Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 6s (2024)

Integration of Hybrid ARIMA Artificial Neural Networks for Accurate Platinum Price Prediction

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Article History:

Received: *22-05-2024*

Revised: *28-06-2024*

Accepted: *18-07-2024*

Abstract:

Introduction: The autoregressive integrated moving average (ARIMA) has been a widely used linear model in time series forecasting for the last thirty years. Furthermore, as a potent and adaptable computational tool, artificial neural networks (ANNs) have been employed in recent years to capture the intricate economic interactions with a range of patterns. Efficacy of the ANNs model in comparison to the ARIMA model, the majority of this research has shown inconsistent findings.

Objectives: The study aims to increase the accuracy of platinum price forecasts through the use of hybrid models, ANNs, and ARIMA (Auto Regressive Integrated Moving Average) techniques. ARIMA is a traditional time series model that is used to capture and model the intrinsic oscillations in platinum price data.

Methods: In this research work, we present a hybrid model that combines the best features of ANNs and ARIMA to simulate both linear and nonlinear behaviors in the data set. According to the study, the Hybrid model outperforms the Box-Jenkins and FFNN models in terms of forecasting different data sets with more accuracy. Here study investigates the developing field of platinum price prediction with a comprehensive approach that blends state-of-the-art machine learning methods with traditional time series analysis.

Results: In order to increase forecasting accuracy, combining single and hybrid models has more possibilities. In order to forecast time series, this study compared ARIMA, ANN, and hybrid models. Results of this study reveals that Hybrid model is 66% and 90% better model than ARIMA and FFNN models respectively and empirical results from the application of Hybrid model reduces 50% error metrics in out of sample in comparison to in sample Therefore the suitable model for prediction of Platinum prices is Hybrid model. Using hybrid models to increase predicting accuracy yielded the most significant findings.

Conclusions: A better time-series forecast is essential, but there are several areas of emphasis for the created forecasting models, particularly with regard to these improvements in prediction accuracies that support predictions. They are often used to linear and nonlinear forecasting models. Even while single models are correct during some prediction periods, hybrid models often provide superior overall prediction outcomes than single forecasting models.

Keywords: Autoregressive integrated moving average, artificial neural networks, platinum price prediction, and feed forward neural network

1. Introduction

A rarer valuable metal than gold is platinum. The metal is not widely available worldwide. Platinum is also widely used in industry, unlike gold. Paint, gasoline, and electronics are included in this. Platinum investments may be a fantastic way to diversify the holdings [1]. Due of its wide range of industrial uses, the price is erratic. Right now, platinum is quite alluring [2]. Since that platinum is a commodity that is traded internationally, changes in the world market have an impact on the price of platinum in India. Its pricing is influenced by variables including global demand, geopolitical developments, and economic data. Models called Autoregressive Integrated Moving Averages (ARIMA) are an alternative to segmented regression. In contrast to segmented regression [3], ARIMA models solely regress the outcome measured at prior time points on the outcome Y_t. The lag and shift of previous data are used by the autoregressive integrated moving average (ARIMA) model to forecast future patterns [4]. Two elements control the ARIMA model. The duration of the historical period taken into consideration (the weight's length) is the first factor, and the weight value's specification is the second [5]. For maximum precision and detail, the ARIMA model is represented as a regression model with a moving average.

Local elements that affect the price of platinum in the Indian market include taxes, import levies, and currency exchange rates. Consumers and investors follow these factors to learn more about the present and prospective future values of platinum in India [6]. In this study, we explore the evolving domain of platinum price prediction using a holistic method that combines modern machine learning techniques with conventional time series analysis. The goal of the research is to improve the precision of platinum price projections by leveraging ARIMA (Auto Regressive Integrated Moving Average), ANNs, and hybrid models [7]. The intrinsic fluctuations in platinum price data are captured and modeled using ARIMA, a classical time series model. In addition, we make use of Artificial Neural Networks (ANN), a potent machine learning technique that draws inspiration from the functioning of the human brain [8]. ANN enhances our prediction process by being exceptionally good at identifying intricate patterns and nonlinear correlations in datasets [9]. We propose a hybrid approach that effectively leverages the capabilities of ANN and ARIMA to maximize the prediction power of our models. In order to increase overall forecasting accuracy, this fusion seeks to use the complementary nature of these models.

