

Comparison of Moving Average and Artificial Neural Network Modelling for the Daily Stock Market of the TASI Index Prediction

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ABSTRACT

Many statisticians and economists are intrigued by the accuracy of predictions from time series models applied to data like stock price indices. The Moving Average Autoregressive Integrated Moving Average (MA-ARIMA) is a linear model used in time series analysis. It transforms the original data into a k th moving average before applying the classical ARIMA. MA-ARIMA includes Simple Moving Average ARIMA (SMA-ARIMA), Weighted Moving Average ARIMA (WMA-ARIMA), and Exponential Weighted Moving Average ARIMA (EWMA-ARIMA). Recently, Artificial Neural Networks (ANN), particularly the forward propagation technique, have been explored as alternatives for forecasting. This paper compares MA-ARIMA and its variants with ANN using a single hidden layer feed-forward network to predict the Saudi Arabia stock market (TASI). The dataset comprises historical daily closing stock prices from January 1, 2020, to May 25, 2023, totaling 887 days. The study evaluates the accuracy and effectiveness of both techniques. To our knowledge, this is the first comparison of MA-ARIMA and ANN for forecasting the Saudi market or any other market. Findings suggest that the 3rd WMA-ARIMA(3,1,2 model outperforms the ANN in predicting stock market trends. The article concludes that there is no significant difference between the accuracy of the MA-ARIMA and ANN methods in predicting future daily stock prices, providing valuable insights for investors and analysts.

Keywords: MA-ARIMA, Artificial Neural Network, SMA-ARIMA, WMA-ARIMA EWMA-ARIMA, TASI Index, Time-series forecasting, Stock Market Prediction.

2000 Mathematics Subject Classification: 49K05, 49K15, 49S05.

1 Introduction

Numerous research have contrasted time series forecasting methods for predicting stock indices and financial markets. Due to the intricate linkages between the market and uncertainty-affecting factors, forecasting financial time series is challenging. Over recent decades, significant attention has been dedicated to developing and enhancing time series forecasting models. The autoregressive integrated moving average (ARIMA) model is among the most important and widely used. The ARIMA model's popularity stems from its robust statistical underpinnings and the established Box-Jenkins methodology used in its development.(Box, Jenkins, Reinsel and Ljung, 2015). In addition, ARIMA models can incorporate different exponential smoothing

techniques (McKenzie, 1984).

The moving average autoregressive integrated moving average (MA-ARIMA) technique involves converting the original time series data into a k th time moving average before applying the traditional ARIMA model. This method has three different forms: simple moving average autoregressive integrated moving average (SMA-ARIMA), weighted moving average autoregressive integrated moving average (WMA-ARIMA), and exponential weighted moving average autoregressive integrated moving average (EWMA-ARIMA) (Shih and Tsokos, 2008; Tsokos, 2010). The parameters for both ARIMA and MA-ARIMA models were estimated through the methods of least squares and maximum likelihood estimation. The least squares method demands rigorous assumptions about the model specifications to ensure meaningful results in parameter estimation. This necessity makes it unsuitable for complex or nonlinear models (Box and Jenkins, 1968).

Artificial Neural Networks (ANNs) offer an alternative approach for forecasting nonlinear time series and addressing nonlinearity and nonstationarity issues. In recent years, ANN applications have garnered significant attention due to their large storage capacity, learning capabilities, and prediction prowess. Particularly in economic forecasting, ANN has been extensively used to predict stock market indicators based on economic developments in different countries. (Trippi and Turban, 1992). The forward propagation technique is a popular implementation of ANN. Forward propagation refers to passing input data through the network layers, from input to output, to make a prediction. The network structure that facilitates the forward propagation process is called a feed-forward network (FNN).

This article compares two time-series forecasting methods: MA-ARIMA, with its three forms (SMA-ARIMA, WMA-ARIMA, EWMA-ARIMA), and the ANN technique, which employs a FNN with one hidden layer. The comparison aims to forecast the daily closing price of the TASI stock market in Saudi Arabia and assess the performance of both methods. While numerous studies have employed ANNs for stock market predictions, relatively few have utilized the MA-ARIMA method.

This study's novelty lies in its comparative analysis of the MA-ARIMA and ANN methods for forecasting the TASI index's daily stock prices in Saudi Arabia. To our knowledge, no study has compared the two methodologies, MA-ARIMA and ANN, to predict the stock market of Saudi Arabia or any other market. In addition, implementing the Box and Jenkins methodology might not be the best approach for providing a prediction model for the original time series data, so transforming this data is suitable for optimization. This study provides a unique contribution by evaluating the accuracy and effectiveness of both techniques using an extensive dataset of historical daily stock prices, covering 887 days from January 1, 2020, to May 25, 2023. The findings revealed that, while both methods can achieve good forecasting results, the MA-ARIMA method outperforms the ANN in accuracy. This research offers investors and financial analysts valuable insights, enhancing their decision-making processes related to market trends, portfolio management, and investment strategies.

