Time Series Analysis and Prediction of Future Commodities Prices with SARIMA

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Abstract: Commodities are one of the most important investing targets in the world. Forecasting the prices of commodities precisely helps investors and corporations make reasonable transactions. This paper is based on the prices of Brent oil, wheat, and aluminum and predicts the future prices of commodities in the energy industry, the manufacturing industry, and the agricultural products industry. The results show that the Seasonal Autoregressive Integrated Moving Average (SARIMA) model has a relatively excellent ability to predict the future movements of the commodities prices. The prediction shows that all the commodities prices will experience a decline in the next 10 months. However, the predictions are not exactly the same as the actual movements. The fluctuation extent of the predictions is much smaller. Therefore, the SARIMA model can help investors establish a broad idea of the future trend of the commodities prices, but it cannot help investors do ultrashort-term trading. If the investors only focus on the trend during a longer period and ignore making profits with the short-term fluctuations, the SARIMA model is suitable for them. In the end, this paper suggests investors combine the fundamental analysis with the forecasting results generated by the SARIMA model to make trading decisions.

1 INTRODUCTION

Commodities are raw materials and resources that are normalized, tradable, and low value-added. They also have a large volume in nature. Commodities are often divided into three categories (Zhou, Song, & Ren, 2022): energy commodities, metal commodities, and agricultural products commodities. As the upstream raw material for many products, commodities have important impacts on the development of the world economy. Metals are unreplaceable resources and are widely used in the manufacturing industry, oil and gas are nonrenewable strategic resources that are the objects of competition between the world's major powers and leading economies, and agricultural products are important in the food industry and can help stabilize society (Guo, 2023). As the indicator of the international situation, the movement of the prices of commodities often represents macroeconomic changes in the world, the change in supply and demand, and the change in the market. Last but not least, commodities can be traded by futures and options. Investors can use commodities to earn revenues and hedge risks. Therefore, it is meaningful to predict the future movement of the prices of commodities. It can help investors, companies, and countries to make more reasonable decisions.

In 2021, Wanjuki et al. researched the Seasonal Autoregressive Integrated Moving Average (SARIMA)'s ability to forecast the price index of food and beverages in Kenya (Wanjuki, Wagala, & Muriithi, 2021). After comparing all the models with different parameters, it turned out that SARIMA (1, 1, 1) (0, 1, 1)12 was the best fit for the data in the study. In 2022, Li et al. applied the ARIMA model to gold prices and gave investing suggestions based on the forecasting results (Li, 2022). The study encouraged investors to combine international situations with the results. In 2023, ARIMA and SARIMA's ability to predict future crude oil prices were compared by Ariyanti, and it turned out that both models were excellent in forecasting (Ariyanti & Yusnitasari, 2023), which meant ARIMA and SARIMA models were suitable for time series analysis of crude oil prices. Gasper et al. conducted a study on forecasting crude oil prices in Tanzania using the ARIMA model

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(Gasper & Mbwambo, 2023). This study found out that even under the serious fluctuation caused by the conflict in Ukraine and the coronavirus outbreak, the ARIMA model could still capture the potential movement in crude oil prices. In 2024, Guzman affirmed ARIMA's ability to predict future corn prices in Mexico (Guzma, 2024). This research also emphasized the importance of forecasting future prices of agricultural products by pointing out that future corn prices would influence farmers' interests and sustainable agricultural development. Bagrecha et al. used the ARIMA model to forecast silver prices in India. However, the results only explained 26% of the observed silver price changes. It suggested that the ARIMA model was too simple for silver price prediction and that more factors should be taken into consideration (Bagrecha et al., 2024). In 2025, Ojha et al. utilized the SARIMA model to predict global wheat prices (Ojha & Karki, 2025). They pointed out its importance in helping investors and countries make reasonable strategic decisions. However, the study claimed that the prediction is only suitable for short-term analysis, and many external factors are not considered. The results may not fit other commodities and periods.