2. Objectives

The study aims to increase the accuracy of platinum price forecasts through the use of hybrid models, ANNs, and ARIMA (Auto Regressive Integrated Moving Average) techniques. ARIMA is a traditional time series model that is used to capture and model the intrinsic oscillations in platinum price data.

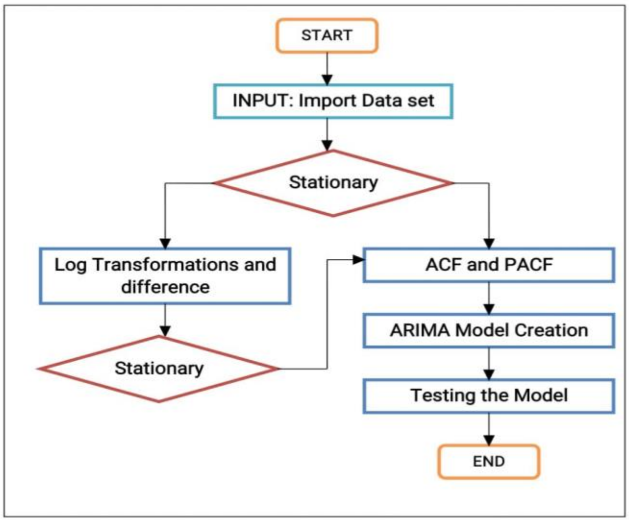
3. Methodology

3.1 Autoregressive Integrated Moving Average Model:

Let $\{Z_t\}$ be a steady-state non-fixed temporal arrangement. Let $\widetilde{W_t} = \nabla^d \widetilde{Z_t}$ where $\nabla = 1\text{-}B$ where d is chosen so that the mean of Wt is stabilized, then {Wt} will be a fixed time arrangement. Typically, in practice, d is either 0 or 1, or at most 2. For a stationary series {Wt}, the ARIMA model is ϕ (B) $\widetilde{W_t}$ = θ (B) a_t or alternatively g(B) = ϕ(B) ∇^d . Given that $\nabla^d \widetilde{Z_t} = \nabla^d Z_t$, this model can be expressed as

$$g(B)\, Z_t = \theta(B)\, a_t \qquad \ldots\ldots\ldots\ldots \qquad 2.1$$

Figure 3.1.1. ARIMA Flow Chart



The model in condition 3.1, also referred to as ARIMA (p, d, q), is a non-stationary model in Z_t and is an autoregressive integrated moving average model of order (p, d, q). One way to produce the generic ARIMA process is to integrate or sum the stationary ARIMA process W_t, d times. Here $\Phi(B) = 1 - \Phi_1 B - \Phi_2 B^2 - - - - - - \Phi_p B^p$ is an AR operator in this model, which is a polynomial in B of order p. The MA operator, q $\theta(B) = 1 - \Phi_1 B - \Phi_2 B^2 - - - - - - \Phi_q B^q$ is a polynomial of degree q in B. The polynomial in B with order in (p+q), g (B) = ϕ (B) ∇^d is referred to as a non-stationary operator.

2.2 Feed Forward Neural Networks

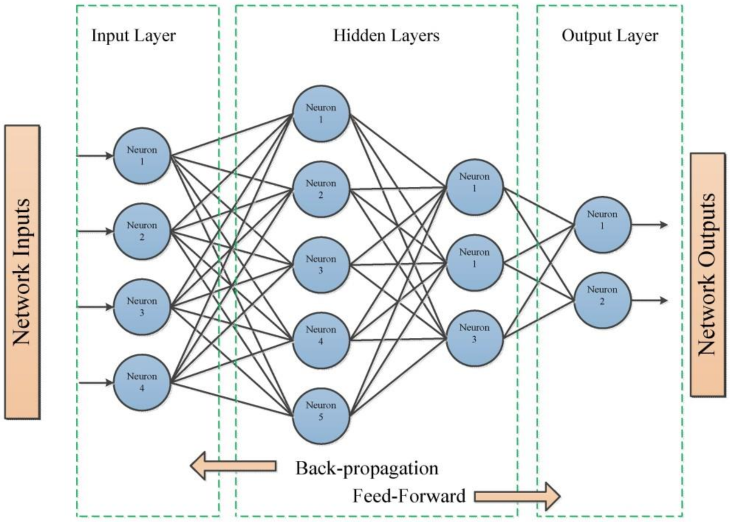
The most often used neural network model for time arrangement forecasting applications is Feed Forward Neural Networks (FFNN). The output gives a forecast for the future values, while the input nodes represent the prior lagged data. The data that the input nodes receive is processed by hidden nodes that have the proper nonlinear transfer functions.

