DOI: 10.33948/ESJ-KSU-17-3-7

Modeling the Future of Saudi Arabia's Economy: An Assessment of Time Series Forecasting Methods Up to 2030

Marwan A. Ashour

Professor, Department of Statistics, College of Administration and Economics, University of Baghdad, Baghdad, Iraq.

dr_Marwan2012@yahoo.com

(Received: August 16, 2024; accepted for publication: October 20, 2024.)

Abstract: *This paper compares three well-known time series forecasting models, ARIMA (autoregressive integrated moving average), NAR (nonlinear autoregressive), and RNN (recurrent neural network), to predict what Saudi Arabia's GDP will be by 2030. Given the nation's significant economic transformation under its Vision 2030 reform plan, accurate GDP forecasting becomes crucial for strategic planning and policy formulation. The study uses historical economic data, augmented by global economic conditions and national economic policies, to model and forecast future economic scenarios. We utilize the ARIMA model for its proficiency in handling linear time-series data with seasonal variations, and we explore the NAR and RNN models for their capacity to process nonlinear dynamics and complex temporal dependencies, respectively. The paper evaluates each model's predictive accuracy using root mean square error (RMSE) and coefficient of determination (R2), providing a comprehensive overview of their performance in forecasting Saudi Arabia's GDP. The findings aim to guide policymakers and economic stakeholders in selecting the most appropriate forecasting tool, given Saudi Arabia's dynamic, rapidly evolving economic landscape. The results show that ARIMA models are good at. Still, RNN models, especially those with LSTM architectures, are better at predicting long-term economic trends, which is important for making sureshort-term predictions. Still, RNN models, especially those with LSTM architectures, are better at predicting long-term economic trends, which is important for ensuring that the strategic goals of Vision 2030 are met.*

Keywords*: Economic Forecasting, Machine Learning, Neural networks, NAR, RRN, ARIMA*

Introduction

As the world's largest oil exporter, Saudi Arabia's economy presents unique dynamics influenced by both global energy markets and domestic economic policies. The nation's Gross Domestic Product (GDP) is a critical barometer for assessing the health and trajectory of its economy. Accurately forecasting Saudi Arabia's GDP is essential for policymakers, investors, and economic planners to make informed decisions that align with the country's strategic objectives, particularly the Vision 2030 reform plan aimed at economic diversification and sustainable development.

This paper aims to forecast Saudi Arabia's GDP 2030, leveraging historical economic data and employing sophisticated econometric models. The study is particularly timely, as it coincides with significant global economic shifts and major domestic reforms in Saudi Arabia, including initiatives to reduce oil dependency, enhance private-sector growth, and develop public service sectors such as health, education, and infrastructure.

The forecasting methodology centers on the Autoregressive Integrated Moving Average (ARIMA) model, renowned for its effectiveness in modeling and forecasting time series data. This model will be calibrated to account for seasonal variations and external economic shocks, providing a robust framework for predicting future economic outcomes. Additionally, this paper will explore the implications of various global and local economic scenarios on Saudi Arabia's GDP, offering a comprehensive outlook and valuable insights into the potential economic future of the nation (Ashour & Abbas, 2018; Ashour & Helmi, 2024; Mubarak Samer Mohammed Jaber and Ashour, 2024).

In recent years, several studies have focused on time series forecasting using three major approaches: ARIMA, NAR, and RNN models, each addressing data processing challenges uniquely. ARIMA models are well-known for their ability to effectively model linear, stationary time series. In 2018, they found widespread use in settings characterized by seasonality and clear trends, providing reliable forecasts within these limits. ARIMA's restrictions become clear, though, when considering non-linear data properties. In this context, NAR models and their enhancements, such as NNAR (Neural Network-based Nonlinear Autoregressive Models), serve as robust substitutes. These models utilize neural networks to capture the complex dynamics present in the data. Comparative investigations, including those by Zhang in 2023, have shown that when data reveal non-linear trends, NAR models can outperform ARIMA models. Recurrent neural networks (RNNs), especially those with LSTM (long short-term memory) or GRU (gated recurrent unit) architectures, have made it much easier to predict the future. They excel at presenting complex variations and long-term dependent data. Gers's 2024 research shows that RNNs have a better capacity than conventional statistical models to learn from past data in a manner much greater than their capacity. Comparative research on these models reveals that none of them consistently outperforms the others under all circumstances. ARIMA might be better suited for scenarios requiring short-term precision, for example, but RNNs may be better suited for situations requiring an awareness of complicated patterns over longer periods. The forecasting goals and the type of data should guide the model selection(Ashour et al., 2020, 2023; Hameed Ashour & Abbas, 2023).