This paper aims to improve the ability to predict the future prices of different commodities with the SARIMA model, hoping to expand from the price prediction of the commodity to the prediction of the future development trend of the industry corresponding to that commodity, and finally explore the changes in industries and changes in the world economy. This study first searches the prices of the commodities in each of the three categories mentioned above. Based on the different characteristics of all the commodities in each category, this study finally chooses aluminum in metals, wheat in agricultural products, and Brent oil in energy as the data to be researched. This paper first applies pre-processing procedures to the data and then uses the SARIMA model to fit the data and make forecasts of future data in the next 10 months. The differences between the future data and the actual data are compared to evaluate the ability of the SARIMA model. Conclusions are reached based on the results and international events during the research period.

2 DATASETS

2.1 Data Collection and Description

This paper extracts the datasets from Kaggle, and the original datasets are extracted from Alpha Vantage API using Python. The dataset contains monthly historical prices of 10 different commodities from January 1990 to March 2023. Prices are reported in USD per unit of measurement for each commodity. The prices of aluminum, wheat, and Brent crude oil were selected in the study.

Crude oil is one of the most important energies in the world. It can represent the energy industry. This paper selects the price of the Brent crude oil which is a blended crude stream produced in the North Sea region. This is because Brent crude oil is one of the most important crude oil pricing benchmarks in the world. It is widely used in international oil price quotation and contract settlement, and it serves as a marker for pricing a number of other crude streams. Compared with OPEC and WTI prices, the price of Brent crude oil is more comprehensive and transparent, because it is not affected by the US domestic factors and the political factors of the Organization of the Petroleum Exporting Countries (OPEC).

Aluminum is widely used in aerospace, automotive, construction, packaging, and many other manufacturing and industrial sectors. It can represent the manufacturing industry. The price movement of aluminum directly reflects the economic performance and industry cycles. Compared to gold and silver, aluminum is less used as a precious metal and investment target. Therefore, its price volatility is usually less influenced by macroeconomic uncertainty and safe-haven demand, which makes it more appealing data in this study.

Wheat is one of the world's leading food crops. It is widely used in food production and is important in global agricultural trade. It can represent the agricultural industry. Compared with other agricultural products, wheat has a wider application. For example, it can be processed into bread and beer.

2.2 Data Pre-processing

Since the characteristics of the prices of different commodities are similar, the data pre-processing is the same. Therefore, this paper will only focus on the overall procedure in this part.

First of all, this paper generates the time series plots of the prices of three commodities, the results are shown in Figures 1, 3, and 5. From the plots, it should be decided whether the prices of the three commodities are stationary. This paper then applies the log transformation to the data to make them stationary. This paper also uses STL decomposition to detect the characteristics of the data. The results are shown in Figures 2, 4, and 6. From the four plots generated by the STL decomposition, the seasonality, trend, and volatility can be checked. Then, it can be decided which model to use.

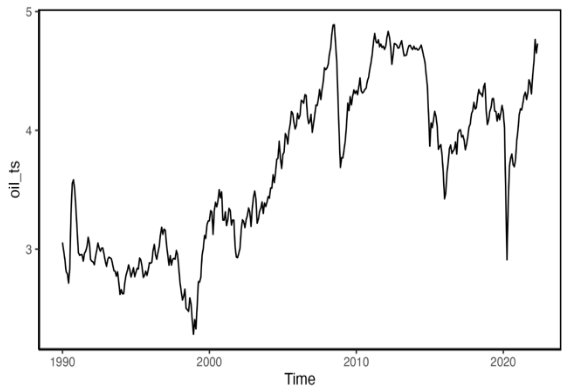

Figure 1: The Time Series Plot of the Brent Oil Prices after Log Transformation. (Picture credit: Original)

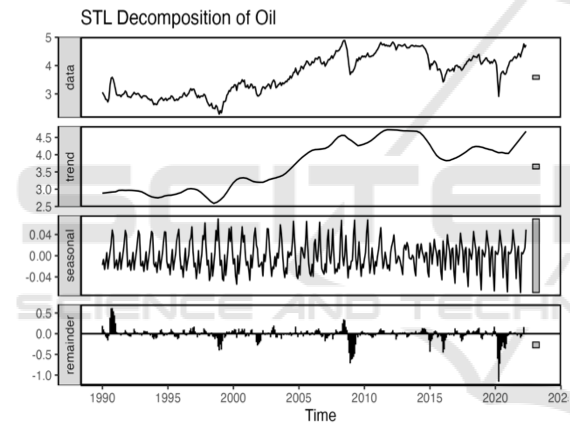

Figure 2: The STL Decomposition on Brent Oil Prices. (Picture credit: Original)