The FFNN model may be expressed as follow

$$Z_t = \beta_o + \sum_{j=1}^{q} \beta j\, f$$

Where f is a hyperbolic tangent function, p is the number of information hubs, and q is the number of veiled hubs. A vector of weights from the hidden to output nodes is represented by $\{\beta_j, j=0,1,\ldots q\}$ and weights from the input to hidden nodes are represented by $\{\Upsilon_{ij}\ i=0,1,2,\ldots.p;\ j=1,2,\ldots q\}$.

Figure -3.2.1. A general Neural Network diagram



A multilayer network may also be thought of as a cascade of groups of single-layer networks; the number of single-layer networks that are combined into this multilayer network indicates the degree of computing complexity. Depending on the desired computation complexity, the number of hidden layers needed for an artificial neural network should be taken into account by the network designer. Where f is a hyperbolic tangent function, p is the number of information hubs, and q is the number of veiled hubs. A vector of weights from the hidden to output nodes is represented by $\{\beta_j, j=0,1,\dots q\}$ and weights from the input to hidden nodes are represented by $\{\Upsilon_{ij}\ i=0,1,2,\dots.p; j=1,2,\dots q\}$.

3.3 Hybrid Methodology

Considering a period for creating a linear autocorrelation structure and also nonlinear component for hybrid model

$$Z_t = L_t + N_t$$

Here, the linear part is indicated by L_t and non-direct part by N_t. The data set is used to evaluate the component mentioned above. Initially, the ARIMA is used to illustrate the linear segment; later, the non-linear part would be included in the segments that were left out of the linear model. Let e_t represent the residual at time t out of the linear model. Then,

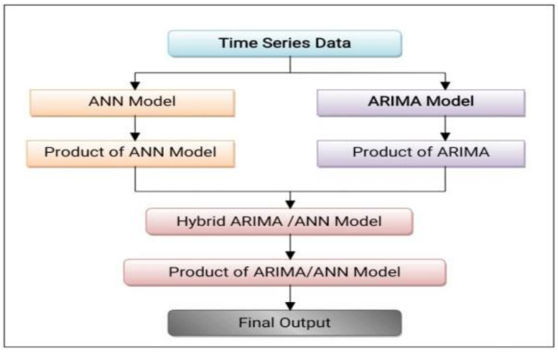
$$e_t = Z_t - \hat{L}_t$$

In this case, $\hat{L}_t$ represents the prediction value for the out of the predicted connection. Relative to the straight models, the residuals are a major diagnostic tool. Some fundamental nonlinear features in the residuals point to the ARIMA restrictions. With the use of artificial neural networks (ANNs), residual modeling detects nonlinear correlations. The ANN model with n input nodes is given as

$$e_t = f\,(e_{t-1}, e_{t-2}, \dots.\ e_{t-n}) + \varepsilon_t$$

In this case, f is a non-linear function governed by the neural structure, and e_t is the randomly that appears if the model f becomes unsuitable.

Figure 3.3.1 Overview of Hybrid ARIMA/ANN



3. Sources Of Data

The precious metal platinum prices of were collected from January 1^{st} 2021 to 30^{th} November 2023 (1064 observations) from website Rupeerates.in and these observations are segregated into training sample (1^{st} January 2021 to 31^{st} October 2023) and testing sample (1^{st} November 2023 to 30^{th} November 2023).