The remaining portion of the study is organised in the following manner: Section 2 offers a concise summary of relevant theoretical and empirical literature. Section 3 outlines the study's methodology, including the MA-ARIMA and ANN techniques. Section 4 provides an examina-

tion of the empirical findings, while Section 5 wraps up with the conclusion of the study.

2 The related works

Predicting stock prices has long been a formidable task for investors and financial analysts. The future trends in stock market prices are heavily influenced by various economic, political, and external factors, rendering the prediction process highly complex. Nonetheless, advancements in machine learning have paved the way for developing various time-series forecasting models tailored for stock market prices. This literature review overviews three prominent modelling techniques for stock market prices: MA-ARIMA, ANN, and ARIMA. It begins with a discussion of MA-ARIMA, followed by a review of studies comparing ARIMA with ANN. The review concludes by highlighting studies that have used ANNs to forecast the future index value of the Saudi stock market, TADAWUL. Our investigation focuses on studies using classical ARIMA for predicting stock market prices. This choice is motivated by the limited number of studies utilizing MA-ARIMA models and the fact that the ARIMA model can be applied to MA-ARIMA models after transforming time series datasets.

Safi and Dawoud performed a comparative analysis of the three models of the MA-ARIMA method using both simulated and actual stock market data from PALTEL. The study examined the sensitivity of each model to selection criteria based on forecasting accuracy. The 3rd SMA-ARIMA model demonstrated superior forecasting accuracy compared to all other models (Safi and Dawoud, 2013). Yagoub and Eledum utilized various statistical models, including the three models of the MA-ARIMA method along with regression, to predict daily confirmed, recovery, and death cases of COVID-19 in Gulf Cooperation Council countries up to November 30, 2020. The findings indicated that WMA-ARIMA, along with EWMA-ARIMA, outperformed traditional ARIMA in forecasting confirmed and recovery cases. Moreover, SMA-ARIMA was more effective in predicting recovery and death cases (Yagoub and Eledum, 2021). Dawoud investigated the cumulative confirmed COVID-19 cases in Palestine employing ARIMA and MA-ARIMA methods. Data from the World Health Organization (WHO) covering the period from March 5 to August 27, 2020, was used for the analysis. The best models identified were ARIMA(1,2,4) and the fifth EWMA-ARIMA(2,2,3) (Dawoud, 2020).

Okasha and Yaseen implemented both ARIMA and ANN models to predict the stock price of the Al-Quds index of the Palestine Stock Exchange (PSE) using time series data. The results indicated that the ANN model provided forecasts that closely matched the actual values, especially when applying a logarithmic transformation to the original time series (Okasha and Yaseen, 2013). Du combined ARIMA with the back-propagation neural network (BPNN) to forecast the Shanghai Securities Composition Stock Index, evaluating its accuracy against a single ARIMA and BPNN method. The findings revealed that the ARIMA-BPNN outperformed the BPNN regarding prediction accuracy. Additionally, the BPNN method exhibited superior performance compared to the ARIMA model alone (Du, 2018). Yoo conducted a study to determine whether the BPNN surpasses the SARIMA model in predicting the Korea Composite Stock Price Index (KOSPI) and its returns. The findings revealed that the SARIMA outperformed the BPNN model in predicting KOSPI (Yoo, KYUNGJOO and John Jongdae, 2007). Merh et

al. presented a comparison of a three-layer feed-forward backpropagation ANN, ARIMA, and other hybrid algorithms for estimating the value of several indexes in the Indian stock market, including the SENSEX, BSE IT, BSE Oil & Gas, BSE 100, and S&P CNX Nifty. The findings indicated that the hybrid ANN-ARIMA model's predictions for the SENSEX, BSE IT, and S&P CNX Nifty were superior to those of the hybrid ARIMA-ANN model. However, the results for the BSE 100 were only marginally better than those of the hybrid ANN-ARIMA (Merh, Saxena and Pardasani, 2010). Wijayael et al. compared the forecasting results for ANTM (PT Aneka Tambang) stock using an ANN and an ARIMA model. The findings revealed that the ANN approach provided higher forecasting accuracy than the ARIMA method (Wijaya, Kom and Napitupulu, 2010).

Adebiyi et al. compared the accuracy of ARIMA and ANN forecasts using stock market data from the New York Stock Exchange. The results demonstrated that both ARIMA and ANN models could accurately predict outcomes in real-world scenarios, making them valuable tools for stock price prediction. However, the findings indicated that the ANN model outperformed the ARIMA model (Adebiyi, Adewumi, Ayo et al., 2014). Wijesinghe et al. focused on forecasting the future index value of the Colombo Stock Exchange (CSE) and compared the BPNN to the ARIMA model. The findings demonstrated that the BPNN method outperformed the classical ARIMA model in terms of performance and accuracy (Wijesinghe and Rathnayaka, 2020).

