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Monthly Gold Price Forecasting Using ANN And ARIMA

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ABSTRACT

Forecasting is a prominent statistical area with several applications, notably in econometrics. Many governments use it to set long-term objectives and make future choices. Establishing a reliable gold price model is critical because gold prices have a significant effect on the financial decisions of people, organizations, and different countries. This research examines the two primary forecasting methodologies in order to determine the optimum forecasting model for monthly gold prices in US dollars per one ounce of gold. The first strategy, known as Box-Jenkins, use the Autoregressive Integrated Moving Average (ARIMA) model, while the second employs the Feed Forward Neural Network (FFNN) model. The information is derived from the official website of IndexMundi, and it covers monthly gold prices in US dollars per one ounce of gold were used from January 2010 to December 2022. Alyuda NeuroIntelligence, R, and SPSS were utilized for analysis. This comparison also includes Akaike Information Criteria (AIC), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2. The results show that the FFNN model fits better than the ARIMA model. Furthermore, because of lower MAE, RMSE, and AIC values, the FFNN model has fewer errors than the ARIMA model and is much better in terms of goodness of fit.

Keywords*: Gold Price, Time Series, ARIMA, Artificial Neural Networks, Forecasting.*

1. INTRODUCTION

Gold is a valuable metal that is also defined as an economic good and a financial asset. Only gold preserves its value at all moments of crisis, whether savings, financial, investment, or political. The changes in the value of gold are both intriguing and relevant from an economic and financial standpoint (Pitigalaarachchi, P.A.A.C et. al 2016). People who make investments in gold have two primary goals: first, it is a protect against inflation because the return on gold investment is in accordance with the rate of inflation throughout time, and second, it will assist them diversify their investment portfolio and thus reduce the overall volatility of their portfolio (Guha, B. and Bandyopadhyay, G., 2016). The two most important issues in the economy are price fluctuations and price forecasting. Mining decision makers, like those in other businesses, accept or reject suggested projects based on mineral price expectations. Reliable gold's price prediction improves in predicting the circumstances of future trends. This gives useful knowledge for stakeholders to take necessary measures to minimize or mitigate risks that might result in financial losses or even insolvency (Shafiee, S. and Topal, E., 2010). In recent years, the worldwide price trend has received a great deal of interest, and the price of gold has experienced a worrying surge when compared to previous years. Consumer preferences are influenced by market

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prices, thus anticipating gold prices is critical in shaping consumer views and purchase behavior.

This study investigates the two basic forecasting approaches in order to establish the best forecasting model for projecting gold prices from 2010 to 2022. The Autoregressive Integrated Moving Average (ARIMA) model is used in the first method, known as Box-Jenkins, and the Artificial Neural Network (ANN) model is used in the second. ARIMA has been used for over five decades and is one of the most popular and frequently used prediction of time series algorithms. According to Box and Jenkins (1970), Hipel and McLeod (1994), and Cochrane (2005), the fundamental assumption of this model is data linearity and normal distribution. As a result, when the data is nonlinear, this model is less effective. ANNs are gaining a lot of study interest in the machine-learning industry right now, and they are extensively relied on for prediction in all sectors of finance, economics, business, technology, and so on. ANNs are differentiated by their insensitivity to a dataset's lack of linearity and normality (Kihoro et al., 2004; Kamruzzaman et al., 2006). Several types of ANN models have been developed during the last three decades, each aimed at tackling a particular set of problems. The Feed Forward neural network, which was employed in this study, has been widely and efficiently used for prediction.

2. LITERATURE REVIEWS

ANN have gotten a lot of interest in recent years. They are being employed in prediction and classification, areas where regression, time series and other similar statistical approaches have historically been applied (Cheng and Titterington, 1994). Hamzaçebi (2008) compared the Seasonal Artificial Neural Network (SANN) with the seasonal autoregressive integrated moving average (SARIMA) to find a suitable model for forecasting seasonal time data. He applied both models to four real-world data sets from around the world: a data set of Taiwanese air passengers, a seasonal sales time series, a data set of soft beverages, and total Taiwanese equipment production. His findings indicated that the ANN model outperforms the SARIMA model in terms of forecast error, and that when the seasonality in the data set is strong, the ANN model is better suited. Adebiyi et al. (2014) investigated the predicting effectiveness of ANNs and the ARIMA model using reported stock market data from the New York Stock Exchange. The empirical data show that the ANN model outperforms the ARIMA model. The findings reconcile and clarify the literature's conflicting views on the superiority of the ARIMA model over NNs, and vice versa. Dhini et al. (2015) examined three forecasting models for weekly consumer product demand in Indonesia: ARMA, ANN, and a hybrid model that incorporates the ANN and ARIMA models. The experimental results demonstrated that the ANN model was significantly more accurate. Because of its distinct qualities, building a precise and accurate gold pricing model is critical for asset management. Mombeini, H., and Yazdani-Chamzini, A. (2015) compared the (ANN) model to the conventional statistical model of ARIMA to forecast the gold price. Gold price data from April 1990 to July 2008 were utilized to build the various models examined in their study. During the training and validation stages, the findings show that the ANN model outperforms the ARIMA model in several performance parameters. White, A. and Safi, S. (2016) Compare three different forecasting approaches: ANNs, ARIMA, and regression models. Using computer simulations, the main discovery demonstrates that in the presence of auto correlated errors, ANNs outperform ARIMA and regression for nonlinear models. The model accuracy for ANN is tested by comparing the simulated forecast results with the real data for unemployment in Palestine, which were found to be in great agreement. Safi (2016) forecasted the Palestine Gross Domestic Product (GDP) quarterly values using ARIMA, ANNs and regression; the results showed that the ANNs outperformed the ARMA and regression models in predicting Palestine GDP. Mishra et al. (2018) applied time series models and ANN to forecast rainfall; the results demonstrate that ANN model gives optimistic predictions for both forecast models and that the one-month forecast model performs better than the two-month forecast mode.

Rhanoui et al. (2019) wanted to identify the most reliable model for predicting budget data, so they compared the ARIMA model with the Recurrent Neural Network (RNN). Their results revealed that the NN model is more accurate and has a lower prediction error than the ARIMA model. Krishna, K.M., et. al (2019) in their article, attempted to create a forecasting algorithm that could accurately anticipate daily gold prices in India. Gold historical prices were compiled from January 1, 2014 to July 24, 2018. Forecasting models for daily gold prices in India were built using ARIMA and ANN. The forecasting model's performance was assessed using MAE, MAPE, and RMSE. According to the findings, the feed forward neural networks (FFNN) model outperforms the standard ARIMA model. Abraham et al. (2020) showed that the artificial neural network is better than the classic time series methods for predicting the Brazilian soybean production, yield, and harvest region from January 1961 to December 2016, where they compared the artificial neural network with classical time series model to predict the Brazilian soybean production, yield and harvest region. However, their results indicated that the ANN is suitable tools to predicting the agriculture time series. Hong, U. and Majid, N.O.R.I.Z.A., (2021) evaluate the ANN and ARIMA models to determine the best model for predicting daily gold prices from 3 September 2018 to 30 October 2020, as gathered by the World Gold Council. The artificial neural network approach of long short-term memory (LSTM) has been adopted to anticipate the gold price. When multiple step forecasting and one step forward forecasting using ARIMA and LSTM are compared, it is discovered that LSTM has a lower RMSE than ARIMA. In their study, they show that the ANN model beats the ARIMA model in forecasting gold prices. Khalil, D.M., 2022, compared the ARIMA model with FFNN model to discover the best forecasting model for the monthly amount of dairy products exported from Turkey to Iraq. The results showed that FFNN model is more accurate than the ARIMA model. Additionally, due to lower MAE, RMSE, and AIC values, the FFNN model has less errors than the ARIMA model and is considerably superior in terms of goodness of fit. Khalil, D.M. and Hamad S.R., 2023, applied two main forecasting approaches are examined in this study to discover the best forecasting model for the monthly amount of aluminium products exported from Turkey to Iraq. The Autoregressive Integrated Moving Average (ARIMA) model is used in the first technique, while the Artificial Neural Network (ANN) model is used in the second. According to their results, the Feed Forward Neural Network (FFNN) model fits better than the ARIMA model.

3. MATERIAL AND METHODS

The global monthly price of gold from January 1, 2010 to December 31, 2022 is used in this article to compare the two models. The information was collected from IndexMundi official webpage. The data was analyzed using three statistical software applications: Alyuda NeuroIntelligence, R, and SPSS. The ARIMA model was created using R and SPSS, whereas the ANN model was created using Alyuda NeuroIntelligence and R.

4. Time Series Definition

A time series is a collection of data points gathered over time. A time series is technically described as a set of vectors x(t), t=0, 1, 2,..., where t represents the length of time elapsed and the variable x(t) is regarded a random variable (Raicharoen et al.; 2003; Cochrane, 2005). Time series are classified into two types: discrete and continuous. A city's population, a company's income, or the currency exchange rate between two currencies are all examples of discrete time series. A discrete time series, on the other hand, gathers data at specific points in time, whereas a continuous time series collects observations at all points in time. Temperature data, river flow, chemical manufacturing activities, and so on may all be recorded using continuous time series (Mohammed, P.A., et. al, 2022). A discrete time series is a sequence of observations that are recorded at regular intervals such as hourly, daily, weekly, monthly, or annual. On a real number scale, a discrete time series variable is expected to be assessed as a continuous variable (Kadir, D., 2020; Hipel, 1994).