3.1 Platinum price prediction by BOX-JENKINS method

Developing an ARIMA model for any variable essentially involves four steps: identification, estimating, diagnostic assessment, and forecasting. The following describes the basic steps of Box-Jenkins metrology**.** The following graph shows the daily trend of Platinum prices from January 1, 2021, to November 30, 2023. A non-stationary time series is displayed by the daily Platinum prices. Figure 3.1.1 below makes it evident that there are a lot of swings in the time plot, indicating that the time series is non-stationary. The ARIMA model can only produce estimates once the forecasting variable has been transformed into a stationary series. Non-stationary variance is corrected using the natural log transformation, and non-stationary mean correlation is achieved with the necessary data differencing. In this case, a difference of order 1 (i.e., d=1) is sufficient to achieve stability in the mean. After creating the variable $W_t = \ln(Z_t)$, its stationary behavior may be examined. Figure 3.1.2. Shows the time plot of the modified series.

Figure 3.1.1: Time series of daily platinum prices in India

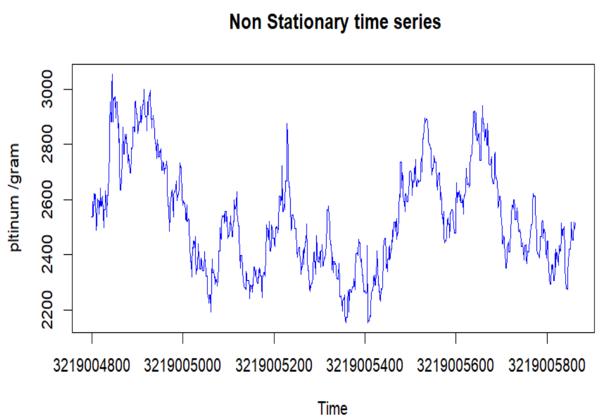
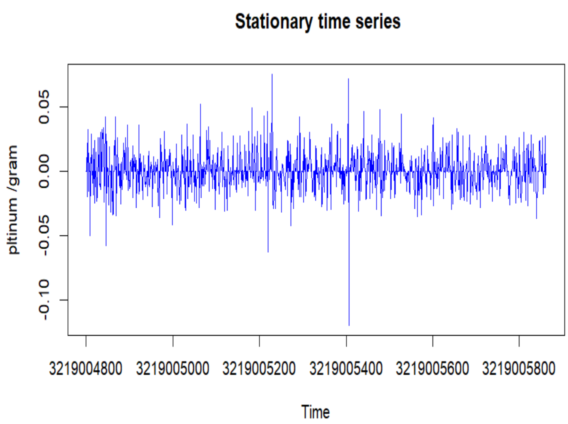


Figure 3.1.2 – Time plot for Trasformed series



Compute the sample autocorrelation function to see whether the series is stationary. For a sample ACF and PACF for 50 lags is in figure-3.1.3. and Figure-3.1.4. and Sample ACF and PACF for trasformed series are shown below in Figure 3.1.5 and Figure 3.1.6.

