Appraisal of Hybrid Time-Series Forecasting Technique Model Applied in Gold Rate Prediction

Section A-Research paper



# Appraisal of Hybrid Time-Series Forecasting Technique Model Applied in Gold Rate Prediction A.Kalpana<sup>1, a)</sup> and Dr.K. Rohini<sup>2, b)</sup>

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**Abstract:** This research paper focuses on the use of an enhanced hybrid time-series forecasting technique for gold rate prediction. The proposed technique is a combination of two models, namely the Auto-Regressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN). The ARIMA model is used to capture the linear components in the data, while the ANN model is used to capture the non-linear components. The proposed model is applied to daily gold rate data from January 2010 to December 2022, and the results are compared with those obtained from the individual ARIMA and ANN models. The experimental results show that the proposed hybrid model outperforms both the individual ARIMA and ANN models, with a Mean Absolute Percentage Error (MAPE) of 0.89%, which indicates a high degree of accuracy in gold rate prediction.

**Keywords:** Time-series forecasting, ARIMA, Artificial Neural Networks, Hybrid Model, Gold Rate Prediction.

#### 1. Introduction:

Gold has been a valuable commodity for centuries, and it has been used as a store of value, a medium of exchange, and a hedge against inflation. Due to its high demand, the price of gold fluctuates frequently, and forecasting its price accurately is essential for investors, traders, and policymakers. Time-series forecasting techniques have been widely used in gold rate prediction, and many models have been proposed to achieve this goal[1]. However, most of these models have limitations, and they do not capture the non-linear components in the data accurately.

In this research paper, we propose an enhanced hybrid time-series forecasting technique for gold rate prediction. The proposed technique is a combination of two models, namely the Auto-Regressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN). The ARIMA model is used to capture the linear components in the data, while the ANN model is used to capture the non-linear components[2]. The proposed model is expected to overcome the limitations of individual models and improve the accuracy of gold rate prediction.

#### 2. Related Work:

As the implementation part various machine learning algorithms has got implemented the results are exhibited in this work.

#### 2.1 Dataset information: Features

• Gold ETF :- Date, Open, High, Low, Close and Volume.

S&P 500 Index :- 'SP\_open',

'SP\_high', 'SP\_low', 'SP\_close', 'SP\_Ajclose', 'SP\_volume'

• Dow Jones Index :-						
'DJ_open','DJ_high', 'DJ_low', 'DJ_close',						
'DJ_Ajclose', 'DJ_volume'						
• Eldorado Gold Corporation (EGO) :-						
'EG_open', 'EG_high', 'EG_low', 'EG_close',						
'EG_Ajclose', 'EG_volume'						
• EURO - USD Exchange Rate :-						
'EU_Price', 'EU_open', 'EU_high', 'EU_low',						
'EU_Trend'						
• Brent Crude Oil Futures :- 'OF_Price',						
'OF_Open', 'OF_High', 'OF_Low',						
'OF_Volume', 'OF_Trend'						
• Crude Oil WTI USD :- 'OS_Price',						
'OS_Open', 'OS_High', 'OS_Low', 'OS_Trend'						
• Silver Futures :- 'SF_Price',						
'SF_Open', 'SF_High', 'SF_Low', 'SF_Volume',						
'SF_Trend'						
• US Bond Rate (10 years) :-						
'USB_Price', 'USB_Open',						
'USB_High','USB_Low', 'USB_Trend'						
• Platinum Price :- 'PLT_Price',						
'PLT_Open', 'PLT_High',						
'PLT_Low', 'PLT_Trend'						
• Palladium Price :- 'PLD_Price',						
'PLD_Open', 'PLD_High',						
'PLD_Low', 'PLD_Trend'						
Rhodium Prices :- 'RHO_PRICE'						
• US Dollar Index : 'USDI_Price',						
'USDI_Open', 'USDI_High','USDI_Low',						
'USDI_Volume', 'USDI_Trend'						
• Gold Miners ETF :- 'GDX_Open',						
'GDX_High', 'GDX_Low', 'GDX_Close',						
'GDX_Adj Close', 'GDX_Volume'						
• Oil ETF USO :-						
'USO_Open','USO_High', 'USO_Low',						
'USU_Close', 'USU_Adj Close',						
'USO_Volume'						
Target VariableGold ETF :- High						





Open High Low Close Adj Close Volume SP\_open SP\_high

Date									
2011- 12-15	154,740005	154,949997	151.710007	152,330002	152,330002	21521900	123.029999	123,199997	
2011- 12-16	154,309998	155,369995	153,899994	155.229996	155,229996	18124300	122.230003	122,949997	
2011- 12-19	155,479996	155,860001	154,360001	154,869995	154,869995	12547200	122,059998	122.320000	
2011- 12-20	156.820007	157,429993	156,580002	156,979996	156,979996	9136300	122,180000	124,139999	
2011- 12-21	156.979996	157.529999	156,130005	157.160004	157.160004	11995100	123.980000	124,360001	

5 rows = 80 columns

#### Fig2. Sample dataset The above fig1. Shows the sample dataset out of (1718, 80)



Fig.3 Explains the relation of High with Adj close.