5. Artificial Neural Networks (ANN)

ANNs, also known as "Neural Networks," are a form of computing tool that replicates the biological processes of the human brain. A neural network is a collection of basic processes connected together. Each unit has a little amount of local memory. These neurons are joined together via communication channels (connections) that transport numerical data. Classification or categorization and prediction are two of the most popular uses of ANNs. The majority of ANN applications use supervised learning, which means that training data should include both input and the desired output, or "Target Value." After successful training, input data with no output value can be supplied to the ANN, and the ANN will compute an output value. (Graupe, 2013; Gurney, 2018).

An ANN model, or network, consists of up of three layers: an input layer, one or more "hidden" layers, and an output layer. Each of the layers can contain a finite number of nodes or "neurons," with each node in each layer usually linked to the next layer via a weighted connection. The data is sent into the NN via the input layer. The hidden layer nodes process the incoming data as the sum of the weighted outputs of the input layer. The output layer nodes create the system output by processing the input data they receive as the total of the weighted outputs of the hidden layers' units (Mishra et al., 2007; Mehlig, 2019). This network can be represented as shown in (Figure 1).

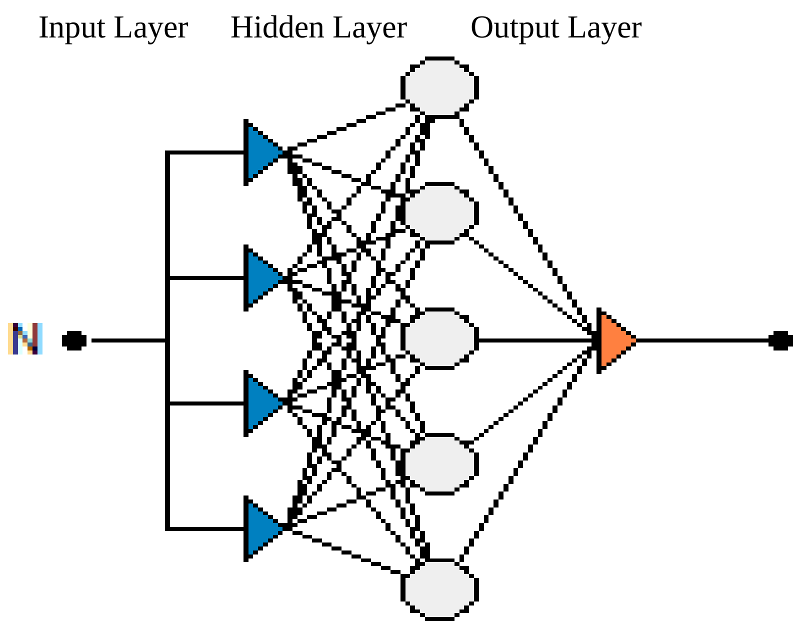

Figure 1. Artificial neural network architecture

6. RESULTS AND DISCUSSION

As stated in Appendix B, the monthly average gold price is 1449.22 US dollars, with the highest gold price in August 2020 at 1969.63 US dollars and the lowest monthly gold price in December 2015 at 1075.74 US dollars. Figure2 displays the monthly gold price's fluctuating attitude from January 2010 to December 2022. There have been a total of 156 observations.

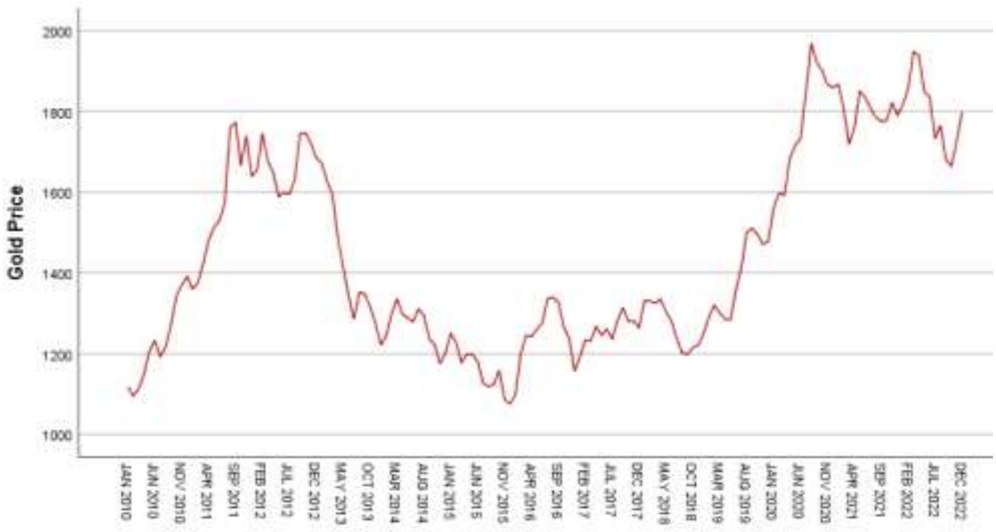

Figure 2. Time series plot of monthly amount of gold price

Because stationarity is the first condition for building a time series model, the non-stationarity from data must be removed and converted to stationary data. Various strategies have been used to determine and make the dataset stationarity. The Augmented Dickey-Fuller test will be used in this study to identify the dataset's stationarity state. Table 1 reveals that the P value is 0.689, which is significantly more than the p-value (0.05). For this reason, the time series data can be considered to have a unit root and to be nonstationary. Here, we do the first differential and see if it is stationary. Otherwise, the second distinction is carried out. The number of differentiations, sometimes referred to as the lag term in ARIMA (p, d, q), is d. After the initial differentiation, the P-value becomes 0.01, indicating that the data series has no unit root and is stationary.

Table 1: Dickey Fuller test value results

	Dickey-Fuller value	P-value
Before Differencing	-1.7298	0.689
After Differencing	-4.2926	**0.01**

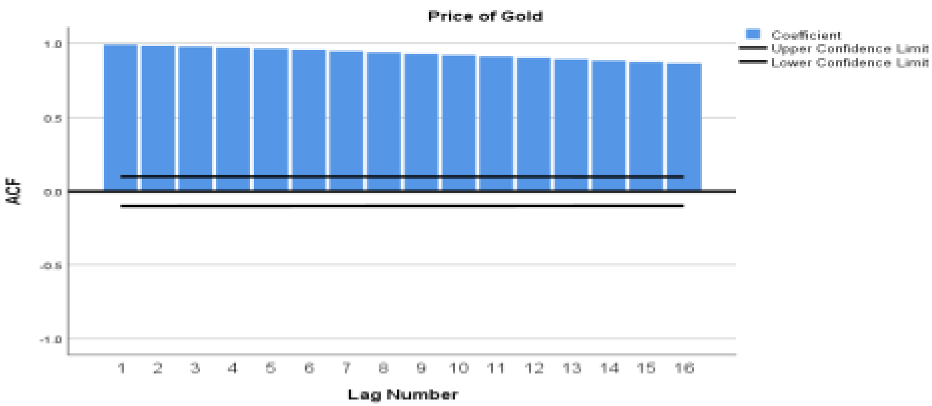

Figure 3. Autocorrelation Function and Partial Autocorrelation Function for gold price time series

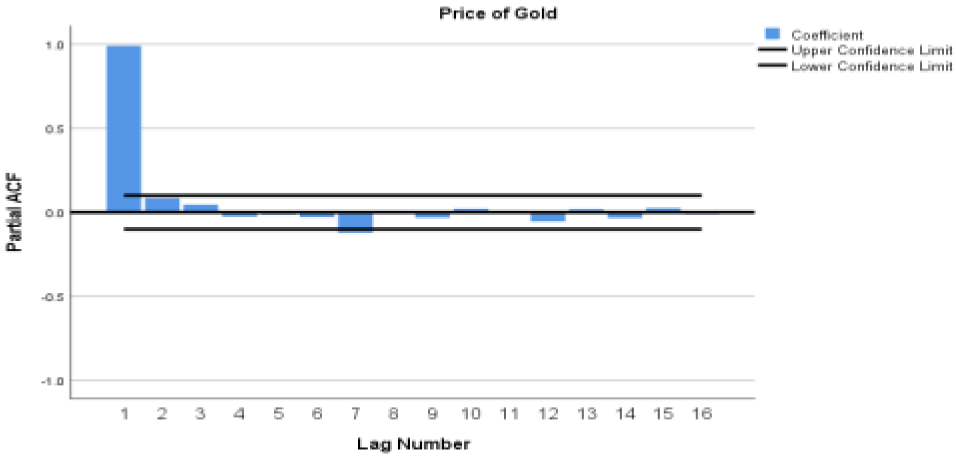

Figure 4. Partial Autocorrelation Function for gold price time series

6.1.1. Choosing an Appropriate Model

After applying 42 different models to the data-set to find the best model, it is discovered that ARIMA(0,1,1) is the best model to forecast the price of gold from 2010 to 2022. The estimated model is statistically significant, as shown in (Table 2). As well as, the model's parameters are also statistically significant, as shown in (Table 3). Appendix B contains a list of the 42 models that were used, along with their AIC values.