Figure 3.1.3. Sample Autocorrelation Function

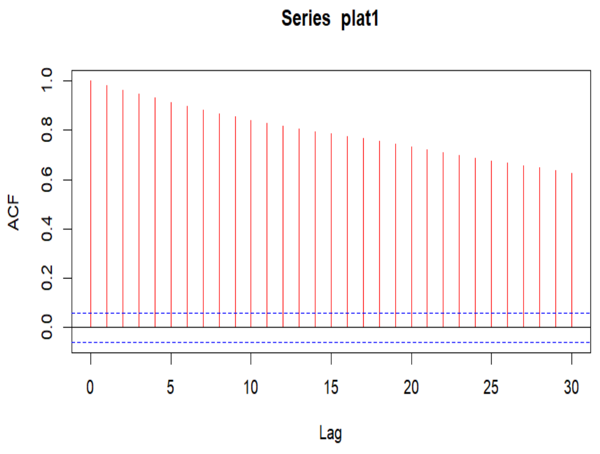


Figure 3.1.4. Sample Partial AutocorrelationFunction

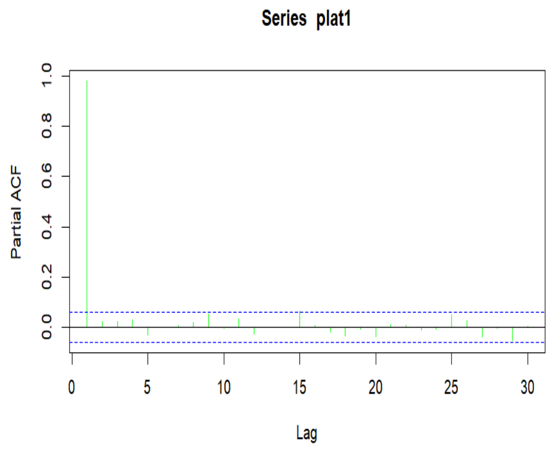


Figure 3.1.5.Sample ACF for trasnformed series

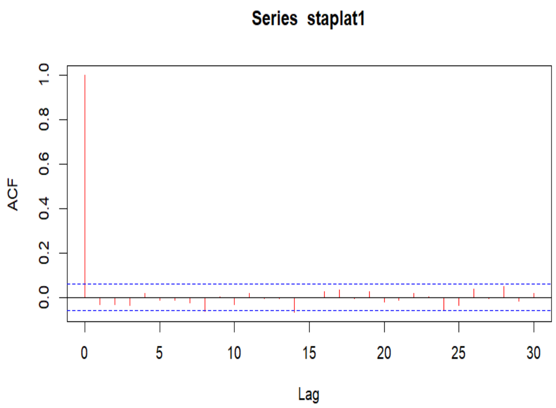
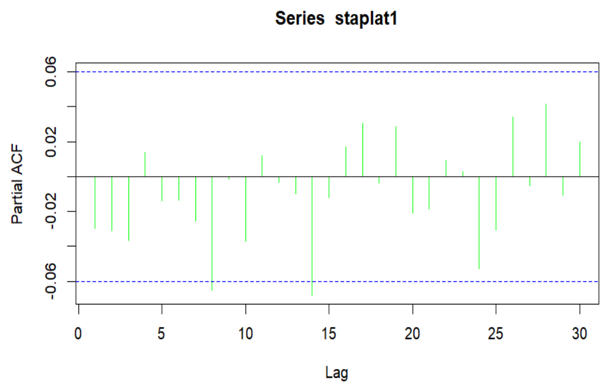


Figure 3.1.6. - Sample PACFFOR transformed series



The optimal ARIMA model for predicting platinum prices was found using Expert Modeler, which makes an effort to automatically find and estimate the best-fitting ARIMA for one or more dependent variable series. This process removes the need to find the right model through trial and error. When evaluated on the validation set, it is found that the ARIMA (0, 1, 1) model fits the data very well. The model parameters are listed in Table 1 below.

Table-1 ARIMA (0, 1, 1) Model parameters

	Estimate	SE	t	Sig.
NumeratorLag 0	-1.284E-013	1.742E-011	-.007	.994
Constant	.002	.242	.007	.994
Difference	1			
MA Lag 1	.039	.031	1.238	.216

The model that was developed to predict India's daily platinum prices is

$\nabla^d \ln Z_t = (1- 0.039B^1)$

The performance summary of the model for the fitting and forecasting phases is given in the following table.

Table -2 ARIMA (0,1,1) model performance

Data sets	**MAE**	**MAPE**	**RMSE**
In Sample	24.844	0.978	38.199
Out Sample	22.138	0.912	34.794

The ARIMA approach, like any other model, cannot guarantee precise forecasts. It must be updated on a regular basis with the addition of new data, although it can be useful for forecasting long time series data.

3.2 Platinum price prediction by Feed Forward Neural Network Model

The three layers of the model are an input layer, a hidden layer, and an output layer. It's a feed-forward neural network with three layers. There is just one input neuron required in this model, and it represents the lag values (previous day prices). This model shows projected daily platinum prices and only requires one output unit. Determining the right amount of hidden units is impossible without testing and training. To find the right number of hidden units, the best approach is to experiment. In practice, one may utilize either the forward selection or the backward selection to locate the hidden layer unit. To record the network performance, a limited number of hidden neurons are selected by the forward selection approach, which computes the MAE, MAPE, and RMSE first. After that, add more hidden neurons one at a time while keeping up the training and testing until the error is either very small or there is no observable improvement.