Many studies have been carried out to forecast the future index value of the Saudi stock market, TADAWUL, using ANN. For example, Alotaibi et al. Investigated the BPNN method to forecast the Saudi stock market's behavior. The proposed ANN model produced effective results (Alotaibi, Nazir, Alroobaea, Alotibi, Alsubeai, Alghamdi and Alsulimani, 2018). Malibari et al. introduced a machine-learning strategy for stock price prediction using transformer neural networks trained on datasets from the Saudi Stock market. The study concluded that the proposed model could forecast the stock prices of the Tadawul All Share Index with an accuracy exceeding 90% (Malibari, Katib and Mehmood, 2021). Jarrah and Erbali used the multivariate long short-term memory deep learning (LSTMDL) algorithm to predict stock market values in the Saudi stock exchange, following removing irrelevant data. Their comparison with the univariate method showed that LSTMDL yielded superior performance in forecasting stock market values (Jarrah and Derbali, 2023).

As seen from the above publications, most studies that compared ANN and ARIMA concluded that ANN was more effective. However, all the studies in which a hybrid model was applied showed that it was superior to ANN and ARIMA. On the other hand, studies that compared MA-ARIMA to the ARIMA model found that the MA-ARIMA model was considerably better at forecasting stock market prices than the classical ARIMA model. At the same time, no published research compares the MA-ARIMA and ANN methodologies for predicting stock market prices for the Saudi market or any other market.

3 Research Methodology

In this research, we used MA-ARIMA and ANN techniques to forecast future values for the daily closing price time series of the TASI stock market in Saudi Arabia. Subsequently, we con-

ducted a comparative analysis of the results from both methods to ascertain which approach is more suitable for similar scenarios. The following procedures were undertaken to achieve this objective:

- Determining the best MA-ARIMA model for predicting future TASI index values.
- Identifying the best ANN model to predict future TASI index values.
- Using the Mean Squares Error (RMSE) and Mean Absolute Percentage Error (MAPE), along with the Diebold-Mariano (DM) test, to compare the future TASI index values of the two methods.
- Finally, we provide pertinent recommendations derived from the results of the preceding comparisons.

3.1 The Moving Average Time-Series Models

After converting it into a k th-order moving average, the MA-ARIMA model applies the classical ARIMA methodology to the original time series data. The MA-ARIMA contains SMA-ARIMA, WMA-ARIMA, as well as EWMA-ARIMA. Once the forecasting model for the converted time series has been developed, a back-shift operator is employed to get estimates of the initial time series.

The stock price index data is typically gathered sequentially over time, classifying it as time series data. These data exhibit pronounced nonlinear behavior and change over time. Therefore, the time series x_t where $t = 1, 2, 3, \dots, n$ represents the closing price of the stock market on day t .

3.1.1 Calculations for MA-ARIMA models and their associated back-shift operators

Equations (3.1), (3.3), and (3.5) illustrate the k^{th} SMA-ARIMA, k^{th} WMA-ARIMA, along with the k^{th} EWMA-ARIMA calculations for a time series x_t , respectively, while Equations (3.2), (3.4), and (3.6) provide the corresponding back-shift operators.

$$y_t = \frac{1}{k} \sum_{j=0}^{k-1} x_{t-k+1+j} \quad \text{for } t = k, k+1, \dots, n \quad (3.1)$$

$$\hat{x}_t = k \hat{y}_t - x_{t-1} - x_{t-2} - \dots - x_{t-k+1} \quad (3.2)$$

$$y_t = \frac{1}{[(1+k)k]/2} \sum_{j=0}^{k-1} (j+1)x_{t-k+1+j} \quad \text{for } t = k, k+1, \dots, n \quad (3.3)$$

$$\hat{x}_t = \frac{1}{k} \left[\frac{(1+k)k}{2} \hat{y}_t - (k-1)x_{t-1} - (k-2)x_{t-2} - \dots - x_{t-k+1} \right] \quad (3.4)$$

$$y_t = \frac{1}{\sum_{j=0}^{k-1} \delta^j} \sum_{j=0}^{k-1} \delta^{k-j-1} x_{t-k+1+j} \quad \text{for } t = k, k+1, \dots, n \quad (3.5)$$

$$\hat{x}_t = \hat{y}_t \sum_{j=0}^{k-1} \delta^j - \delta x_{t-1} - \delta^2 x_{t-2} - \dots - \delta^{k-1} x_{t-k+1} \quad \text{for } \delta = 1 - 2/(k+1) \quad (3.6)$$

where $\hat{y}_t$ is the fitted value of the y_t for the ARIMA model, and $\hat{x}_t$ is the corresponding fitted value of the x_t .

3.1.2 The best MA-ARIMA model

To ascertain the best model among SMA-ARIMA, WMA-ARIMA, as well as EWMA-ARIMA to predict future TASI values, we apply the steps below:

Step 1. Transform the original time series x_t using Eq.(3.1) for SMA-ARIMA, Eq.(3.3) for WMA-ARIMA, and Eq.(3.5) for EWMA-ARIMA, setting $k = 2, 3, \dots, 5$ to obtain the new time series data y_t .

Step 2. Apply an ARIMA model to the new time series data y_t using the Box-Jenkins Methodology.