Table 2. ARIMA Model Parameters

	Estimate	SE	T-test	P-value
MA1	-0.246	0.078	-3.313	0.002

Table 3. ARIMA(0,1,1) Model Statistics

R-squared	RMSE	MAPE	MAE	AIC
0.962	48.12924	2.582	37.802	1645.84

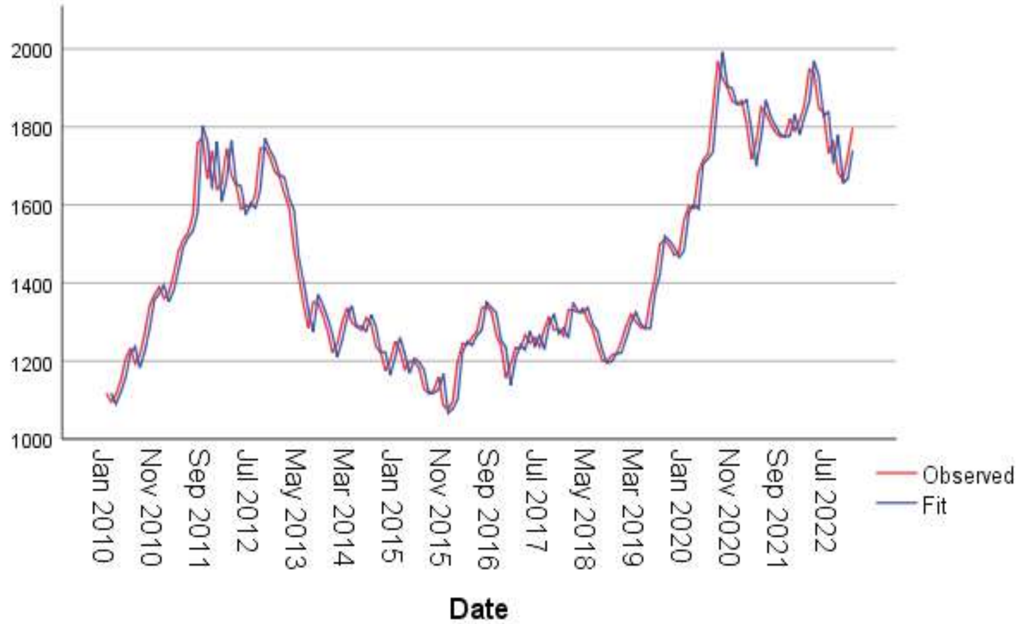

Figure 5. Predicted value and actual values of gold price by using ARIMA(0,1,1)

6.1.2. Checking the Model

After identifying and estimating the candidate ARIMA(0,1,1) model, it must assess the model's fit to the data. This step in the model diagnostic checking process includes both parameter and residual analysis. Diagnostic testing of the residuals for the ARIMA(0,1,1) model using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for residuals, as shown in Figure 6, reveals that all ACF and PACF residuals values are statistically significant at the %95 confidence level. This indicates that the residuals are random white noise, and the model is appropriate for the data.

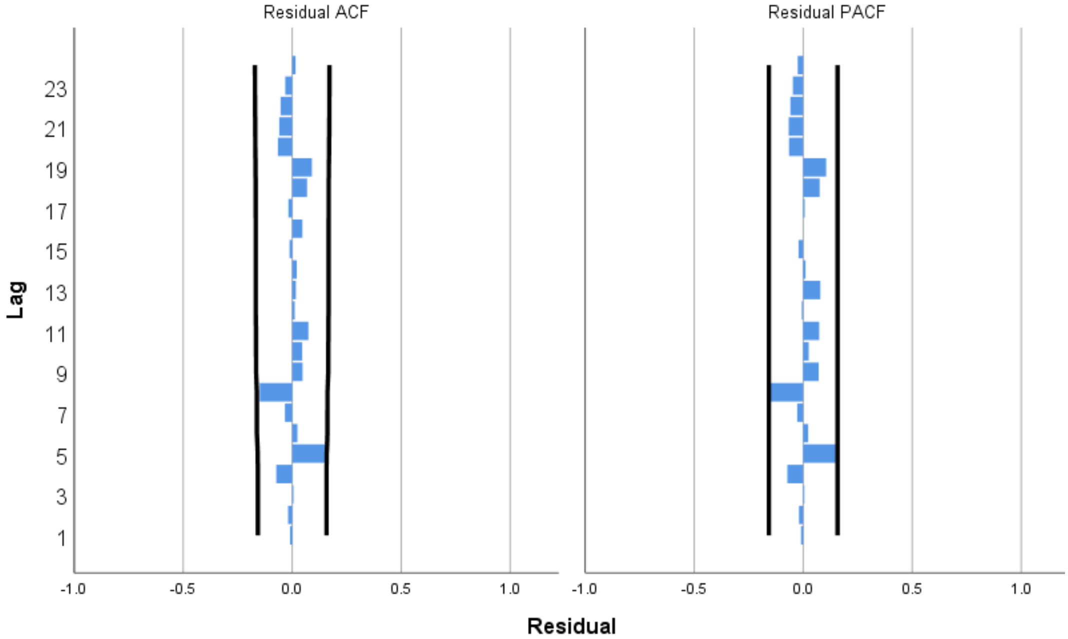

Figure 6. Residual ACF and PACF for ARIMA (0,1,1)

In the last step of model performance checking, the Box-Pierce test used to verify the correct user model and the residual autocorrelation test to see if there is any autocorrelation.

The Box-Pierce value is 11.593, and the p-value for this test is 0.824, which is considerably more than 0.05, meaning that the residuals have no autocorrelation and are consequently white noise. So, it conclude that the model ARIMA(0,1,1) is the best fit for the gold price dataset because it passed model construction diagnostic tests.

After diagnosing the fitted model and selecting the best one, forward forecasting is the final stage in time series analysis. The monthly price of gold in 2023 was predicted using the actual data and the estimated model, as shown in (Table 4).

Table 4. Actual and predicted value of Gold price in 2023

Date	**Actual**	**Forecast**
Jan-23	1,897.71	1793.733
Feb-23	1,854.54	1804.381
Mar-23	1,912.73	1805.091
Apr-23	1,999.77	1805.547
May-23	1,992.13	1815.939
Jun-23	1,942.90	1812.834
Jul-23	1,951.02	1818.812
Aug-23	1,918.70	1825.246
Sep-23	1,915.95	1822.290
Oct-23	1,916.25	1831.880
Nov-23	1,984.11	1833.174
Dec-23	2036.13	1833.842

7. Application of artificial neural networks on time series

Tang et al., (1991); Sharda, Patil (1992), Khalil D.M. (2022), and Khalil D.M. and Hamad S.R. (2023) all agree that the total number of input neurons required in this model must be 12 since the data is monthly and has no seasonality. Then only one output unit is needed. Trial and error is the most effective approach for identifying the optimal number of hidden units. In this case, 80% of the data was utilized for training, 10% for validation, and 10% for testing. Both the hidden and output layers have used the logistics activation function. The conjugate gradient descent approach was used to train the network in order to determine the ideal architectural neural network. Furthermore, 1000 iterations with a single time retrain were done, with the learning rate set to 0.9 and the momentum set to 0.5. Following training the network several times and evaluating 728 various networks (listed in the appendix B), it is determined that the optimal network has two hidden layers, the first of which has 12 nodes and the second of which has 5 nodes. The structure of the intended network is shown in Figure 7.

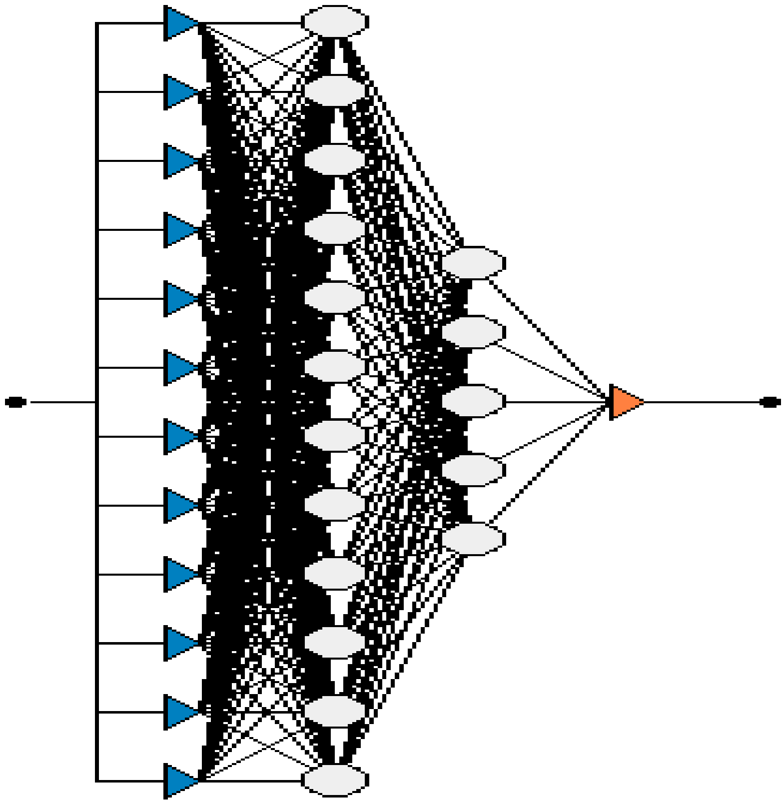

Figure 7. Architecture of ANN (12:12:5:1) for predicting the gold price

The forecasting skills of the network were determined using statistical metrics such as RMSE, MAPE, MAE, R^2 and AIC. The findings are summarized in (Table 5).