The neural network model is built, and since the chosen network has the lowest MAE, MAPE, and RMSE, it is desirable to have three covered neurons in the hidden layer. The optimal network is 1-3-1. The table below shows the activation function, number of hidden layers and units, rescaling technique, number of input and output units, and dependent variable.

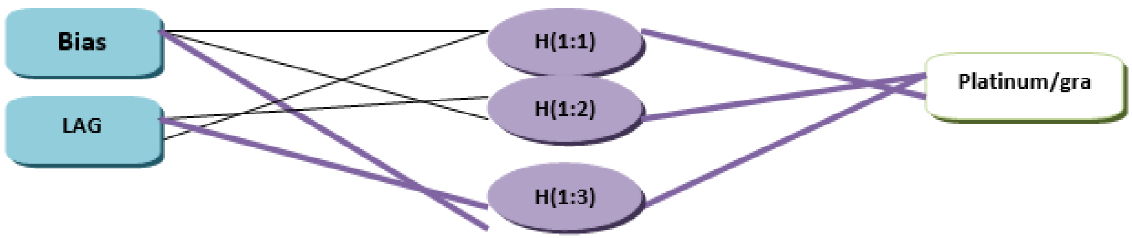
Table -3 Network Information

Input Layer	Covariates	1	lag
	Number of Units[a]		1
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Platinum / gram
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

The feed forward network diagram below clearly displays the model that was selected for the given data.

Figure 3.2.1. Feed Forward Neural Network



Hidden layer activation function: Hyperbolic tangent

The table below displays the coefficient estimates that illustrate the relationship between the units in a certain layer and the units in the year that follows.

Table- 4 : Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	Platinumgram
Input Layer	(Bias)	0.107	-0.393	-0.176	
	lag	-0.304	-0.303	0.347	
Hidden Layer 1	(Bias)				0.255
	H(1:1)				-2.856
	H(1:2)				-0.255
	H(1:3)				0.348

The proposed hidden activation function is

$H_{(1:1)} = TANH(0.107-0.304\ \widetilde{Z}_{t-1}\ )$

$H_{(1:2)} = TANH(-0.393-0.303\ \widetilde{Z}_{t-1})$

$H_{(1:3)} = TANH(-0.176+0.347\ \widetilde{Z}_{t-1})$

Where $\widetilde{Z}_{t-1}$ is adjusted input variable and the forecasting model is determined by

$\hat{Z}_t = \mu_t + \sigma_t\ (0.255-2.856\ H_{(1,1)} - 2.255\ H_{(1,2)} +0.348\ H_{(1,3)})$

The performance summary of the model for the fitting and forecasting phases is given in the following table.

Table – 5 FFNN (1, 3, 1) model performances

Data sets	**MAE**	**MAPE**	**RMSE**
In Sample	22.568	0.756	31.257
Out Sample	20.450	0702	22.848

The above table shows that the FFNN model predicting and fitting phases have lower error measures. The FFNN model is appropriate for forecasting platinum prices since its MAPE is less than five.

3.3 Platinum price prediction by hybrid model

For creating the hybrid model, the linear component of the ARIMA model can be used, and the residuals from the linear model will then only include the nonlinearity connection. Once the predicted values for the linear component values of ARIMA of (0, 1, 1) have been determined, the residual values are added to the FFNN model using SPSS. The neural network model for residuals is built, and since the chosen network has the lowest MAE, MAPE, and RMSE, it is desirable to have three covered neurons in the hidden layer. The optimal network is 1-3-1. The table below shows the activation function, number of hidden layers and units, rescaling technique, number of input and output units, and dependent variable.