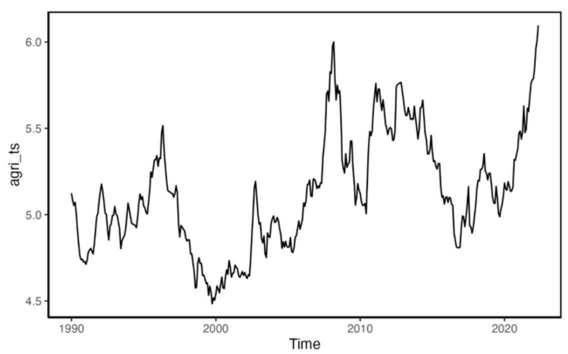

Figure 3: The Time Series Plot of the Wheat Prices after Log Transformation. (Picture credit: Original)

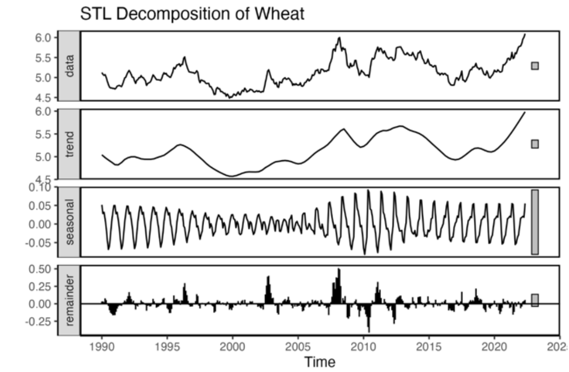

Figure 4: The STL Decomposition on Wheat Prices. (Picture credit: Original)

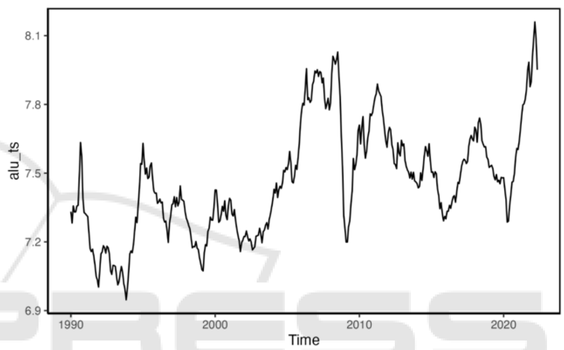

Figure 5: The Time Series Plot of the Aluminum Prices after Log Transformation. (Picture credit: Original)

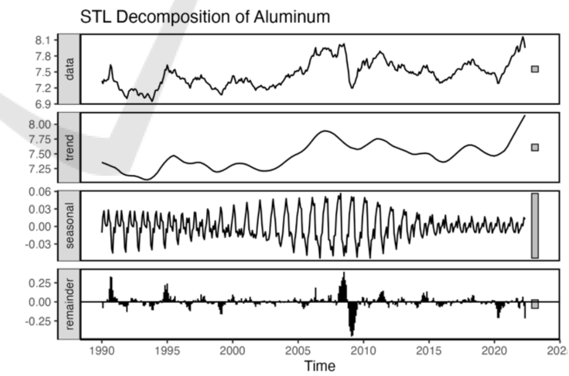

Figure 6: The STL Decomposition on Alunimun Prices. (Picture credit: Original)

From the time series plot of the Brent oil prices, wheat prices, and aluminum prices, it is obvious that the data is not stationary even after the log transformation. It means that the data need a differencing process. According to the decomposition, all the data show a slightly upward trend and seasonality. The remainders show that the characteristics of the data have been nearly fully extracted by the trend and seasonality.