Step 3. Choose the best model of order k among each type of MA-ARIMA based on the smallest value of the AIC criterion.

Step 4. Apply the back-shift operator for the model in Step 3 using Eq.(3.2) for SMA-ARIMA, Eq.(3.4) for WMA-ARIMA, and Eq.(3.6) for EWMA-ARIMA to obtain the original fitted values $\hat{x}_t$.

Step 5. Choose the best model among each type of MA-ARIMA using the smallest value RMSE and MAPE criteria.

Note that the testing data, which constitute the last 10% of the entire time series data, are utilised to compute the RMSE and MAPE.

3.2 The Neural Network approach to time series modelling

Neural networks are often employed to analyze and forecast time series data. One crucial architecture in ANNs is the FNN, commonly known as a multilayer perceptron (MLP). This architecture consists of at least three layers of nodes: an input layer, one or more hidden layers, and an output layer. In such a network, data moves only in a forward direction, from the input nodes to the output nodes through the hidden nodes, without any cycles or loops (Heaton, 2018).

In the current study, the daily closing price of the TASI stock market is modelled using FNN with one hidden layer. The mathematical model for FNN with one hidden layer contains diverse processes, including computations in the input, hidden, and output layers.

The input layer gets input variables $x_{t*} = (x_{t-1}, x_{t-2}, \dots, x_{t-p})$, where p is the number of neurons. The hidden layer contained k neurons. The computations for each neuron involve two steps: first, calculating the linear weighted sum of the inputs, and second, applying the activation function element-wise to this result (Bishop and Nasrabadi, 2006).

Let $w(i, k)$ be the weight between the i th input and the k th neuron, $w(0, k)$ be the bias of the k th neuron, and $g(\cdot)$ be the activation function applied to the weighted sum of the inputs. Then,

we can figure out the k th neuron's output in the hidden layer as follows:

$$\alpha(k) = g \left(w_{(0,k)} + \sum_{i=1}^p w_{(i,k)} x_{t-i} \right)$$

if $v(j, m)$ stands for the weight between the j th neuron in the hidden layer and the m th neuron in the output layer. $v(0, m)$ stands for the bias of the m th neuron. $h(\cdot)$ stands for the activation function. Then, the m th neuron's output is found by:

$$x_m = h \left(v(0, m) + \sum_{j=1}^k v(j, m) \alpha(j) \right)$$

Figure 1 shows the FNN with one hidden layer design. It has a hidden layer with two neurons (1 and 2), an input layer with three variables (x_{t-1} , x_{t-2} , and x_{t-3}), and an output layer for the m th neuron.

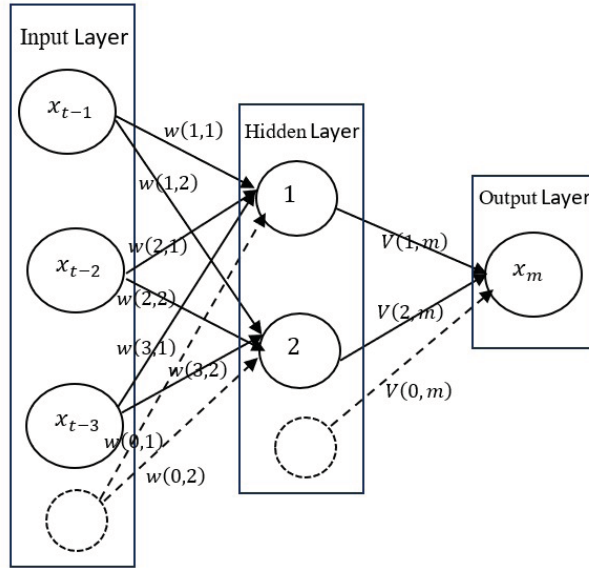


Figure 1. The FNN with Single hidden layer architecture

To demonstrate the link between the output (x_t) and the inputs ($x_{t-1}, x_{t-2}, \dots, x_{t-p}$), it is convenient to describe the FNN model with one hidden layer, as given in Eq. (3.7) [see (Diebold and Mariano, 2002)].

$$x_t = \alpha_0 + \sum_{j=1}^q \alpha_j g \left(\beta_{0j} + \sum_{i=1}^p \beta_{ij} x_{t-i} \right) + u_t \quad (3.7)$$

α_j ($j = 0, 1, 2, \dots, q$) and β_{ij} ($i = 0, 1, 2, \dots, p; j = 1, 2, \dots, q$) represent model parameters or connection weights. p is the number of input neurons, while q is the number of hidden neurons. The function $g(\cdot)$ represents the hidden layer transfer function, whereas u_t denotes the random error at time t .

The ANN model uses a nonlinear functional mapping to predict future value x_t . This is expressed as

$$x_t = f(x_{t-1}, x_{t-2}, \dots, x_{t-p}, \omega) + u_t$$

where $f(\cdot)$ represents a function determined by the network structure and the connections' weights, and ω is a vector containing all the parameters.