The objective of this study is not only to forecast future economic conditions but also to assess the influence of Saudi Arabia's economic policies and external economic factors. The objective of the findings is to enhance the strategic planning anticipated opportunities and challenges.

Method

ARIMA model

A well-liked method for predicting time series is the ARIMA model, which stands for Autoregressive Integrated Moving Average. It the three main components: moving average (MA), autoregressive (AR), and differencing (I). The autoregressive component (AR) considers an observation's correlation with a predetermined number of lag observations. It presupposes that one may infer a variable's future value from its previous value. To make a non-stationary time series stationary, one uses the differencing component. It entails taking differences between consecutive observations to remove any trend or seasonality from the data. An observation's dependence on the residual error of a moving average model applied to lag observations is considered by the moving average component (MA) (Ashour & Al-Dahhan, 2020, 2021). You can write the ARIMA model as ARIMA (p, d, q), where d is the differencing order. Q represents the order of the moving average component. With the right parameter values for p, d, and q, the ARIMA model can accurately forecast time series by capturing their underlying patterns and characteristics. Common methods for identifying the model parameters include examining partial and autocorrelation plots, estimating parameters using maximum likelihood estimation, performing a grid search, and evaluating the model using goodness-of-fit metrics. Figure 1 shows the approach of the ARIMA model(Ashour & Al-Dahhan, 2020; Munim et al., 2019; Wirawan et al., 2019).

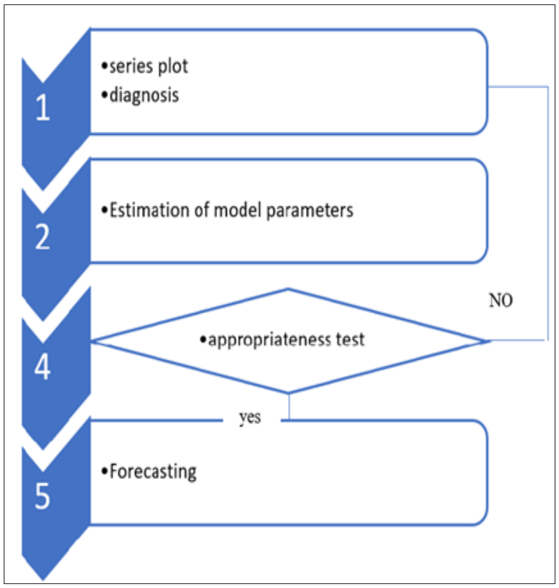

Figure 1. Architecture of ARIMA

NAR model

Nonlinear autoregressive (NAR) models are a more advanced version of traditional autoregressive methods. They are designed to understand the nonlinear dynamics common to many time-series datasets. Unlike linear models, such as ARIMA, which may fail to capture complex patterns, NAR models incorporate nonlinear functions of past values, making them highly effective in fields like finance, meteorology, and engineering, where data behavior is dynamic and complex. These models vary from polynomial NAR, which uses polynomial functions of past values, to neural network NAR (NNAR), which employs neural networks to model nonlinear dependencies. The challenge in using NAR models lies in requires advanced techniques such as optimization algorithms and regularization to ensure robustness and accuracy. Despite these challenges, NAR models' ability to improve forecasting in nonlinear scenarios makes them invaluable tools for advanced time series analysis. NAR models are expressed as(Ashour, 2022; Ferdiansyah et al., 2023) .

$$X_t = f(X_{t-1}, \ldots, X_{t-p}) + \epsilon_t \tag{1}$$

where f is a nonlinear function, x time series data, p is the order of the model, and ϵ is noise.