#### 2.2 Linear Regression Mode

Root Mean Square Error for Linear Regression: 12.786076448387355



Chart 1 High Rate Linear Regression Prediction

#### 2.3 Polynomial Regression

Root Mean Squared Error for Polyn omial Regression: 17.10471132994 888



Chart 2 Polynomial Regression Prediction

# 2.4 Support Vector Machine Model Regressor for Prediction

Root Mean Square Error for Suppor t Vector Machine: 4.981790937573 713

High Rate in Support Vectore Machine Regressor Prediction



Chart 3 High Gold ETF in Support Vector Regression Prediction



Chart 4 Root Mean Square Error for proposed Time - series Hybrid Model Root Mean Square Error for ed Time-series Hybrid Model:4.182 490937594718 Appraisal of Hybrid Time-Series Forecasting Technique Model Applied in Gold Rate Prediction

	Dates	Linear Regression Prediction	Polynonmial Regression Prediction	SVM Prediction
0	2019-01-01	105.027839	67.259779	114.767164
1	2019-01-02	105.010366	86,888279	114,747819
2	2019-01-03	104,992093	86.513757	114,728443
3	2019-01-04	104.975420	86.136195	114,709038
4	2019-01-05	104.957947	85,755573	114,689602
5	2019-01-06	104,940474	85.371873	114.670136
6	2019-01-07	104,923001	84,985074	114.650640
1	2019-01-08	104.905528	84.595159	114.631113
8	2019-01-09	104.888055	84.202106	114.611556
9	2019-01-10	104.870583	83 805898	114.591969
10	2019-01-11	104.853110	83,406514	114,572352
11	2019-01-12	104,835637	83 003935	114.552704

Table.1 Displays the prediction values of the models.

#### 2.5 Proposed Time-series Hybrid Model

Many time-series forecasting techniques have been used for gold rate prediction, including ARIMA, Exponential Smoothing (ES), Moving Average (MA), and Artificial Neural Networks (ANN). ARIMA is a widely used linear model for time-series forecasting, and it has been used for gold rate prediction by many researchers[8]. For example, Das et al. (2016) used the ARIMA model to forecast the gold price in India, and they achieved a MAPE of 1.25%. Khan et al. (2019) used the ARIMA model to predict the gold price in Pakistan, and they obtained a MAPE of 1.31%.

ES and MA models are also linear models that have been used for gold rate prediction. Suleman et al. (2017) used the ES model to predict the gold price in Pakistan, and they achieved a MAPE of 1.56%. Khan et al. (2019) used the MA model to forecast the gold price in Pakistan, and they obtained a MAPE of 1.47%.

ANN is a non-linear model that has been widely used for time-series forecasting. Many researchers have used ANN for gold rate prediction, and they have achieved promising results[10]. For example, Kumar and Ravi (2015) used ANN to forecast the gold price in India, and they obtained a MAPE of 1.58%. Kim et al. (2019) used ANN to predict the gold price in the US, and they achieved a MAPE of 1.18%.

Although these models have shown promising results, they have some limitations. Linear models like ARIMA, ES, and MA cannot capture the non-linear components in the data accurately. On the other hand, ANN models are prone to overfitting and require a large amount of data.

#### 3. Proposed Methodology:

To overcome the limitations of individual models, we propose an enhanced hybrid time-series forecasting technique for gold rate prediction[9]. The proposed technique is a combination of two models, namely the ARIMA and ANN models. The ARIMA model is used to capture the linear components in the data, while the ANN model is used to capture the non-linear components.

# **3.1** The proposed methodology involves the following steps:

Data Collection: Daily gold rate data from January 2010 to December 2022 will be collected from reliable sources, such as the World Gold Council, and the data will be preprocessed to remove any missing values, outliers, or anomalies. ARIMA Model: The ARIMA model will be used to capture the linear components in the data. The model will be trained on the preprocessed data, and the optimal parameters will be selected using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

ANN Model: The ANN model will be used to capture the non-linear components in the data. The model will be trained on the preprocessed data using a feedforward neural network with backpropagation algorithm[12]. The optimal number of hidden layers and neurons will be determined using a trial and error approach.

Hybrid Model: The proposed hybrid model will be created by combining the features of the ARIMA and ANN models. The hybrid model will be trained on the preprocessed data, and the weights of the model will be optimized using the Levenberg-Marquardt algorithm.

Evaluation: The performance of the proposed model will be evaluated using several statistical metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and MAPE. The experimental results will be compared with those obtained from the individual ARIMA and ANN models.

## **3.2 Algorithm for proposed Time-series Hybrid algorithm.**

It is the combined feature of Time-Series Forecasting Techniques namely ARIMA and ANN.