3.3 Assessing the Model's Fit Accuracy

Once the time series model has been estimated using MA-ARIMA and ANN, the subsequent task is to assess its goodness of fit to verify its ability to effectively represent the fundamental trends and relationships present in the data. This evaluation involves residual analysis and statistical tests. A good model should have normally distributed residuals with a zero mean and constant variance. This can be verified by plotting the residuals' ACF and PACF. The Ljung-Box test is also used to check for autocorrelation in the residuals. If the p-value of the Ljung-Box test is greater than the significance level, it indicates that the residuals do not have significant autocorrelation, suggesting that the model is a good fit.

3.4 Evaluation Metrics for Forecasting Accuracy

The accuracy of the model's forecasts is assessed using several statistical measures, the most important being the RMSE and MAPE. These measures are applied to compare the performance of the MA-ARIMA and ANN forecasting models, aiding in determining which model performs better.

Suppose x_t represents the closing price at t^{th} day and $\hat{x}_t$, denotes the forecast of x_t , the forecast error is shown as $e_t = x_t - \hat{x}_t$. Accordingly,

$$RMSE = \sqrt{\frac{1}{n} \sum e_t^2} \quad (3.8)$$

$$MAPE = \frac{1}{n} \sum \left| \frac{e_t}{y_t} \right| \quad (3.9)$$

Note that Eq.(3.8) and Eq.(3.9) are calculated using the testing data, which is the last 10% of the entire closing price time series data.

3.5 Comparison of Two Forecasts' Predictive Accuracy

The Diebold-Mariano (DM) test evaluates the predictive power of one model against another. It was initially introduced by Francis Diebold and Roberto Mariano in 1995. If there are two models estimated at the same data sample, generating forecasts $\hat{x}_{1t}$ and $\hat{x}_{2t}$, then forecast errors are defined

$$e_{it} = x_t - \hat{x}_{it} \quad i = 1, 2$$

The forecast error e_{it} is considered to be a function of the loss associated with forecasting i , which is denoted as $g(e_{it})$. The mean loss is defined as follows:

$$\bar{d} = \frac{1}{H} \sum_{t=1}^H d_t \quad \mu = E(d_t)$$

where H is the number of forecasts generated by each model, $d_t = g(e_{1t}) - g(e_{2t})$.

The time series $d_t = g(e_{1t}) - g(e_{2t})$ is called the loss-differential between the two forecasts,

and $g(e_{it})$ is loss function of the forecast error e_{it} , Typically, $g(e_{it}) = e_{it}^2$ or $g(e_{it}) = |e_{it}|$, that is d_t is related to the MSE error statistic or the MAE error statistic.

Two forecasts are considered to have equal accuracy if and only if the expected value of the loss differential is zero for all periods t . Therefore, we would like to test $H_0 : \mu = 0$ that the two forecasts have the same accuracy against $H_a : \mu \neq 0$ that the levels of accuracy are different for the two forecasts .

The DM statistic is defined as (Diebold and Mariano, 2002)

$$S = \frac{\bar{d}}{\sqrt{\frac{\gamma_0 + 2\gamma_1 + \dots + 2\gamma_q}{H-1}}} \quad (3.10)$$

Where γ_q is the autocovariance at lag q .

4 Results and Discussions

This section presents the time series for TASI's daily closing stock market price used in this research. It discusses modelling these daily stock prices using the MA-ARIMA and ANN methods. This Section further investigates the diagnostics of residuals within each model, presents forecasts generated by each model, and compares the accuracy of the estimates from the two models.

4.1 Input Data

The current study focuses on the Saudi Stock market, which operates from Sunday to Thursday. It uses the historical daily stock prices of the Tadawul All Share Index (TASI) for modelling and forecasting purposes. The dataset comprises closing prices, representing the final transaction price during regular daily trading hours. The TASI is a major stock market index in Saudi Arabia, tracking the performance of all companies listed on the Tadawul exchange and being market-capitalized. The data covers the period from January 1, 2020, to May 25, 2023, encompassing 887 days. The closing price of the TASI is shown in Figure 2. The data sources used for this study are the Saudi Arabia Stock Market and the website Investing.com. The calculations were performed using R Studio software.



Figure 2. The line graph of the stock price for the TASI index

According to the graph in Figure 2, it can be observed that the closing price for the TASI index went down at the start of the COVID-19 outbreak. At the end of March 2020, it starts to go up, and it keeps going up slowly until it reaches its peak on May 9, 2022. Subsequently, it goes down slowly until it increases again in 2023. In general, the time series of the closing price shows an apparent increasing trend and a nonseasonal pattern, indicating that it is nonstationary.