RNN model

Recurrent neural networks (RNNs) are specialized artificial neural networks optimized for processing sequential data, making them highly suitable for analyzing time-series data. In contrast to conventional feedforward neural networks, recurrent neural networks (RNNs) have cyclic connections, enabling them to retain a memory of past inputs and efficiently capture temporal interactions. By leveraging this feature, recurrent neural networks (RNNs) can effectively represent intricate temporal patterns, hence improving their effectiveness in a wide range of applications, including financial forecasting, weather prediction, anomaly detection in industrial environments, and healthcare outcome prediction. Recurrent neural networks (RNNs) are great at handling variable sequence lengths and remembering past events. This makes them reliable tools for studying and predicting things that change over time. Novel techniques, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), have been developed to address issues encountered by conventional RNNs, such as vanishing gradients(Hossain et al., 2023; Lazcano et al., 2023). Long Short-Term Memory (LSTM) models include memory cells and gating mechanisms, such as input, forget, and output gates, to regulate the flow of information and preserve long-term patterns. Group Regression Units (GRUs) streamline this architecture by merging forget and input gates into a unified update gate, thereby reducing complexity while maintaining the capacity to represent long-term relationships. These improvements have broadened the scope of applications for recurrent neural networks (RNNs) and enhanced their ability to capture temporal dependencies. Nevertheless, recurrent neural networks (RNNs) also pose challenges, particularly due to their substantial computational requirements and the potential for overfitting. requires substantial computational resources and time. Recurrent Neural Networks (RNNs) can overfit because of their complex structure and ability to show complex temporal connections. This means that they need careful regularization and validation methods. Notwithstanding these obstacles, the advantages of employing RNNs to record and predict complex time-dependent patterns surpass the problems. These tools will remain essential for data scientists and machine learning experts specializing in time series analysis. Continuous improvements in processing capabilities and optimization techniques are further improving the feasibility and effectiveness of recurrent neural networks (RNNs), therefore guaranteeing their substantial contribution to the future of time series forecasting and analysis. The functioning of the RNN model is illustrated in Figure(Ashour, 2022; Ashour & Al-Dahhan, 2021; Ferdiansyah et al., 2023).

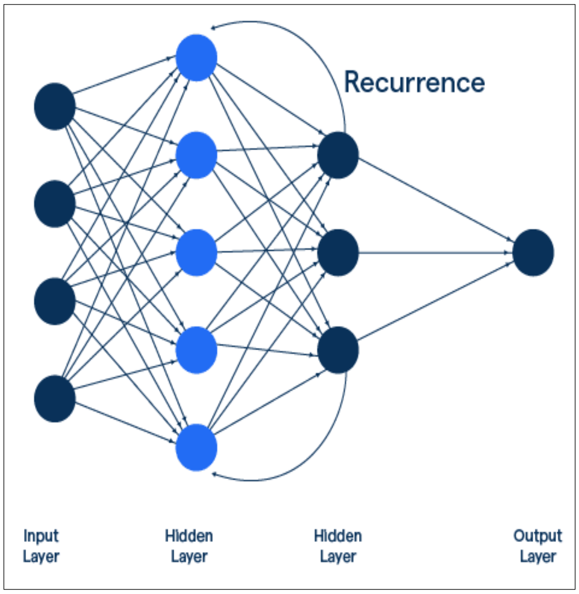

Figure 2. Architecture of the recurrent neural network.

