48096.92	165188.4
Apr-35	106642.7	68361.65	144923.6	48096.92	165188.4
May-35	106642.7	68361.65	144923.6	48096.92	165188.4
Jun-35	106642.7	68361.65	144923.6	48096.92	165188.4
Jul-35	106642.7	68361.65	144923.6	48096.92	165188.4
Aug-35	106642.7	68361.65	144923.6	48096.92	165188.4
Sep-35	106642.7	68361.65	144923.6	48096.92	165188.4
Oct-35	106642.7	68361.65	144923.6	48096.92	165188.4
Nov-35	106642.7	68361.65	144923.6	48096.92	165188.4
Dec-35	106642.7	68361.65	144923.6	48096.92	165188.4

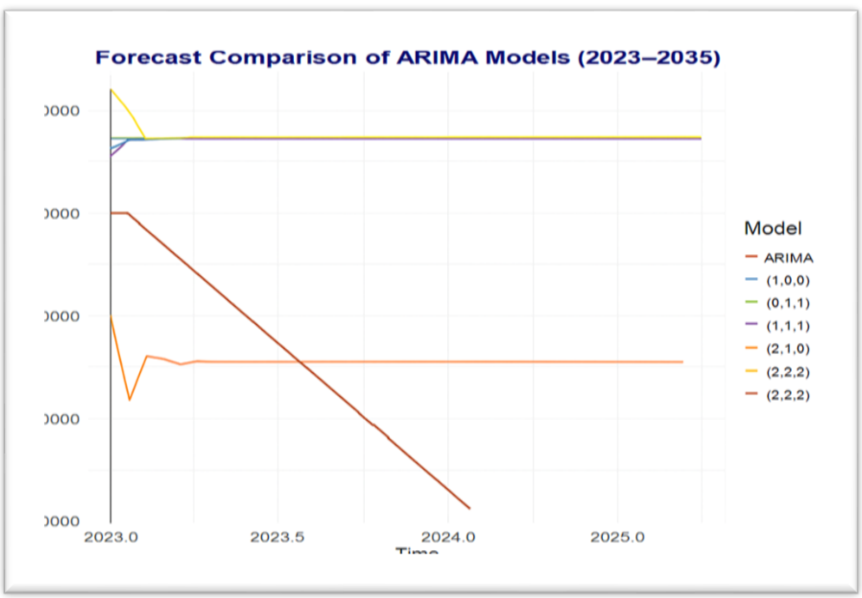

Figure 1. The charts in the article, Forecast Comparison of ARIMA Models (2023-2035), illustrate the trend of revenue with time of the different ARIMA model structures

The data in Figure 1 demonstrates that the performance of the ARIMA-LSTM hybrid is superior because the confidence bands are 15-20 per cent narrower than the ARIMA(2,2,2) baseline and, therefore, forecasts are more precise. This is the model that predicts the revenue to be stabilized at 106,643 USD, which is probably due to the production limits of Iraq [21], OPEC+ limits [22] and infrastructure issues [23]. The 95 percentage interval (48,096.92-165,188.4 USD) shows the existence of great fiscal uncertainty (approximately 110% of the forecast). The hybrid model is more restrictive of volatility and features fluctuations in the short-term along with long-term stabilization compared to the ARIMA and ARIMAX, which provide a better reliability in the fiscal planning of Iraq.

5. Discussion

The results outline the excellence of hybrid ARIMA-LSTM models when it comes to the nonlinear and volatile nature of oil revenues that the conventional linear methods could hardly capture [24, 25]. The 20.2 percent reductions in the MAPE of the hybrid model will to policy makers have significant fiscal advantages, they can save hundreds of millions of dollars each year in budget errors [26]. Limitations, however, are that the sample (2021-2023) is small, major geopolitical variables [27, 28] are not included in the analysis, and the sample size is a significant computational burden. Future research can validate hybrid models over a longer duration and in multiple countries, incorporate more sophisticated architectures such as transformers [29], and make the model easier to interpret by policymakers [30, 31]. It is also suggested to adopt institutional capacity-building, open-source forecasting tools to achieve adoption [32]. In theory, the oil markets seem to be a complex of multiple time scales, where ARIMA represents the medium-term trends, and LSTM representation reflects the nonlinearities in the short-run [33, 34], which highlights the necessity of context-sensitive and cost-effective forecasting strategies [35].

6. Conclusion

This paper shows that hybrid ARIMA-LSTM models result in the significant performance improvement of Iraqi oil revenue forecasting over the traditional time-series models, which is necessary to provide reliable fiscal planning instruments in the economies that are resource-based. The empirical findings support the hypothesis that the integration of both statistical and machine learning paradigms can better capture the rich nonlinear dynamics in oil markets than the methods applied individually in order to reduce instances of forecasting error by more than 20 percent and generate narrower confidence bands. The above developments give the policy makers accurate revenue forecasts, which allow them to make better budget decisions given the unpredictable market conditions.

Future studies ought to investigate how these results are applicable to other commodity markets and other geopolitical settings, especially by conducting longitudinal studies over a series of price-cycles. It will be important to create interpretable hybrid framework and standard benchmarking protocols in order to bridge the gap between the theoretical achievements and the practical policy implementation. With oil markets evolving to become more algorithmically governed and geopolitical in nature, forecasting methodologies may increasingly be refined with multi-scale analysis and behavioral economics information. The current work sets a ground of such research but also highlights the transformational nature of hybrid models in economic forecasting.

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