4.2 Modelling of the daily stock price using MA-ARIMA Models

Based on Subsection 3.1.2, to conduct the MA-ARIMA models, the original time series x_t is transformed using Eq. (3.1) for SMA-ARIMA, Eq. (3.3), for WMA-ARIMA and Eq. (3.5) for EWMA-ARIMA, setting $k = 2, 3, \dots, 5$. Then, the augmented Dickey-Fuller test (ADF) is performed, and the findings in Table 1 indicate that all transformed stock price time series data showed stationary at first differences with constant and linear trend during the study period. Consequently, Step 2 of applying an ARIMA using the Box-Jenkins methodology is conducted. The minimum AIC is used to determine the best model of order k for each type of MA-ARIMA method, and the results are presented in Table 2. For instance, the 2nd SMA-ARIMA(5,1,4) is selected as the best model among all candidate SMA-ARIMA models for $k = 2$. Similarly, the 3rd EWMA-ARIMA(2,1,5) is identified as the best model among all candidate EWMA-ARIMA models for $k = 3$. Table 2 also provides the RMSE and MAPE for each model, noting that these measures are calculated using the testing data, which is the last 10% of the daily stock price time series data.

After evaluating the MA-ARIMA models for ($k = 2, 3, 4$, and 5), the best forecasting model is selected based on the smallest RMSE and MAPE values. For SMA-ARIMA, the best model is the 4th SMA-ARIMA(5,1,3) with RMSE=72.93 and MAPE=0.539%. The 3rd WMA-ARIMA(3,1,2) is identified as the best model for WMA-ARIMA with RMSE=72.46 and MAPE=0.540%, while the 2nd EWMA-ARIMA(2,1,3) is determined to be the best model among all EWMA-ARIMA models with RMSE=72.45 and MAPE=0.533% (refer to Table 2).

Table 1. The ADF unit root test for the transformed stock price time series data

k	SMA-ARIMA		WMA-ARIMA		EWMA-ARIMA	
	diff. order.	test stat.	diff. order	test stat.	diff. order	test stat.
2	1st difference	-9.0013**	1st difference	-8.7472**	1st difference	-8.8542**
3	1st difference	-7.5534**	1st difference	-8.4282**	1st difference	-8.5658**
4	1st difference	-7.7917**	1st difference	-8.2315**	1st difference	-8.2737**
5	1st difference	-8.6761**	1st difference	-7.8935**	1st difference	-8.0053**

Note: **Significant at 1%.

Table 2. The best MA-ARIMA Models for Stock Prices with Corresponding RMSE, MAPE, and AIC Values

k	SMA-ARIMA	RMSE MAPE	AIC	WMA-ARIMA	RMSE MAPE	AIC	EWMA-ARIMA	RMSE MAPE	AIC
2	2-(5,1,4)	73.11 0.548%	9449.97	2-(2,1,3)	72.46 0.541%	9949.966	2-(2,1,3)	72.45 0.533%	10159.14
3	3-(5,1,5)	73.97 0.571%	8728.26	3-(3,1,2)	72.46 0.540%	9662.579	3-(2,1,5)	72.48 0.541%	9426.88
4	4-(5,1,3)	72.93 0.539%	8218.29	4-(2,1,5)	72.61 0.541%	9270.448	4-(2,1,5)	72.50 0.536%	9025.81
5	5-(5,1,5)	74.28 0.563%	7818.08	5-(1,1,5)	72.58 0.541%	8941.46	5-(2,1,3)	72.72 0.543%	8939.011

4.2.1 Diagnostics of Residuals from MA-ARIMA Models

We examine the residuals from the fitted models: 4th SMA-ARIMA(5,1,3), 3rd WMA-ARIMA(3,1,2), and 2nd EWMA-ARIMA(2,1,3) for autocorrelation at different lags. We generate plots for the ACF and the PACF to identify any remaining autocorrelation. If significant correlations are still present, it may suggest that the model fails to capture some important data features. We then conduct the Box-Ljung test to assess the independence of residuals from these time series models.

For all three models, the ACF and PACF plots show no autocorrelations among the residuals, as the autocorrelation and partial autocorrelation values are within the 95% control limits (refer to Figures A1 , A2, and A3 in the Appendix). The results shown in Table 3, summarizing the Box-Ljung test outcomes, verify no remaining autocorrelation in the residuals for these models. The null hypothesis of residuals being white noise cannot be rejected. Consequently, the 4th SMA-ARIMA(5,1,3), 3rd WMA-ARIMA(3,1,2), and 2nd EWMA-ARIMA(2,1,3) models demonstrate a good fit.

Table 3. The Box-Ljung test outputs for the best MA-ARIMA models

Model	Q*	p-value
4 th SMA-ARIMA(5,1,3)	13.898	0.5333
3 rd WMA-ARIMA(3,1,2)	3.3919	0.9981
2 nd EWMA-ARIMA(2,1,3)	14.966	0.454

The 3rd WMA-ARIMA(3,1,2) model, which demonstrates the highest p-value (0.9981) in the Box-Ljung test, indicates the best fit with white noise residuals. This model's estimated parameters are statistically significant, further validating its effectiveness and reliability. This combination of statistical significance in parameter estimation and the highest p-value for residual independence makes the 3rd WMA-ARIMA(3,1,2) model the most appropriate choice as the best model among all MA-ARIMA models.