Table 5. FFNN(12:12:5:1) Model Results

R-squared	MAE	AIC	MAPE	RMSE
0.989	34.625	339.726	2.305	43.41

As well as, The FFNN(12:12:5:1) predicted and actual values are showed in (Figure 8).

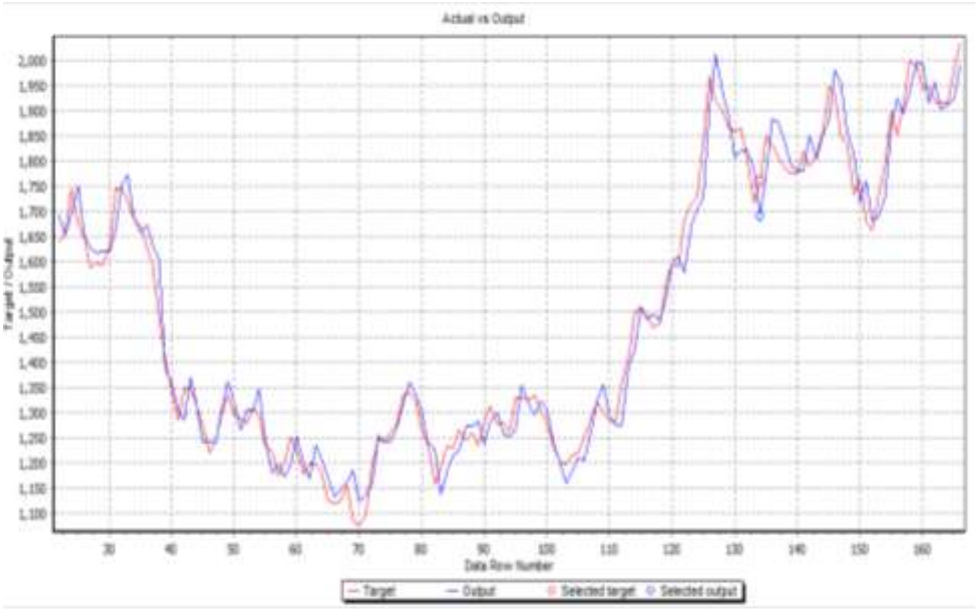

Figure 8. Predicted and actual values of gold price exports by FFNN(12:12:5:1)

Table 6 shows the actual and expected monthly values of gold price in 2023 based on FFNN (12:12:5:1).

Table 6. FFNN (12:12:5:1) predicted and actual values of Gold price

No.	**Date**	**Actual**	**Forecast**
1	Jan-23	1897.71	1871.345
2	Feb-23	1854.54	1925.114
3	Mar-23	1912.73	1896.679
4	Apr-23	1999.77	1935.038
5	May-23	1992.13	1997.363
6	Jun-23	1942.90	1993.576
7	Jul-23	1951.02	1916.529
8	Aug-23	1918.70	1958.049
9	Sep-23	1915.95	1904.264
10	Oct-23	1916.25	1913.991
11	Nov-23	1984.11	1923.436
12	Dec-23	2036.13	1993.976

8. Comparison of ARIMA and FFNN Results

The results of using the FFNN and ARIMA models to forecast the monthly gold price were compared to see which model was superior. Because the AIC values of the FFNN models are much lower than those of the ARIMA models, the FFNN models outperform the ARIMA models in terms of goodness of fit. As a result, FFNN models outperform ARIMA models. Furthermore, the RMSE value of the FFNN models in this study is significantly lower than that of the ARIMA models, indicating that the FFNN models have a lower error rate than the ARIMA models. The FFNN models fit better than the ARIMA models when the MAE values of the two models are compared. As seen in tables 7 and 8, when both models are used for prediction, the FFNN models are substantially more accurate and have less errors than the ARIMA models.

Table 7. Comparison of the FFNN and ARIMA

Model	MAPE	RMSE	MAE	AIC	R^2
ARIMA(0,1,1)	2.582	48.12924	37.802	1645.84	0.962
FFNN (12:12:5:1)	2.305	43.41	34.625	339.726	0.989

Table 8. Real and Forecasted values of gold price in 2023

Date	Actual	Forecast by FFNN (12:12:5:1)	Forecast by ARIMA (0,1,1)
Jan-23	1897.71	1871.345	1793.733
Feb-23	1854.54	1925.114	1804.381
Mar-23	1912.73	1896.679	1805.091
Apr-23	1999.77	1935.038	1805.547
May-23	1992.13	1997.363	1815.939
Jun-23	1942.90	1993.576	1812.834
Jul-23	1951.02	1916.529	1818.812
Aug-23	1918.70	1958.049	1825.246
Sep-23	1915.95	1904.264	1822.290
Oct-23	1916.25	1913.991	1831.880
Nov-23	1984.11	1923.436	1833.174
Dec-23	2036.13	1993.976	1833.842

Figure 9 shows that predicted values produced by both approaches closely match the actual values, but the FFNN model values appear to outperform the ARIMA models in terms of forecasting performance, supporting accuracy of the FFNN models' for forecasting.

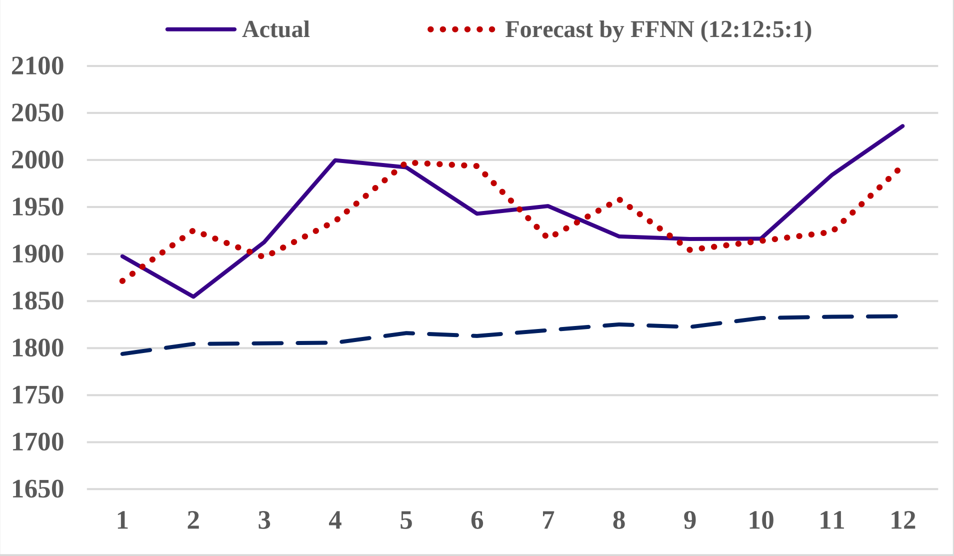

Figure 9. Actual and predicted values of gold price in 2023 using FFNN and ARIMA models.

9. Conclusions

The results of the study show that the ANN models are more accurate and have less error than the ARIMA models. Furthermore, prediction values generated by ANN models appear to be more accurate and behaved more like real values than those created by the ARIMA model. Furthermore, the ANN models outperform the ARIMA models in terms of goodness of fit. In terms of network design and the best network learning technique, it was concluded that two hidden layers are the best fit for this network. Additionally, no systematic approaches exist for deciding which network design can best mimic the function by linking inputs to outputs. As a result, time-consuming experiments and methods that involve trial and error are widely used.