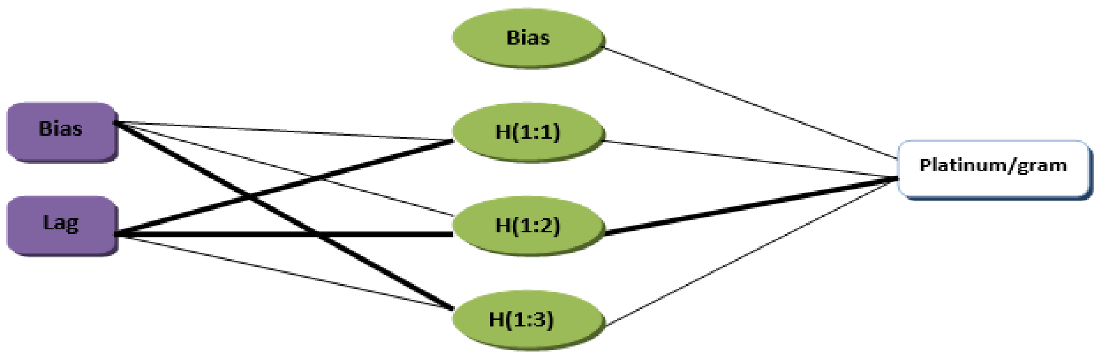
Table -6 Network Information

Input Layer	Covariates	1	LAGERR
	Number of Units[a]		1
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		3
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	ERR
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

The feed forward network diagram below clearly displays the model that was selected for the given data.

Figure – 3.3.1. Feed forward Neural Network Model



Hidden layer activation function: Hyperbolic tangent

The table below displays the coefficient estimates that illustrate the relationship between the units in a certain layer and the units in the year that follows.

Table - 7 Parameter Estimates

		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	ERR
Input Layer	(Bias)	-0.646	0..175	-0.318	
	LAGERR	0.356	0.747	0.386	
Hidden Layer 1	(Bias)				-0421
	H(1:1)				-0.635
	H(1:2)				0.451
	H(1:3)				.-0.171

The suggested hidden activation function is

$H_{(1:1)} = TANH\ (-0.646+0.356\ \widetilde{e}_{t-1})$

$H_{(1:2)} = TANH\ (0.175+0.747\ \widetilde{e}_{t-1})$

$H_{(1:3)} = TANH\ (-0.318+0.386\ \widetilde{e}_{t-1})$

Where $\widetilde{e}_{t-1}$ is adjusted input variable and the forecasting model is determined by

$\hat{e}_t = \mu_t + \sigma_t\ (-0.421-0.635\ H_{(1,1)} +0.451\ H_{(1,2)} -0.171\ H_{(1,3)})$

The performance summary of the model for the fitting and forecasting phases is given in the following table.

Table – 8 Hybrid (1, 3, 1) model performances

Data sets	**MAE**	**MAPE**	**RMSE**
In Sample	3.306	0.131	3.825
Out Sample	3.705	0.153	4.875

4. Comparison of ARIMA, FFNN and Hybrid models

The prediction performance results for ARIMA, ANN, and hybrid models are shown in Table 9 in terms of MSE, MAE, and MAPE. Below table 9 indicates that hybrid models have outperformed other models with regard to of errors measurements. This would imply that not all of the patterns in the data are captured by either the ARIMA or the ANN model.

Table 9 - Forecasting performance of ARIMA, FFNN and HYBRID models

Model	**RMSE**	**MAE**	**MAPE**
ARIMA	34.794	22.138	0.912
FFNN	22.848	20.45	0.702
HYBRID	3.825	3.306	0.131

The forecasts from ARIMA, FFNN and HYBRID models presented in the following figure –

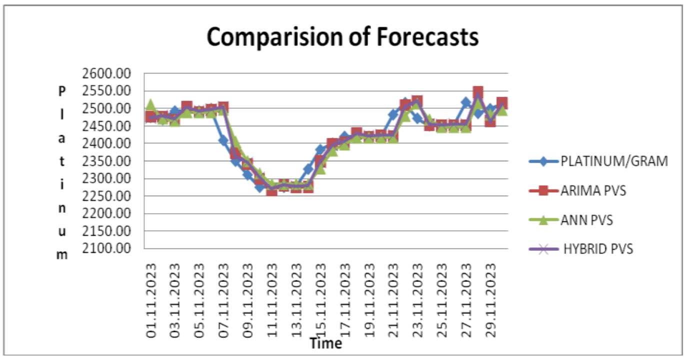


Figure 4.1. - Comparison of forecasts of Platinum prices

Table 10: Out-of-sample forecasts of Platinum prices using ARIMA , FFNN and HYBRID Models