4.2.2 Forecasting using 3rd WMA-ARIMA(3,1,2)

To evaluate the accuracy of the forecasted values from the third WMA-ARIMA(3,1,2) model, we split the entire time series data into two parts. The first part, which represented 90% of the data, was used for training (in-sample), while the remaining 10% was used for testing (out-of-sample). We applied the third WMA-ARIMA(3,1,2) model to the training dataset to obtain forecasted values for the test dataset (in-sample forecast). We then compared the in-sample forecast with the out-of-sample forecast or testing dataset. The statistical measures RMSE and MAPE were 409.228 and 3.34%, respectively. Subsequently, the third WMA-ARIMA(3,1,2) model was used to obtain forecasted values of the stock price for the next two weeks (Sun, 28 May 2023 to Thu, 8 June 2023), and the results are presented in Table 4.

Table 4. The 2-weeks forecast of the stock price using 3rd WMA-ARIMA(3,1,2) model

Days	28 May	29 May	30 May	31 May	1 Jun
Stock price	11030.00	11208.10	11181.72	11128.04	11163.56
Days	4 Jun	5 Jun	6 Jun	7 Jun	8 Jun
Stock price	11156.13	11149.37	11154.00	11151.41	11152.22

4.3 Modelling of the daily stock price using ANN

The lagged values of the daily stock price time series data serve as inputs to a FNN model with one hidden layer and multiple neurons. The R forecast package's *nnetar()* function fits an $NNAR(p, k)$ model. There are 20 fitted networks in all, each with random starting weights. When calculating predictions, these are then averaged. $NNAR(8, 4)$, which has lags of 8 and 4 neurons in the hidden layer, is the best ANN for fitting daily stock price data.

4.3.1 Diagnostics of Residuals from ANN Model

The residuals from the fitted $NNAR(8, 4)$ model are examined for autocorrelation at various lags. The ACF and PACF plots indicate no significant autocorrelations among the residuals, with autocorrelation and partial autocorrelation values lying within lie between 95% control limits. The test statistic of the Box-Ljung test equals 22.6 with a corresponding p-value of 0.6126, indicating no autocorrelation remaining on the residuals for this model. The null hypothesis claiming the residuals are white noise cannot be rejected; thus, the $NNAR(8, 4)$ model displays goodness of fit. As a result, the model went through the necessary tests and is ready to forecast.

4.3.2 Forecasting using $NNAR(8, 4)$ Model

To check the accuracy of the forecasted values using the $NNAR(8, 4)$ model, the $NNAR(8, 4)$ is applied to the training dataset to obtain predicted values (in-sample forecast) of length equal to the test dataset. The in-sample forecast is compared with the testing dataset. The statistical measures RMSE and MAPE are 511.053 and 3.53%, respectively. Subsequently, forecasting was conducted to obtain the projected values of the stock price for the upcoming two weeks (Sun, 28 May 2023 to Thu, 4 June 2023); the results are demonstrated in Table 5.

Table 5. 2-week forecast of stock price using $NNAR(8, 4)$ Model

Days	28 May	29 May	30 May	31 May	1 Jun
Stock price	11168.77	11160.2	11156.77	11157.99	11162.39
Days	4Jun	5 Jun	6 Jun	7 Jun	8 Jun
Stock price	11168.78	11175.7	11180.72	11184.97	11188.53

4.4 Comparing Forecast Accuracy between MA-ARIMA and ANN methods

The primary purpose of this study is to compare two time-series forecasting methods, MA-ARIMA and ANN modelling, in predicting the daily closing price of the TASI stock market in Saudi Arabia. To achieve this, the accuracy and effectiveness of both methods in forecasting the stock market are assessed using the RMSE and MAPE criteria and the DM test for comparison. Table 6 summarizes the results of the forecast accuracy measures for the two methods.

Table 6. The forecast accuracy for MA-ARIMA and ANN methods

Model	RMSE	MAPE
3 rd WMA-ARIMA(3,1,2)	409.228	3.34%
$NNAR(8, 4)$	511.053	3.53%

Table 6 shows that for daily stock price time series forecasting, the MA-ARIMA method achieves

lower RMSE and MAPE values than the ANN method. Therefore, the ANN model is less suitable for the current dataset.

The DM test is performed on the residuals of MA-ARIMA and ANN to evaluate the time series forecast accuracy of the two forecast techniques. The DM statistic is 1.336, with a corresponding p-value of 0.185. These results suggest no significant difference in the predictive accuracy of the MA-ARIMA and ANN methods for daily stock price time series data.

In essence, the study comparing MA-ARIMA and ANN models for forecasting the TASI index's daily stock prices revealed that the WMA-ARIMA(3,1,2) model slightly outperformed the ANN regarding predictive accuracy. Despite this, the overall conclusion drawn from the research was that there is no substantial difference in the accuracy between MA-ARIMA and ANN models when predicting future stock prices. This indicates that both methodologies are equally viable for financial forecasting, allowing investors and analysts to choose either approach based on specific data characteristics and personal proficiency with the models.