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https://www.indexmundi.com/commodities/?commodity=gold&months=240

Appendix A: ARIMA models with them AIC

Model		AIC	Model		AIC
ARIMA(0,1,0)		1652.49	ARIMA(1,1,4)	with drift	1650.503
ARIMA(0,1,0)	with drift	1653.329	ARIMA(2,1,0)		1648.049
ARIMA(0,1,1)		1645.914	ARIMA(2,1,0)	with drift	1649.258
ARIMA(0,1,1)	with drift	1647.148	ARIMA(2,1,1)		1646.262
ARIMA(0,1,2)		1647.887	ARIMA(2,1,1)	with drift	1647.508
ARIMA(0,1,2)	with drift	1649.102	ARIMA(2,1,2)		1648.39
ARIMA(0,1,3)		1649.816	ARIMA(2,1,2)	with drift	1649.67
ARIMA(0,1,3)	with drift	1651.098	ARIMA(2,1,3)		1650.516
ARIMA(0,1,4)		1649.282	ARIMA(2,1,3)	with drift	1650.942
ARIMA(0,1,4)	with drift	1650.409	ARIMA(3,1,0)		1650.146
ARIMA(0,1,5)		1648.684	ARIMA(3,1,0)	with drift	1651.392
ARIMA(0,1,5)	with drift	1650.013	ARIMA(3,1,1)		1651.968
ARIMA(1,1,0)		1646.666	ARIMA(3,1,1)	with drift	1653.405
ARIMA(1,1,0)	with drift	1647.941	ARIMA(3,1,2)		1650.453
ARIMA(1,1,1)		1646.273	ARIMA(3,1,2)	with drift	1651.848
ARIMA(1,1,1)	with drift	1647.287	ARIMA(4,1,0)		1652.107
ARIMA(1,1,2)		1646.45	ARIMA(4,1,0)	with drift	1653.326
ARIMA(1,1,2)	with drift	1647.654	ARIMA(4,1,1)		1649.629
ARIMA(1,1,3)		1648.153	ARIMA(4,1,1)	with drift	1650.816
ARIMA(1,1,3)	with drift	1649.468	ARIMA(5,1,0)		1649.747
ARIMA(1,1,4)		1649.284	ARIMA(5,1,0)	with drift	1651.198

Appendix B: FFNN Architecture with them Fitness Value

Network	Fitness	Network	Fitness	Network	Fitness	Network	Fitness
[12-5-9-3-1]	0.004143	[12-4-3-4-1]	0.016361	[12-4-11-5-1]	0.018847	[12-12-2-3-1]	0.020292

[12-8-9-5-1]	**0.004143**	**[12-12-3-3-1]**	**0.016699**	**[12-7-8-5-1]**	**0.018897**	**[12-4-8-2-1]**	**0.020318**
[12-12-10-5-1]	**0.004143**	**[12-5-6-3-1]**	**0.016711**	**[12-8-9-2-1]**	**0.0189**	**[12-10-10-4-1]**	**0.020342**
[12-4-6-5-1]	**0.005525**	**[12-2-2-4-1]**	**0.016913**	**[12-11-7-3-1]**	**0.018943**	**[12-10-9-6-1]**	**0.020342**
[12-4-9-5-1]	**0.006372**	**[12-9-5-4-1]**	**0.017025**	**[12-7-8-3-1]**	**0.018967**	**[12-4-5-6-1]**	**0.020382**
[12-3-7-5-1]	**0.007329**	**[12-2-4-3-1]**	**0.017036**	**[12-11-6-4-1]**	**0.019075**	**[12-11-5-4-1]**	**0.0204**
[12-2-3-2-1]	**0.008389**	**[12-5-8-1]**	**0.017069**	**[12-7-10-6-1]**	**0.019128**	**[12-2-10-2-1]**	**0.02043**
[12-4-11-4-1]	**0.009349**	**[12-7-3-2-1]**	**0.017232**	**[12-9-12-4-1]**	**0.019212**	**[12-8-4-1]**	**0.020434**
[12-2-10-3-1]	**0.009682**	**[12-3-9-4-1]**	**0.017259**	**[12-9-3-6-1]**	**0.019264**	**[12-10-4-2-1]**	**0.020443**
[12-2-9-6-1]	**0.00971**	**[12-9-8-5-1]**	**0.017342**	**[12-3-4-2-1]**	**0.019305**	**[12-7-7-2-1]**	**0.020463**
[12-2-9-5-1]	**0.009739**	**[12-10-12-3-1]**	**0.017491**	**[12-10-6-6-1]**	**0.019314**	**[12-12-5-6-1]**	**0.020468**
[12-12-2-6-1]	**0.009836**	**[12-4-12-3-1]**	**0.017504**	**[12-2-8-5-1]**	**0.019335**	**[12-2-7-1]**	**0.020504**
[12-5-10-2-1]	**0.01013**	**[12-2-11-2-1]**	**0.017665**	**[12-2-9-3-1]**	**0.019356**	**[12-10-9-4-1]**	**0.020521**
[12-5-7-4-1]	**0.011022**	**[12-6-5-4-1]**	**0.017678**	**[12-7-5-6-1]**	**0.019364**	**[12-6-6-6-1]**	**0.020532**
[12-3-2-6-1]	**0.011084**	**[12-5-2-3-1]**	**0.017728**	**[12-6-5-3-1]**	**0.019428**	**[12-4-10-3-1]**	**0.020533**
[12-2-10-5-1]	**0.011477**	**[12-12-12-4-1]**	**0.017941**	**[12-3-11-3-1]**	**0.019743**	**[12-4-12-5-1]**	**0.020537**
[12-4-2-2-1]	**0.011778**	**[12-6-10-4-1]**	**0.018067**	**[12-11-3-2-1]**	**0.019762**	**[12-7-7-4-1]**	**0.02054**
[12-3-8-3-1]	**0.011861**	**[12-4-6-4-1]**	**0.01807**	**[12-11-4-5-1]**	**0.019776**	**[12-7-2-2-1]**	**0.020558**
[12-12-5-2-1]	**0.0123**	**[12-5-3-5-1]**	**0.018118**	**[12-2-6-2-1]**	**0.019852**	**[12-6-11-4-1]**	**0.02059**
[12-9-3-2-1]	**0.01253**	**[12-7-6-4-1]**	**0.018174**	**[12-10-5-4-1]**	**0.019873**	**[12-9-12-3-1]**	**0.020612**
[12-4-10-2-1]	**0.012875**	**[12-8-7-4-1]**	**0.018264**	**[12-6-11-5-1]**	**0.019944**	**[12-8-10-4-1]**	**0.020661**
[12-12-2-4-1]	**0.01288**	**[12-7-6-6-1]**	**0.01846**	**[12-4-3-1]**	**0.019998**	**[12-10-6-3-1]**	**0.020695**
[12-9-5-3-1]	**0.014458**	**[12-8-4-2-1]**	**0.018484**	**[12-9-2-3-1]**	**0.02**	**[12-3-3-3-1]**	**0.020699**
[12-8-5-3-1]	**0.014574**	**[12-5-12-5-1]**	**0.018504**	**[12-7-2-6-1]**	**0.020018**	**[12-3-4-6-1]**	**0.020729**
[12-3-5-4-1]	**0.015089**	**[12-5-3-2-1]**	**0.01864**	**[12-8-3-4-1]**	**0.020036**	**[12-8-12-3-1]**	**0.020815**
[12-9-12-2-1]	**0.015285**	**[12-9-10-6-1]**	**0.01866**	**[12-5-4-4-1]**	**0.020092**	**[12-8-11-3-1]**	**0.020822**
[12-12-2-2-1]	**0.015513**	**[12-7-12-4-1]**	**0.018756**	**[12-6-8-2-1]**	**0.020131**	**[12-3-2-4-1]**	**0.020822**