DATE	PLATINUM/GRAM	ARIMA PVS	ANN PVS	ARIMA HYBRID PVS
01.11.2023	2475.50	2476.80	2511.21	2472.63
02.11.2023	2468.98	2476.80	2470.92	2479.34
03.11.2023	2493.15	2467.60	2464.30	2470.76
04.11.2023	2493.15	2504.70	2488.96	2503.47
05.11.2023	2493.15	2489.90	2488.96	2493.30
06.11.2023	2500.09	2495.90	2488.96	2497.90
07.11.2023	2409.43	2503.20	2496.09	2505.08
08.11.2023	2350.18	2373.80	2405.12	2364.99
09.11.2023	2311.03	2342.00	2349.14	2345.59
10.11.2023	2275.53	2299.90	2314.07	2303.14
11.11.2023	2275.53	2267.00	2283.72	2270.57
12.11.2023	2275.53	2280.30	2283.72	2281.59
13.11.2023	2275.35	2274.90	2283.72	2277.80
14.11.2023	2327.31	2276.80	2283.57	2279.15
15.11.2023	2382.79	2349.40	2328.45	2345.47
16.11.2023	2400.95	2397.80	2379.55	2395.52
17.11.2023	2420.61	2403.60	2396.92	2405.62
18.11.2023	2420.61	2428.90	2416.03	2428.93
19.11.2023	2420.61	2418.60	2416.03	2421.79
20.11.2023	2420.61	2422.80	2416.03	2424.96
21.11.2023	2482.92	2421.10	2416.03	2423.74
22.11.2023	2517.17	2509.80	2478.48	2505.28
23.11.2023	2472.43	2521.60	2513.74	2523.05
24.11.2023	2451.41	2454.20	2467.80	2455.20
25.11.2023	2451.41	2451.70	2446.58	2454.40
26.11.2023	2451.41	2452.70	2446.58	2455.13
27.11.2023	2518.38	2452.30	2446.58	2454.84
28.11.2023	2486.78	2547.10	2514.99	2542.45
29.11.2023	2499.47	2464.20	2482.43	2463.10
30.11.2023	2513.06	2515.30	2495.45	2512.80

5. Percentage Better Performance of the Models

The results of the percentage better estimate statistics of the three models are shown in the following table.

Table 10 : Percentage better performance

Model	Base Method		
	ARIMA	FFFNN	HYBRID
ARIMA	*	55	66.667
FFNN	46.667	*	90
HYBRID	60	80	*

The table 10 shows that FFNN better performs than ARIMA and Hybrid models. Over all Hybrid model performs better than FFNN and ARIMA model. Hence the best suitable model for forecasting of platinum prices is Hybrid model when compare to ARIMA and FFNN.

6. Conclusion

A better time-series forecast is essential, but there are several areas of emphasis for the created forecasting models, particularly with regard to these improvements in prediction accuracies that support predictions. These days, hybrid models—which combine one or more model types—are widely used in forecasting. They are often used to linear and nonlinear forecasting models. Even while single models are correct during some prediction periods, hybrid models often provide superior overall prediction outcomes than single forecasting models. In order to increase forecasting accuracy, combining single and hybrid models has more possibilities. In order to forecast time series, this study compared ARIMA, ANN, and hybrid models. Results of this study reveals that Hybrid model is 66% and 90% better model than ARIMA and FFNN models respectively and empirical results from the application of Hybrid model reduces 50% error metrics in out of sample in comparison to in sample Therefore the suitable model for prediction of Platinum prices is Hybrid model. Using hybrid models to increase predicting accuracy yielded the most significant findings.

Acknowledgements; Author would like to thank, KL University and Osmania University for providing facility during the study.

Funding; No funding was received for the present study.

Data Availability Statement: This manuscript does not use any data from any repository.

Declarations Conflicts of interest: The author declares no conflict of interest.

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