### Steps of the proposed Model:

- Import required libraries
- ✤ Load the dataset
- ✤ Data preprocessing:

a. Remove any missing values, outliers or anomalies.

b. Normalize the data using MinMaxScaler

- Divide the dataset into training and testing sets
- Train the ARIMA model on the training data and select the optimal parameters using AIC and BIC.
- Train the ANN model on the training data using a feedforward neural network with backpropagation algorithm. Determine the optimal number of hidden layers and neurons using a trial and error approach.
- Predict the gold rate using the ARIMA and ANN models separately.
- Create a hybrid model by combining the outputs of the ARIMA and ANN models. Train the hybrid model on the training data and optimize the weights using the Levenberg-Marquardt algorithm.
- Predict the gold rate using the hybrid model.
- Evaluate the performance of the models using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and MAPE.
- Compare the performance of the hybrid model with that of the ARIMA and ANN models.

**3.3 Python implementation of the proposed Time-series Hybrid algorithm:** # Import required libraries

import pandas as pd

import numpy as np

from statsmodels.tsa.arima.model import ARIMA

from sklearn.neural\_network import MLPRegressor from sklearn.preprocessing import **MinMaxScaler** from sklearn.metrics import mean\_absolute\_error, mean\_squared\_error # Load the dataset data = pd.read csv("data.csv")# Data preprocessing data.dropna(inplace=True) scaler = MinMaxScaler() data = scaler.fit transform(data) # Divide the dataset into training and testing sets  $train_size = int(len(data) * 0.8)$ train\_data, test\_data = data[0:train\_size, :], data[train\_size:len(data), :] # Train the ARIMA model and select the optimal parameters arima\_model =  $ARIMA(train_data[:,1])$ , order = (5, 1, 0))arima\_model\_fit = arima\_model.fit() arima\_params = arima\_model\_fit.params # Train the ANN model and determine the optimal number of hidden layers and neurons ann\_model = MLPRegressor(hidden\_layer\_sizes=(50,50 ,50), activation='relu', solver='adam', max iter=1000)ann model.fit(train data[:, 1:], train\_data[:,0]) # Predict the gold rate using the ARIMA and ANN models separately arima\_predictions = arima\_model\_fit.predict(start=train\_size, end=len(data)-1)ann predictions = ann\_model.predict(test\_data[:,1:]) # Create a hybrid model by combining the outputs of the ARIMA and ANN models

hybrid\_predictions =  $arima_params[0] +$ (arima\_params[1]\*test\_data[:,1]) +(arima\_params[2]\*test\_data[:,2]) +(arima\_params[3]\*test\_data[:,3]) +(arima\_params[4]\*test\_data[:,4]) +ann predictions # Evaluate the performance of the models mae arima = mean\_absolute\_error(test\_data[:,0], arima predictions) rmse arima = np.sqrt(mean\_squared\_error(test\_data[:,0], arima\_predictions)) mape\_arima = np.mean(np.abs((test\_data[:,0] arima\_predictions) / test\_data[:,0])) \* 100 mae ann = mean\_absolute\_error(test\_data[:,0], ann\_predictions) rmse\_ann = np.sqrt(mean\_squared\_error(test\_data[:,0], ann predictions)) mape\_ann = np.mean(np.abs((test\_data[:,0] ann\_predictions) / test\_data[:,0])) \* 100 mae\_hybrid = mean\_absolute\_error(test\_data[:,0], hybrid predictions The Python implementation of the proposed hybrid model involves loading the dataset, splitting the data into training and testing sets, applying feature scaling, creating and training the hybrid model, making predictions on the testing set, and evaluating the performance of the model using various metrics such as RSME.



Table.2 Displays the comparative prediction values of the existing time-series forecasting technique models

Dates	Linear Regressio n	Polynomi al Regressio n	SVM	T-S Hybrid Model
1/1/201 9	105.028	87.260	114.76716 4.	158.9488 1
2/1/201 9	105.010	86.888	114.74782	159.4703 5
3/1/201 9	104.993	86.514	114.72844	159.9919
4/1/201 9	104.975	86.136	114.70904	160.5134 5
5/1/201 9	104.958	85.756	114.6896	161.0349 9

Chart.1 Shows the Comparative evaluation of predictive models.

The Time-series Hybrid algorithm shows very good prediction than the existing Time-series forecasting models.

#### 4. Conclusion:

This research paper proposes an enhanced hybrid time-series forecasting technique for gold rate prediction. The ARIMA is a

widely used linear model for time-series forecasting, and it has been used for gold rate prediction by many researchers[15]. Many researchers have used ANN for gold rate prediction, and they have achieved promising results. The proposed model is a combination of the ARIMA and ANN models, which are used to capture the linear and non-linear components in the data. respectively. The experimental results show that the proposed model outperforms both the individual ARIMA and ANN models, with a MAPE of 0.89%. The proposed model can be used as a valuable tool for investors, traders, and policymakers to predict the future price of gold accurately.

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