[12-3-8-6-1]	**0.015526**	**[12-4-10-6-1]**	**0.018773**	**[12-3-12-1]**	**0.020182**	**[12-3-5-2-1]**	**0.020868**
[12-3-7-4-1]	**0.016002**	**[12-10-12-2-1]**	**0.018774**	**[12-9-6-1]**	**0.020206**	**[12-6-4-5-1]**	**0.020871**
[12-7-5-2-1]	**0.016059**	**[12-6-11-2-1]**	**0.018782**	**[12-2-9-4-1]**	**0.020286**	**[12-2-6-3-1]**	**0.0209**
[12-4-5-2-1]	**0.020922**	**[12-10-5-1]**	**0.021606**	**[12-7-6-1]**	**0.022176**	**[12-10-3-3-1]**	**0.023033**
[12-10-4-5-1]	**0.020934**	**[12-8-7-5-1]**	**0.021613**	**[12-2-4-1]**	**0.022183**	**[12-2-2-2-1]**	**0.023047**
[12-2-2-6-1]	**0.020945**	**[12-7-10-5-1]**	**0.021615**	**[12-5-12-4-1]**	**0.022184**	**[12-11-10-3-1]**	**0.02309**
[12-3-12-6-1]	**0.020945**	**[12-12-12-5-1]**	**0.02162**	**[12-3-3-5-1]**	**0.022199**	**[12-5-7-5-1]**	**0.023112**
[12-11-11-4-1]	**0.020948**	**[12-2-12-2-1]**	**0.021621**	**[12-3-4-1]**	**0.022204**	**[12-2-6-1]**	**0.023115**
[12-4-6-3-1]	**0.020953**	**[12-2-3-3-1]**	**0.021629**	**[12-11-12-4-1]**	**0.022206**	**[12-5-2-4-1]**	**0.023119**
[12-2-8-6-1]	**0.021007**	**[12-8-8-4-1]**	**0.021683**	**[12-3-7-3-1]**	**0.022225**	**[12-8-3-3-1]**	**0.023141**
[12-11-11-3-1]	**0.021036**	**[12-7-9-6-1]**	**0.021687**	**[12-11-5-2-1]**	**0.022234**	**[12-5-5-2-1]**	**0.023154**
[12-6-2-3-1]	**0.021044**	**[12-12-4-1]**	**0.021699**	**[12-7-4-6-1]**	**0.022242**	**[12-7-4-4-1]**	**0.023159**
[12-2-4-2-1]	**0.021203**	**[12-3-7-1]**	**0.021713**	**[12-7-11-4-1]**	**0.022251**	**[12-4-6-6-1]**	**0.023168**
[12-5-10-6-1]	**0.02122**	**[12-2-6-5-1]**	**0.021719**	**[12-5-12-2-1]**	**0.022264**	**[12-12-8-6-1]**	**0.023181**
[12-2-6-6-1]	**0.021245**	**[12-6-8-4-1]**	**0.02176**	**[12-11-12-5-1]**	**0.022264**	**[12-11-3-5-1]**	**0.023225**
[12-2-8-3-1]	**0.021266**	**[12-5-6-4-1]**	**0.021843**	**[12-2-11-5-1]**	**0.022271**	**[12-3-4-4-1]**	**0.023227**
[12-3-9-3-1]	**0.021314**	**[12-7-11-2-1]**	**0.021844**	**[12-6-3-5-1]**	**0.022273**	**[12-5-8-6-1]**	**0.023235**
[12-2-5-1]	**0.021321**	**[12-11-6-2-1]**	**0.021868**	**[12-2-12-3-1]**	**0.02228**	**[12-3-5-6-1]**	**0.023244**
[12-7-3-4-1]	**0.021331**	**[12-5-8-4-1]**	**0.021889**	**[12-10-3-2-1]**	**0.022283**	**[12-9-7-6-1]**	**0.023276**
[12-10-8-3-1]	**0.021332**	**[12-4-10-5-1]**	**0.021889**	**[12-2-4-4-1]**	**0.022348**	**[12-6-6-2-1]**	**0.023301**
[12-12-12-2-1]	**0.021346**	**[12-8-5-4-1]**	**0.021891**	**[12-12-6-4-1]**	**0.02237**	**[12-7-4-1]**	**0.023308**
[12-2-6-4-1]	**0.021357**	**[12-12-3-4-1]**	**0.021919**	**[12-11-6-3-1]**	**0.022388**	**[12-2-8-4-1]**	**0.023317**
[12-2-3-4-1]	**0.021363**	**[12-12-9-6-1]**	**0.021927**	**[12-3-6-5-1]**	**0.022408**	**[12-10-4-4-1]**	**0.023331**
[12-2-3-5-1]	**0.021394**	**[12-4-2-4-1]**	**0.02196**	**[12-7-10-2-1]**	**0.022427**	**[12-2-5-2-1]**	**0.023338**
[12-3-12-3-1]	**0.021413**	**[12-3-3-2-1]**	**0.02197**	**[12-9-4-3-1]**	**0.022427**	**[12-10-2-2-1]**	**0.023373**
[12-4-11-2-1]	**0.021434**	**[12-5-12-3-1]**	**0.022017**	**[12-4-9-3-1]**	**0.022428**	**[12-6-9-6-1]**	**0.023409**
[12-2-5-5-1]	**0.02144**	**[12-12-11-2-1]**	**0.022061**	**[12-4-2-3-1]**	**0.022467**	**[12-7-4-5-1]**	**0.023426**

[12-5-3-6-1]	**0.021463**	**[12-9-9-6-1]**	**0.022092**	**[12-2-4-5-1]**	**0.02249**	**[12-6-9-1]**	**0.023436**
[12-8-12-5-1]	**0.02148**	**[12-2-5-3-1]**	**0.022093**	**[12-10-2-6-1]**	**0.022499**	**[12-11-6-6-1]**	**0.02344**
[12-8-3-6-1]	**0.021495**	**[12-12-10-1]**	**0.022107**	**[12-7-11-6-1]**	**0.022514**	**[12-12-11-3-1]**	**0.023444**
[12-5-3-3-1]	**0.021524**	**[12-12-7-2-1]**	**0.022114**	**[12-4-5-5-1]**	**0.022518**	**[12-4-3-6-1]**	**0.023502**
[12-11-4-2-1]	**0.021542**	**[12-12-3-2-1]**	**0.022155**	**[12-6-12-5-1]**	**0.022518**	**[12-10-3-5-1]**	**0.023518**
[12-6-4-2-1]	**0.021587**	**[12-10-6-4-1]**	**0.02216**	**[12-8-12-4-1]**	**0.02252**	**[12-6-4-1]**	**0.023526**
[12-3-2-5-1]	**0.023923**	**[12-3-3-4-1]**	**0.024409**	**[12-9-5-5-1]**	**0.022521**	**[12-2-8-1]**	**0.023533**
[12-7-9-2-1]	**0.023927**	**[12-10-2-4-1]**	**0.024412**	**[12-2-3-6-1]**	**0.022543**	**[12-9-4-5-1]**	**0.023533**
[12-3-3-6-1]	**0.023952**	**[12-8-9-3-1]**	**0.02443**	**[12-7-7-1]**	**0.022579**	**[12-4-6-2-1]**	**0.02358**
[12-10-2-5-1]	**0.023954**	**[12-9-9-4-1]**	**0.024433**	**[12-5-10-3-1]**	**0.022587**	**[12-3-5-3-1]**	**0.023598**
[12-11-10-5-1]	**0.023959**	**[12-2-12-1]**	**0.024447**	**[12-9-3-5-1]**	**0.022598**	**[12-9-6-6-1]**	**0.023627**
[12-6-7-5-1]	**0.02396**	**[12-9-4-6-1]**	**0.024459**	**[12-8-8-1]**	**0.022603**	**[12-3-3-1]**	**0.023637**
[12-9-11-3-1]	**0.023985**	**[12-10-7-3-1]**	**0.024461**	**[12-10-5-5-1]**	**0.022632**	**[12-12-2-5-1]**	**0.023639**
[12-5-6-1]	**0.02401**	**[12-8-10-1]**	**0.024505**	**[12-4-9-4-1]**	**0.022638**	**[12-11-7-4-1]**	**0.023649**
[12-5-4-3-1]	**0.02401**	**[12-4-7-4-1]**	**0.024512**	**[12-9-5-2-1]**	**0.022645**	**[12-5-9-6-1]**	**0.023664**
[12-10-7-1]	**0.024021**	**[12-3-10-6-1]**	**0.024524**	**[12-12-4-4-1]**	**0.022672**	**[12-11-8-4-1]**	**0.023677**
[12-10-3-1]	**0.024028**	**[12-6-4-4-1]**	**0.024525**	**[12-11-12-2-1]**	**0.022677**	**[12-12-9-5-1]**	**0.023683**
[12-10-2-1]	**0.024031**	**[12-3-8-2-1]**	**0.024527**	**[12-9-3-4-1]**	**0.022752**	**[12-10-9-5-1]**	**0.02371**
[12-12-9-1]	**0.02407**	**[12-11-7-5-1]**	**0.024537**	**[12-5-2-2-1]**	**0.022777**	**[12-6-11-3-1]**	**0.023743**
[12-7-9-1]	**0.024088**	**[12-12-8-4-1]**	**0.024542**	**[12-10-10-3-1]**	**0.022787**	**[12-2-7-5-1]**	**0.023745**
[12-5-8-5-1]	**0.024107**	**[12-8-11-4-1]**	**0.024543**	**[12-4-11-6-1]**	**0.022808**	**[12-6-8-3-1]**	**0.02375**
[12-12-4-2-1]	**0.024127**	**[12-4-8-3-1]**	**0.024544**	**[12-4-5-4-1]**	**0.022849**	**[12-7-8-4-1]**	**0.023765**
[12-9-12-5-1]	**0.024182**	**[12-7-4-2-1]**	**0.024567**	**[12-8-5-6-1]**	**0.022872**	**[12-5-7-3-1]**	**0.023766**
[12-11-8-3-1]	**0.024218**	**[12-12-6-2-1]**	**0.02457**	**[12-10-10-6-1]**	**0.022882**	**[12-11-9-6-1]**	**0.023769**
[12-10-11-3-1]	**0.024218**	**[12-6-2-4-1]**	**0.024574**	**[12-11-2-3-1]**	**0.022888**	**[12-7-12-2-1]**	**0.023798**
[12-4-11-1]	**0.024264**	**[12-7-9-3-1]**	**0.02458**	**[12-6-9-4-1]**	**0.02289**	**[12-9-11-2-1]**	**0.023801**
[12-10-5-6-1]	**0.024268**	**[12-7-8-1]**	**0.024608**	**[12-5-7-6-1]**	**0.022913**	**[12-3-9-5-1]**	**0.023823**