Evaluating accuracy

To determine how effective prediction models are in time series analysis, it is necessary to assess their performance. Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) are two popular performance measures. These measures shed light on the models' precision and ability to explain data. I will demonstrate how to calculate these measures. It stands for Root Mean Square Error: When comparing anticipated and observed values, the root mean squared error (RMSE) is a good metric. We calculate it using the following formula(Ashour & Alashari, 2022; Minu et al., 2010):

$$RMSE = \sqrt{\frac{\sum(actual - predict)^2}{n}} \quad (2)$$

Where n is the total number of data points in the time series, actual and predicted are the predicted and actual values, respectively. R^2: Determination Coefficient. One measure of how well the predicted data fits the data is the coefficient of determination, which goes by several names, such as R-squared and R^2. The formula for its calculation is

$$R^2 = 1 - (SSR/SST) \quad (3)$$

Specifically, SSR stands for the unexplained variance in the projected data, while SST is the overall variation in the observed data. To decipher the findings, the better the match between the anticipated and observed values, with fewer errors, the lower the RMSE number. A higher R^2 value implies that the projected values explain a larger fraction of the variation in the observed data, which in turn suggests that the model is performing better (Abdul et al., 2023; Ferdiansyah et al., 2023; Lazcano et al., 2023).

Results

Figure 3 illustrates data on Saudi Arabia's Gross Domestic Product (GDP) from 1960 to 2023, demonstrating significant economic growth driven by expansions in the industrial and service sectors alongside abundant natural resources, such as oil. The data highlights periods of substantial increase, often associated with surges in oil prices or expanded production, while downturns reflect the economy's sensitivity to global crises such as oil price declines and global economic slowdowns, particularly evident during the pandemic and other global economic disruptions.

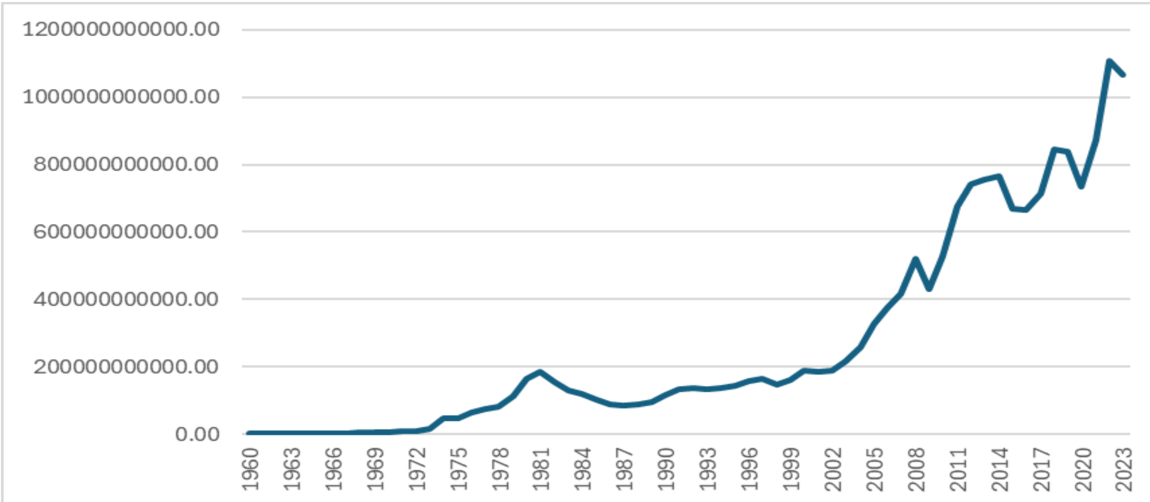

Figure.3 Saudi Arabia's GDP

Table 1 displays the results of the ARIMA analysis, indicating that ARIMA (1,0,0) is the best model. The table shows that the ARIMA model has a significant relationship.

Table 1. Statistics model

Model	Number of Predictors	Model Fit statistics			Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	Statistics	DF	Sig.	
VAR00001-Model_1	0	.954	.954	6.569E+10	12.643	17	.760	0

The ARIMA model results displayed in the table indicate a robust performance, with an R-squared value of.954, suggesting that the model accounts for 95.4% of the variance in the data. The high RMSE value might initially appear concerning, but its significance is context-dependent and should be evaluated against the scale of the data. Additionally, the Ljung-Box test results, with a p-value of.760 indicates no significant autocorrelation in the model residuals, suggesting that the residuals are random and demonstrating the model's predictive accuracy. Overall, the model appears to perform well, effectively handling the data without any outliers, showcasing its high efficacy in capturing the underlying data patterns.