Therefore, this paper generates the ACF plot and the PACF plot to further check whether the data are stationary. The results show that the autocorrelation of all three datasets has a downward trend as the lag increases. In addition, the PACF values of the data are extremely large when the lag equals one. All in all, it means that the data are not stationary even after the log transformation. The data may need differencing.

To further ensure whether the data need differencing, this study also utilizes the Augmented Dickey-Fuller unit root test as the stationary test. The test can identify stationary data and judge whether the data needs differencing. If the p-value is bigger than 0.05, the test will reject the null hypothesis that the time series data is not stationary and has a unit root. The results are shown in Table 1.

Table 1: The Results of ADF Tests on Commodities Before Differencing.

Commodity	ADF test before differencing
Oil	p-value = 0.3696
Wheat	p-value = 0.4663
Aluminum	p-value = 0.03145

From Table 1, the p-values of the Brent oil prices, the wheat prices, and the aluminum prices are 0.3696, 0.4663, and 0.03145 respectively. It can be seen that the p-values of the Brent oil prices and the wheat prices are much larger than 0.05, while the p-value of the aluminum prices is less than 0.05. Combined with all the results reached above, this research conducts a first-order differencing to all the data.

After the differencing, both the ACF and PACF plots and the ADF test are utilized again to decide whether the data needs more processing procedures. The results are shown in Figures 7, 8, 9, 10, 11, and 12 and Table 2.

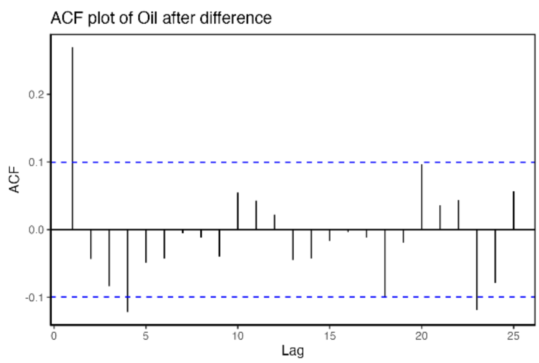

Figure 7: The ACF Plot of the Brent Oil Prices after Differencing. (Picture credit: Original)

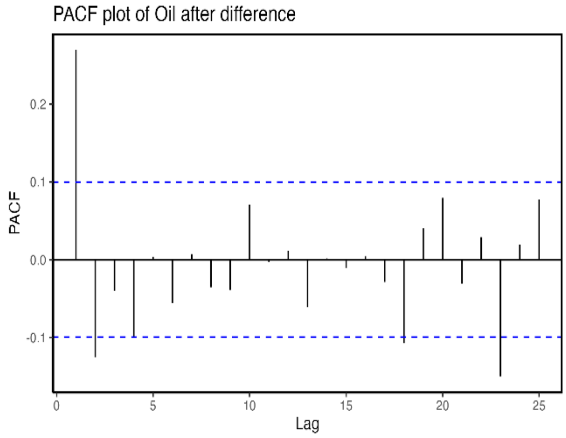

Figure 8: The PACF Plot of the Brent Oil Prices after Differencing. (Picture credit: Original)

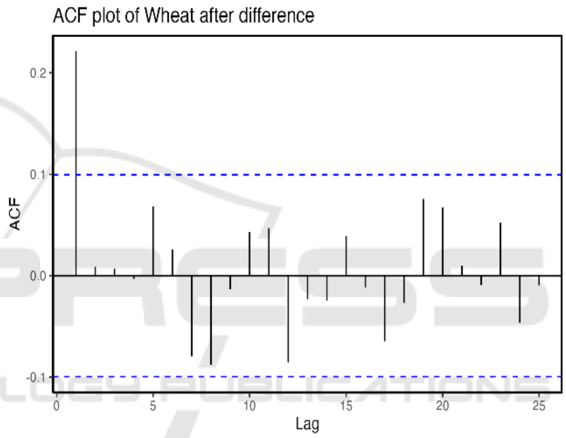

Figure 9: The ACF Plot of the Wheat Prices after Differencing. (Picture credit: Original)