[12-12-3-5-1]	**0.024279**	**[12-2-10-1]**	**0.024626**	**[12-12-6-6-1]**	**0.022939**	**[12-12-7-6-1]**	**0.023824**
[12-5-11-6-1]	**0.024337**	**[12-11-5-6-1]**	**0.024629**	**[12-9-2-1]**	**0.02294**	**[12-4-9-1]**	**0.023836**
[12-8-2-5-1]	**0.02435**	**[12-11-11-5-1]**	**0.024633**	**[12-12-8-5-1]**	**0.022988**	**[12-3-12-2-1]**	**0.023842**
[12-9-7-4-1]	**0.024351**	**[12-6-2-5-1]**	**0.024635**	**[12-9-7-2-1]**	**0.022989**	**[12-6-2-2-1]**	**0.023867**
[12-3-11-5-1]	**0.024365**	**[12-6-9-5-1]**	**0.024645**	**[12-12-7-3-1]**	**0.02299**	**[12-2-9-2-1]**	**0.023872**
[12-2-2-1]	**0.024374**	**[12-8-5-5-1]**	**0.024651**	**[12-9-5-6-1]**	**0.022998**	**[12-10-8-6-1]**	**0.023894**
[12-10-12-4-1]	**0.024378**	**[12-9-2-5-1]**	**0.024698**	**[12-10-7-2-1]**	**0.023009**	**[12-12-8-3-1]**	**0.023908**
[12-8-6-5-1]	**0.024386**	**[12-11-6-5-1]**	**0.024705**	**[12-4-8-6-1]**	**0.023011**	**[12-11-10-4-1]**	**0.023912**
[12-9-10-2-1]	**0.024393**	**[12-7-12-1]**	**0.024718**	**[12-3-10-5-1]**	**0.023015**	**[12-6-6-4-1]**	**0.023915**
[12-5-11-2-1]	**0.028543**	**[12-10-8-2-1]**	**0.024722**	**[12-11-4-1]**	**0.02539**	**[12-12-9-3-1]**	**0.026097**
[12-11-9-3-1]	**0.028556**	**[12-8-11-5-1]**	**0.024727**	**[12-8-7-2-1]**	**0.02539**	**[12-10-3-6-1]**	**0.026114**
[12-4-7-1]	**0.028571**	**[12-9-8-6-1]**	**0.024748**	**[12-6-6-1]**	**0.025391**	**[12-6-11-6-1]**	**0.026117**
[12-7-1]	**0.028586**	**[12-11-9-4-1]**	**0.024758**	**[12-10-4-6-1]**	**0.025404**	**[12-9-9-2-1]**	**0.026127**
[12-11-11-1]	**0.028658**	**[12-9-10-1]**	**0.024762**	**[12-11-3-6-1]**	**0.025406**	**[12-11-12-3-1]**	**0.026127**
[12-3-6-1]	**0.028682**	**[12-8-10-6-1]**	**0.024764**	**[12-6-7-1]**	**0.025427**	**[12-10-6-5-1]**	**0.026132**
[12-12-4-5-1]	**0.02869**	**[12-5-2-1]**	**0.024775**	**[12-6-10-1]**	**0.025431**	**[12-4-11-3-1]**	**0.026145**
[12-11-8-5-1]	**0.028724**	**[12-10-7-6-1]**	**0.024775**	**[12-4-7-5-1]**	**0.025441**	**[12-12-11-5-1]**	**0.026148**
[12-3-6-2-1]	**0.028759**	**[12-6-6-3-1]**	**0.024812**	**[12-2-10-4-1]**	**0.025463**	**[12-3-2-2-1]**	**0.026158**
[12-3-6-3-1]	**0.028816**	**[12-9-7-5-1]**	**0.024827**	**[12-9-6-5-1]**	**0.02549**	**[12-9-4-2-1]**	**0.026162**
[12-6-3-3-1]	**0.028833**	**[12-8-5-2-1]**	**0.024831**	**[12-9-2-6-1]**	**0.025491**	**[12-3-5-5-1]**	**0.026167**
[12-7-8-6-1]	**0.028842**	**[12-10-10-2-1]**	**0.024831**	**[12-2-4-6-1]**	**0.025493**	**[12-12-10-3-1]**	**0.026175**
[12-11-3-3-1]	**0.028867**	**[12-10-9-2-1]**	**0.024835**	**[12-3-2-1]**	**0.025502**	**[12-5-9-2-1]**	**0.026184**
[12-11-2-4-1]	**0.028878**	**[12-6-12-3-1]**	**0.02487**	**[12-6-3-2-1]**	**0.025508**	**[12-7-2-3-1]**	**0.026186**
[12-2-3-1]	**0.028882**	**[12-5-7-1]**	**0.024871**	**[12-6-10-2-1]**	**0.025511**	**[12-11-8-2-1]**	**0.026197**
[12-7-11-3-1]	**0.028886**	**[12-11-8-6-1]**	**0.024883**	**[12-3-11-4-1]**	**0.025519**	**[12-6-3-1]**	**0.026221**
[12-3-6-6-1]	**0.028888**	**[12-3-10-3-1]**	**0.02493**	**[12-4-5-1]**	**0.025521**	**[12-8-9-1]**	**0.026221**
[12-11-4-3-1]	**0.028911**	**[12-8-10-5-1]**	**0.024947**	**[12-8-4-3-1]**	**0.025527**	**[12-9-3-1]**	**0.026234**

[12-9-4-1]	0.028921	[12-11-5-5-1]	0.024954	[12-7-5-1]	0.025531	[12-8-4-6-1]	0.026247
[12-8-2-6-1]	0.02894	[12-7-10-4-1]	0.024958	[12-12-6-5-1]	0.025558	[12-8-11-2-1]	0.026255
[12-8-2-3-1]	0.028961	[12-6-10-5-1]	0.02496	[12-5-11-4-1]	0.025567	[12-10-11-2-1]	0.02626
[12-5-12-1]	0.028987	[12-5-5-4-1]	0.024968	[12-11-5-3-1]	0.025575	[12-3-10-2-1]	0.026271
[12-3-8-1]	0.029052	[12-4-2-6-1]	0.024971	[12-9-3-3-1]	0.025578	[12-8-4-4-1]	0.026277
[12-4-4-6-1]	0.02906	[12-5-7-2-1]	0.024973	[12-6-6-5-1]	0.025581	[12-9-6-3-1]	0.026289
[12-6-1]	0.029086	[12-2-7-6-1]	0.024981	[12-5-5-1]	0.025585	[12-9-8-2-1]	0.02631
[12-7-2-5-1]	0.02912	[12-10-6-1]	0.024985	[12-7-10-3-1]	0.025586	[12-12-8-1]	0.026352
[12-6-12-4-1]	0.029128	[12-7-9-5-1]	0.025003	[12-6-8-5-1]	0.025601	[12-11-2-1]	0.026358
[12-3-10-1]	0.029132	[12-6-5-1]	0.025011	[12-7-7-6-1]	0.025605	[12-2-8-2-1]	0.026368
[12-9-11-6-1]	0.029257	[12-8-6-4-1]	0.025011	[12-7-6-5-1]	0.025612	[12-8-10-3-1]	0.026414
[12-12-4-6-1]	0.029309	[12-7-5-5-1]	0.02502	[12-2-12-5-1]	0.025634	[12-2-9-1]	0.026439
[12-2-1]	0.029368	[12-9-7-3-1]	0.025028	[12-11-2-2-1]	0.025638	[12-2-2-5-1]	0.026441
[12-11-6-1]	0.029382	[12-3-4-5-1]	0.025031	[12-9-11-4-1]	0.025664	[12-3-10-4-1]	0.026463
[12-6-7-2-1]	0.029389	[12-5-9-1]	0.025036	[12-4-2-5-1]	0.025683	[12-8-10-2-1]	0.026473
[12-5-5-3-1]	0.029518	[12-8-4-5-1]	0.025069	[12-10-5-3-1]	0.025691	[12-8-2-4-1]	0.026483
[12-5-5-5-1]	0.029522	[12-12-1]	0.025071	[12-6-7-3-1]	0.025701	[12-12-9-2-1]	0.0265
[12-9-10-4-1]	0.029526	[12-9-10-3-1]	0.025083	[12-7-12-3-1]	0.025734	[12-2-5-4-1]	0.026504
[12-11-2-6-1]	0.029698	[12-4-4-3-1]	0.025092	[12-5-2-5-1]	0.025801	[12-10-8-5-1]	0.026509
[12-8-2-2-1]	0.029711	[12-2-7-3-1]	0.02511	[12-5-6-5-1]	0.025806	[12-12-7-5-1]	0.026514
[12-5-1]	0.029717	[12-4-5-3-1]	0.025123	[12-12-3-1]	0.025838	[12-12-5-3-1]	0.026532
[12-11-4-4-1]	0.029768	[12-6-7-6-1]	0.025142	[12-4-7-6-1]	0.025886	[12-4-4-4-1]	0.026533
[12-10-4-3-1]	0.029836	[12-6-4-3-1]	0.025159	[12-3-9-2-1]	0.025898	[12-5-8-2-1]	0.026546
[12-3-6-4-1]	0.029837	[12-10-4-1]	0.025162	[12-11-7-6-1]	0.025899	[12-8-8-5-1]	0.026547
[12-3-2-3-1]	0.029857	[12-7-4-3-1]	0.025165	[12-9-4-4-1]	0.025925	[12-12-6-1]	0.026561
[12-9-8-4-1]	0.029857	[12-12-10-6-1]	0.025167	[12-7-6-2-1]	0.025935	[12-4-8-4-1]	0.026561
[12-11-1]	0.029979	[12-10-6-2-1]	0.025174	[12-11-2-5-1]	0.025939	[12-8-7-1]	0.026564