The performance indicators for ARIMA, NAR, and RNN are presented in Table 2.

Table 2. Key Performance Metrics

Method	**RMSE**	**R^2**
ARIMA	65694884915.53	0.954
NAR	490977214666	0.960
RNN	20696000000	1.000

Table 2 presents the performance metrics for three forecasting methodologies: ARIMA, NAR, and RNN. The table utilizes two primary performance indicators, the root mean square error (RMSE) and the coefficient of determination (R^2), to evaluate each method.

ARIMA (Autoregressive Integrated Moving Average): This method, used for analyzing time series data, shows excellent performance, with an R^2 of 0.954. However, it has a relatively high RMSE, suggesting larger average prediction errors.

NAR (Nonlinear Autoregressive): As a form of neural network, it exhibits the highest RMSE among the methods, indicating the largest predictive errors, with an R^2 of 0.96. This could imply a slightly better fit to the data's variance than ARIMA.

RNN (Recurrent Neural Network): This type of neural network achieves a perfect R2 of 1, indicating highly accurate predictions.

These results are useful in assessing the effectiveness of each method for analyzing and forecasting time series data. The significance of each metric may vary depending on the specific context of use. Overall, these metrics suggest that the RRN models possess excellent predictive ability, effectively adapting to complex datasets and proving highly reliable in forecasting. This reliability is indispensable in decision-making processes where the cost of prediction errors is high, underscoring the models' applicability in critical and dynamic environments.

The seven-year prediction is in Table 3.

Table 3. Prediction value

year	prediction
2024	1549133993996.17
2025	1702164118944.95
2026	1870311218430.86
2027	2055068612277.26
2028	2258077136868.38
2029	2481139717470.31
2030	2726237380068.51

The data depicted in Table 3 provides a comprehensive forecast of a specific variable for ten years, revealing a notable and large upward trend in projected values from 2024 to 2033. Each successive year observes a consistent upward trajectory, indicating a robust pattern of expansion throughout the decade. The projected values commence at an estimated 1.549 trillion in 2024 and exhibit a consistent upward trend, reaching roughly 2.726 trillion by 2030. The observed exponential growth trajectory implies that the underlying model predicts substantial growth or accumulation in the measured variable. This could potentially indicate economic growth, population growth, technological advancements, or other sector-specific escalations, depending on the specific context of the data presented. The observed growth trend may suggest a compounding effect, in which the rate of expansion itself may exhibit an upward trajectory over time. Alternatively, a multitude of causes could gradually amplify or gain greater influence for the decade. The forecasts play a crucial role in the formulation of long-term plans and strategies across several domains, including corporations, government policies, investment strategies, and other applications that rely heavily on the ability to anticipate future circumstances. The assess stakeholders' preparedness and adaptive approaches to mitigate or alleviate the consequences of this anticipated expansion.

Conclusion

In the Conclusion of this paper, three well-known time series forecasting methods: ARIMA, NAR, and RNN—were carefully looked at. Each had its pros and cons in predicting the future and in the reliability of its models. With its ability to find patterns in time series data through a mix of differencing, autoregression, and moving-average components, the ARIMA model has shown impressive predictive power, even though its RMSE values indicate it makes more mistakes. On the other hand, the NAR model, by incorporating nonlinear dynamics, offers a significant improvement in handling complex patterns that are particularly prevalent in chaotic data sets. However, it also suffers from the highest predictive errors among the three models.

The RNN model stands out with the lowest RMSE and a perfect R^2 score, showcasing its exceptional ability to model temporal dependencies and complex interactions in time series data. This makes RNNs particularly valuable in environments where accurate forecasting can significantly impact decision-making processes. Moreover, advancements in neural network architectures, such as LSTM and GRUs, have further enhanced the RNN's ability to capture long-term dependencies without succumbing to issues like the vanishing gradient problem.