5 Conclusion Remarks

The study looks at how well the MA-ARIMA and ANN methods can guess the daily closing prices of the Saudi Arabian TASI index stock market. Using historical daily stock prices from January 1, 2020, to May 25, 2023, covering a total of 887 days, the study identifies the 3rd WMA-ARIMA(3,1,2) model as the best among all MA-ARIMA models, achieving the highest p-value for residual independence compared to other MA-ARIMA models, in addition to being the only model in which all its parameters were statistically significant. In contrast, the best ANN model for fitting daily stock price data is the $NNAR(8,4)$, which averaged predictions from 20 networks. Residual analysis revealed that both the 3rd WMA-ARIMA(3,1,2) and $NNAR(8,4)$ models exhibited goodness of fit, with no significant autocorrelations in their residuals. The MA-ARIMA model achieved superior forecasting accuracy, with an RMSE of 409.228 and MAPE of 3.34%, compared to the ANN model's RMSE of 511.053 and MAPE of 3.53%. Moreover, the Diebold-Mariano (DM) test revealed no significant difference in the predictive accuracy between the MA-ARIMA and ANN methods for daily stock price time series data. The study concludes that both methods can yield satisfactory forecasting results in real-world scenarios, with the MA-ARIMA method exhibiting greater accuracy for the specific dataset examined than the ANN method. Investors and financial analysts can leverage these findings to make informed decisions regarding market trends, portfolio management, and investment strategies.

data availability

This study's findings are supported by data available on the Tadawul and investing.com websites

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Appendix

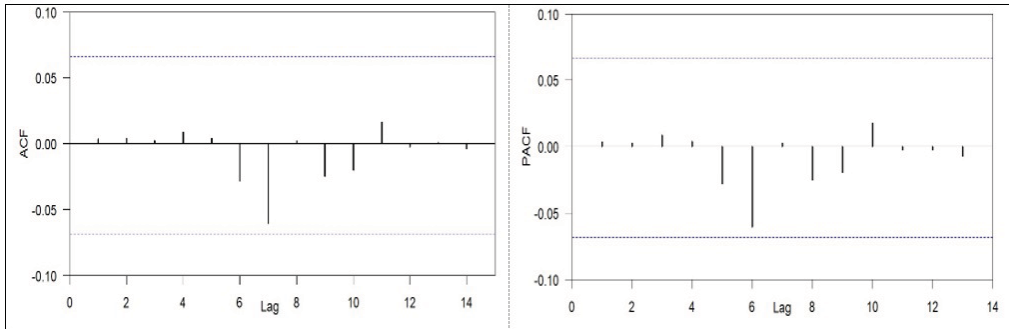


Figure A1. ACF and PACF of residuals from the 4th SMA-ARIMA(5,1,3) model

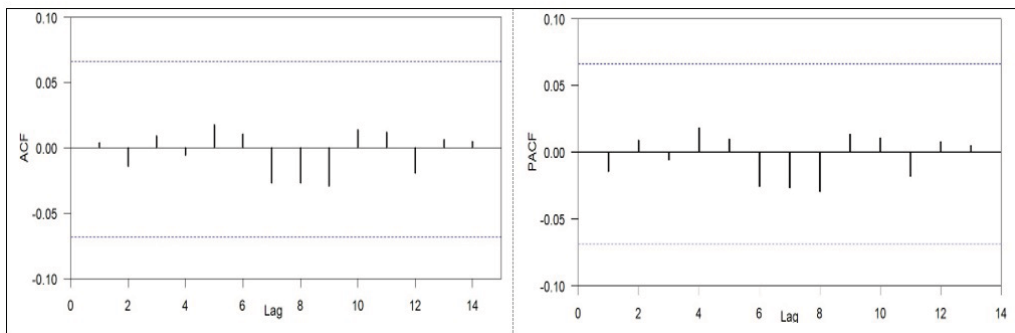


Figure A2. ACF and PACF of residuals from the 3rd WMA-ARIMA(3,1,2) model

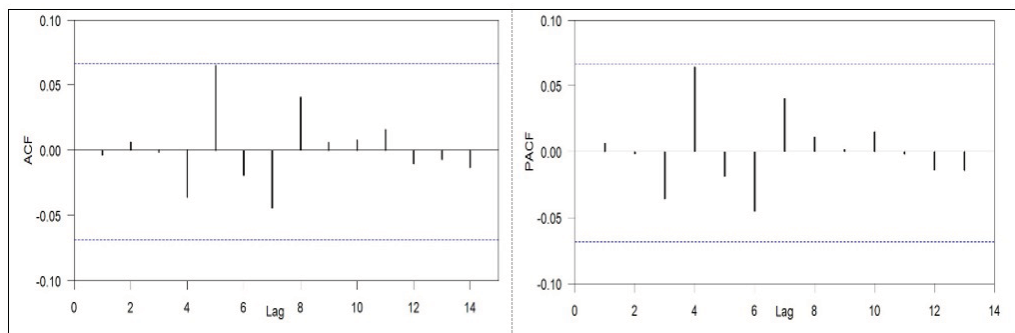


Figure A3. ACF and PACF of residuals from the 2nd EWMA-ARIMA(2,1,3) model