[12-2-11-6-1]	**0.030091**	**[12-11-9-2-1]**	**0.02518**	**[12-11-5-1]**	**0.025943**	**[12-4-7-2-1]**	**0.026564**
[12-6-3-4-1]	**0.030385**	**[12-5-11-3-1]**	**0.025181**	**[12-7-11-1]**	**0.02595**	**[12-12-2-1]**	**0.026578**
[12-2-5-6-1]	**0.030392**	**[12-9-11-1]**	**0.025231**	**[12-4-12-1]**	**0.025984**	**[12-9-10-5-1]**	**0.026583**
[12-4-10-4-1]	**0.030408**	**[12-10-7-4-1]**	**0.025238**	**[12-2-10-6-1]**	**0.025985**	**[12-9-12-1]**	**0.026584**
[12-5-3-4-1]	**0.030445**	**[12-9-9-1]**	**0.025248**	**[12-6-8-6-1]**	**0.025986**	**[12-6-5-5-1]**	**0.026592**
[12-6-2-6-1]	**0.030645**	**[12-8-11-6-1]**	**0.025255**	**[12-11-12-1]**	**0.026014**	**[12-11-10-1]**	**0.026595**
[12-3-5-1]	**0.030872**	**[12-6-10-6-1]**	**0.02526**	**[12-10-5-2-1]**	**0.026021**	**[12-10-3-4-1]**	**0.026596**
[12-3-7-2-1]	**0.030967**	**[12-9-11-5-1]**	**0.02527**	**[12-6-9-3-1]**	**0.026023**	**[12-9-9-3-1]**	**0.026601**
[12-3-1]	**0.031015**	**[12-10-11-6-1]**	**0.025278**	**[12-7-5-4-1]**	**0.026024**	**[12-8-6-6-1]**	**0.026603**
[12-11-9-5-1]	**0.031071**	**[12-8-11-1]**	**0.02529**	**[12-8-3-1]**	**0.026054**	**[12-8-7-3-1]**	**0.026616**
[12-4-6-1]	**0.031425**	**[12-12-11-6-1]**	**0.025316**	**[12-5-4-2-1]**	**0.026062**	**[12-6-8-1]**	**0.026621**
[12-9-6-4-1]	**0.031475**	**[12-6-4-6-1]**	**0.025338**	**[12-6-12-1]**	**0.026069**	**[12-10-12-1]**	**0.026621**
[12-6-12-2-1]	**0.031808**	**[12-12-3-6-1]**	**0.025384**	**[12-7-3-6-1]**	**0.026071**	**[12-12-5-4-1]**	**0.026628**
[12-11-4-6-1]	**0.032267**	**[12-3-8-5-1]**	**0.025386**	**[12-7-6-3-1]**	**0.026079**	**[12-11-8-1]**	**0.02666**
[12-12-5-1]	**0.033657**	**[12-12-11-4-1]**	**0.025388**	**[12-4-9-6-1]**	**0.026093**	**[12-8-8-2-1]**	**0.026663**
[12-12-12-3-1]	**0.027661**	**[12-7-9-4-1]**	**0.027342**	**[12-12-10-4-1]**	**0.026946**	**[12-6-11-1]**	**0.026665**
[12-6-2-1]	**0.027677**	**[12-8-5-1]**	**0.027351**	**[12-3-11-1]**	**0.026968**	**[12-8-9-6-1]**	**0.026668**
[12-5-11-5-1]	**0.027684**	**[12-7-3-3-1]**	**0.02736**	**[12-7-3-1]**	**0.02697**	**[12-4-1]**	**0.026694**
[12-8-12-1]	**0.027711**	**[12-8-8-6-1]**	**0.027415**	**[12-4-12-4-1]**	**0.026987**	**[12-10-9-1]**	**0.026709**
[12-9-6-2-1]	**0.027718**	**[12-11-11-6-1]**	**0.027419**	**[12-4-3-2-1]**	**0.02699**	**[12-10-9-3-1]**	**0.026725**
[12-10-8-4-1]	**0.027738**	**[12-8-9-4-1]**	**0.027434**	**[12-10-8-1]**	**0.026991**	**[12-4-3-3-1]**	**0.026727**
[12-5-2-6-1]	**0.027738**	**[12-3-12-5-1]**	**0.027474**	**[12-9-5-1]**	**0.027008**	**[12-5-9-5-1]**	**0.026749**
[12-8-3-5-1]	**0.027765**	**[12-12-12-1]**	**0.027479**	**[12-10-1]**	**0.02703**	**[12-11-7-1]**	**0.026752**
[12-5-11-1]	**0.027772**	**[12-12-9-4-1]**	**0.027481**	**[12-10-7-5-1]**	**0.027063**	**[12-8-1]**	**0.02678**
[12-8-6-1]	**0.027782**	**[12-7-10-1]**	**0.027485**	**[12-5-10-1]**	**0.027076**	**[12-7-7-5-1]**	**0.02678**
[12-8-3-2-1]	**0.027789**	**[12-10-2-3-1]**	**0.027492**	**[12-6-5-2-1]**	**0.027076**	**[12-5-4-1]**	**0.02679**
[12-3-12-4-1]	**0.027805**	**[12-8-12-2-1]**	**0.027529**	**[12-8-2-1]**	**0.027096**	**[12-4-10-1]**	**0.026813**
[12-8-8-3-1]	**0.027823**	**[12-5-8-3-1]**	**0.027535**	**[12-8-6-2-1]**	**0.027108**	**[12-4-2-1]**	**0.026831**

[12-4-8-1]	**0.027826**	**[12-9-1]**	**0.027538**	**[12-2-11-4-1]**	**0.027112**	**[12-9-9-5-1]**	**0.026834**
[12-7-12-5-1]	**0.027831**	**[12-11-10-2-1]**	**0.02756**	**[12-5-6-6-1]**	**0.027116**	**[12-10-11-5-1]**	**0.026855**
[12-2-11-1]	**0.027856**	**[12-8-7-6-1]**	**0.02756**	**[12-3-9-6-1]**	**0.027123**	**[12-2-12-6-1]**	**0.026865**
[12-5-10-5-1]	**0.027867**	**[12-10-11-1]**	**0.027566**	**[12-4-12-2-1]**	**0.02713**	**[12-8-6-3-1]**	**0.026866**
[12-5-5-6-1]	**0.02788**	**[12-3-11-6-1]**	**0.027575**	**[12-12-11-1]**	**0.027155**	**[12-12-5-5-1]**	**0.026874**
[12-2-7-4-1]	**0.027888**	**[12-5-3-1]**	**0.027614**	**[12-3-7-6-1]**	**0.027156**	**[12-11-9-1]**	**0.026913**
[12-9-8-1]	**0.027892**	**[12-9-8-3-1]**	**0.027655**	**[12-7-7-3-1]**	**0.027157**	**[12-3-8-4-1]**	**0.026941**
[12-7-2-1]	**0.027901**	**[12-7-8-2-1]**	**0.028122**	**[12-7-3-5-1]**	**0.027157**	**[12-12-4-3-1]**	**0.028357**
[12-11-3-4-1]	**0.027904**	**[12-3-11-2-1]**	**0.028173**	**[12-5-4-5-1]**	**0.027163**	**[12-9-7-1]**	**0.028364**
[12-11-3-1]	**0.027913**	**[12-4-8-5-1]**	**0.028193**	**[12-12-7-1]**	**0.027207**	**[12-4-4-2-1]**	**0.028369**
[12-7-2-4-1]	**0.027918**	**[12-10-11-4-1]**	**0.028222**	**[12-10-10-1]**	**0.02724**	**[12-6-5-6-1]**	**0.028375**
[12-4-9-2-1]	**0.027974**	**[12-4-7-3-1]**	**0.028235**	**[12-12-7-4-1]**	**0.02724**	**[12-10-12-5-1]**	**0.028462**
[12-7-11-5-1]	**0.027981**	**[12-4-4-1]**	**0.028281**	**[12-6-9-2-1]**	**0.027243**	**[12-2-12-4-1]**	**0.02848**
[12-3-4-3-1]	**0.027988**	**[12-2-2-3-1]**	**0.028281**	**[12-5-4-6-1]**	**0.027254**	**[12-6-10-3-1]**	**0.028496**
[12-11-7-2-1]	**0.027996**	**[12-11-10-6-1]**	**0.028284**	**[12-6-3-6-1]**	**0.027256**	**[12-5-10-4-1]**	**0.028533**
[12-2-7-2-1]	**0.028011**	**[12-9-2-4-1]**	**0.028321**	**[12-5-9-4-1]**	**0.027319**	**[12-7-5-3-1]**	**0.027334**
[12-10-10-5-1]	**0.028015**	**[12-12-6-3-1]**	**0.028337**	**[12-11-11-2-1]**	**0.027323**	**[12-2-11-3-1]**	**0.028111**
[12-6-7-4-1]	**0.028054**	**[12-4-3-5-1]**	**0.028337**	**[12-4-4-5-1]**	**0.027331**	**[12-9-2-2-1]**	**0.028353**
[12-12-8-2-1]	**0.028097**	**[12-3-9-1]**	**0.028348**	**[12-5-6-2-1]**	**0.027333**	**[12-12-10-2-1]**	**0.027334**