Comparing these models using key performance metrics such as RMSE and R^2 shows that time series analysis technologies are continually evolving. It also shows how important it is to choose the right model based on the data set's unique features and needs. Future research should continue to refine these models, address their respective weaknesses, and explore hybrid approaches that can leverage the strengths of each to improve overall forecasting accuracy.

This exploration not only enhances our understanding of time series modelling but also contributes to the broader field of predictive analytics, where forecast future events is paramount. As demonstrated by the predictive outputs, the ongoing advancements in time series modelling are likely to play a crucial role in shaping strategies across various sectors, making this an exciting area for further academic inquiry and practical application.

Reference

Abdul, M., Ashour, H., & Ahmed, A. S. (2023). Bitcoin prediction with a hybrid model. *Original Research*, *11*(1), 186–196.

Ashour, Marwan Abdul Hameed. (2022). Optimized Artificial Neural network models to time series. *Baghdad Science Journal*, *19*(4), 899–904. doi: 10.21123/bsj.2022.19.4.0899

Ashour, Marwan Abdul Hameed, & Alashari, O. M. N. (2022). Electricity Consumption Forecasting in Iraq with Artificial Neural Network. T. Ahram & R. Taiar (Eds.), Human Interaction, Emerging Technologies and Future Systems V (pp. 922–927). Cham: Springer International Publishing.

Ashour, Marwan Abdul Hameed, & Al-Dahhan, I. A. H. (2020). Turkish lira Exchange rate forecasting using time series models. *International E-Journal of Advances in Social Sciences*, *6*(16), 294–300.

Ashour, Marwan Abdul Hameed, & Al-Dahhan, I. A. H. (2021). Optimal Prediction Using Artificial Intelligence Application. T. Ahram, R. Taiar, & F. Groff (Eds.), Human Interaction, Emerging Technologies and Future Applications IV (pp. 76–83). Cham: Springer International Publishing.

Ashour, Marwan Abdul Hameed, Al-Dahhan, I. A. H., & Hassan, A. K. (2020). Forecasting by using the optimal time series method. *Human Interaction, Emerging Technologies and Future Applications II: Proceedings of the 2nd International Conference on Human Interaction and Emerging Technologies: Future Applications (IHIET–AI 2020), April 23-25, 2020, Lausanne, Switzerland*, 148–154.

Ashour, Marwan Abdul Hameed, Al-Dahhan, I. A. H., & Sherzad, S. S. (2023). Utilizing Artificial Intelligence for Accurate Population Predictions for Iraq Through 2030. *2023 IEEE 11th Conference on Systems, Process & Control (ICSPC)*, 17–21. doi: 10.1109/ICSPC59664.2023.10420232

Ashour, Marwan Abdul Hameed, & Helmi, R. A. A. (2024). Predicting the Youth Unemployment Rate in Iraq Until 2035 Using Artificial Intelligence. *2024 14th International Conference on System Engineering and Technology (ICSET)*, 73–77. doi: 10.1109/ICSET63729.2024.10774860

Ashour, Marwan Abdul Hammed, & Abbas, R. A. (2018). Improving time series' forecast errors by using recurrent neural networks. *ACM International Conference Proceeding Series*, 229–232. doi: 10.1145/3185089.3185151

Ferdiansyah, Othman, S. H., Radzi, R. Z. M., Stiawan, D., & Sutikno, T. (2023). Hybrid gated recurrent unit bidirectional-long short-term memory model to improve cryptocurrency prediction accuracy. *IAES International Journal of Artificial Intelligence*, *12*(1), 251–261. doi: 10.11591/ijai.v12.i1.pp251-261

Hameed Ashour, M. A., & Abbas, R. A. (2023). A Comparison of Predictive Models for Rice Imports in Iraq: Artificial Neural Networks vs. Traditional Techniques. *2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 1–5. doi: 10.1109/ICECCME57830.2023.10252366

Hossain, M. A., Gray, E., Lu, J., Islam, M. R., Alam, M. S., Chakrabortty, R., & Pota, H. R. (2023). Optimized Forecasting Model to Improve the Accuracy of Very Short-Term Wind Power Prediction. *IEEE Transactions on Industrial Informatics*, 1–13. doi: 10.1109/tii.2022.3230726

Lazcano, A., Herrera, P. J., & Monge, M. (2023). A Combined Model Based on Recurrent Neural Networks and Graph Convolutional Networks for Financial Time Series Forecasting. *Mathematics*, *11*(1). doi: 10.3390/math11010224

Minu, K. K., Lineesh, M. C., & Jessy John, C. (2010). Wavelet neural networks for nonlinear time series analysis. *Applied Mathematical Sciences*, *4*(49–52), 2485–2495.

Mubarak Samer Mohammed Jaber and Ashour, M. A. H. (2024). Forecasting Egypt's Death Rate for Sustainable Development Planning Using Artificial Intelligence. In A. Al Mubarak Muneer and Hamdan (Ed.), Innovative and Intelligent Digital Technologies; Towards an Increased Efficiency: Volume 1 (pp. 451–459). Cham: Springer Nature Switzerland. doi: 10.1007/978-3-031-70399-7_34

Munim, Z. H., Shakil, M. H., & Alon, I. (2019). Next-day bitcoin price forecast. *Journal of Risk and Financial Management*, *12*(2), 103.

Wirawan, I. M., Widiyaningtyas, T., & Hasan, M. M. (2019). Short Term Prediction on Bitcoin Price Using ARIMA Method. *2019 International Seminar on Application for Technology of Information and Communication (ISemantic)*, 260–265.

نمذجة مستقبل الاقتصاد السعودي: تقييم لأساليب تنبؤ السلاسل الزمنية الى عام 2030

أ.د. مروان عبدالحميد عاشور

أستاذ الإحصاء وبحوث العمليات، قسم الإحصاء،

كلية الإدارة والاقتصاد، جامعة بغداد، جمهورية العراق.

dr_Marwan2012@yahoo.com

(قُدِّم للنشر: 16 أغسطس، 2024م- وقُبِل للنشر: 20 أكتوبر، 2024م)

المستخلص: للتنبؤ بالناتج المحلي الإجمالي للمملكة العربية السعودية بحلول عام 2030، يناقش هذا البحث ثلاثة نماذج معروفة للتنبؤ بالسلاسل الزمنية ARIMA :(المتوسط المتحرك المتكامل الذاتي الانحداري)، و NAR(الانحدار الذاتي غير الخطي)، و RNN(الشبكة العصبية المتكررة). بالنظر إلى خطة الإصلاح الطموحة لرؤية 2030 الهادفة إلى التحول الاقتصادي، يعد التنبؤ الدقيق بالناتج المحلي الإجمالي ضروريًا للتخطيط الاستراتيجي الفعال وتطوير السياسات. يستخدم الدراسة بيانات اقتصادية تاريخية مدعومة بالظروف الاقتصادية العالمية والسياسات الوطنية لنمذجة السيناريوهات المستقبلية. نختار نموذج ARIMA لفعاليته في إدارة البيانات الخطية مع التقلبات الموسمية، ونستكشف النماذج NAR و RNN لقدرتها على التعامل مع الديناميكيات غير الخطية والتبعيات الزمنية المعقدة. نقيّم دقة التنبؤ لكل نموذج باستخدام خطأ المتوسط التربيعي الجذري (RMSE) ومعامل القرار .(R2) تشير النتائج إلى أنه، بينما يبرع نموذج ARIMA في التنبؤات قصيرة المدى، فإن نماذجRNN ، وخاصة تلك التي تستخدم هياكلLSTM ، تتفوق في التنبؤ بالاتجاهات الاقتصادية طويلة المدى. هذا التمييز حاسم للتوافق مع الأهداف الاستراتيجية لرؤية 2030، مما يساعد صانعي السياسات والأطراف المعنية بالاقتصاد في اختيار النهج الأنسب للتنبؤ .

الكلمات المفتاحية: التنبؤ الاقتصادي، التعلم الآلي، الشبكات العصبية، NAR، RNN، ARIMA.