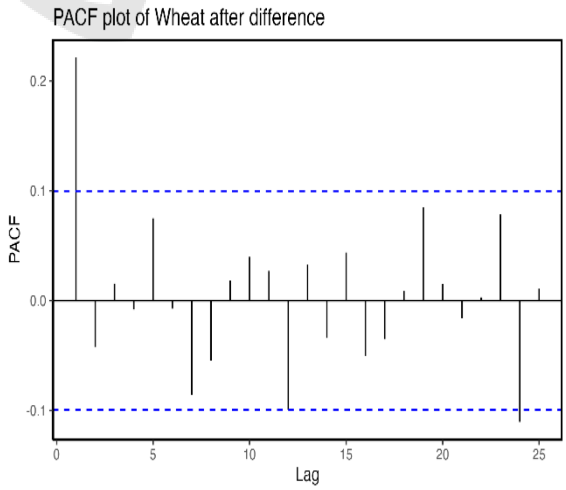

Figure 10: The PACF Plot of the Wheat Prices after Differencing. (Picture credit: Original)

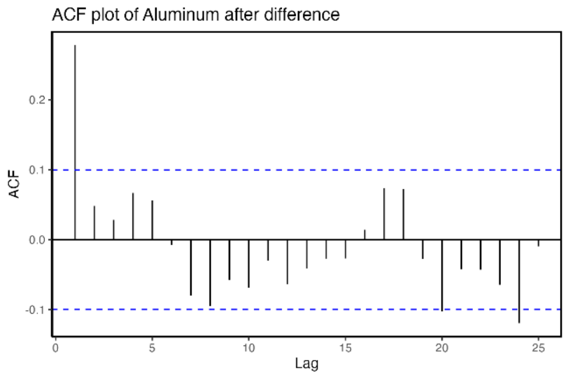

Figure 11: The ACF Plot of the Aluminum Prices after Differencing. (Picture credit: Original)

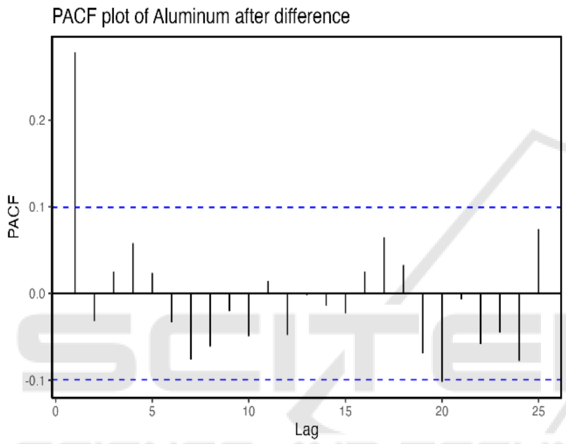

Figure 12: The PACF Plot of the Aluminum Prices after Differencing. (Picture credit: Original)

Table 2: The Results of ADF Tests on Commodities after Differencing.

Commodity	ADF test after differencing
Oil	p-value = 0.01
Wheat	p-value = 0.01
Aluminum	p-value = 0.01

Based on the ACF and PACF plots, it can be detected that the ACF and PACF are the largest when the lag equals one. As the lag increases, the ACF and PACF decrease immediately to zero. It means that the AR (1) model is suitable for all the data and all the data are stationary now.

After the differencing, all the data pass the ADF test. Therefore, all the data are certainly stationary.

2.3 Model

This paper uses the decomposition method, plotting, and the SARIMA model for analysis and prediction.

The ARIMA (Autoregressive Integrated Moving Average) model developed by Box and Jenkins is one of the most basic and important models in time series analysis. The SARIMA model adds seasonal factors to the original ARIMA model. It is more suitable for the data with high seasonality. The SARIMA model can be expressed as (1):

$$\mathrm{ARIMA}(p,d,q)(P,D,Q)_m \tag{1}$$

the parameter p represents the order of the AR (Autoregressive) component, which captures the linear relationship between the current observation and its previous observations. The parameter d means subtracting the previous observation from the current one d times to remove trends and make the series stationary. The parameter q is the order of the MA (Moving Average) component, which shows the relationship between an observation and a residual error from a moving average model applied to lagged observations. On the other hand, the parameters P, D, and Q have similar functions with p, d, and q, but they are applied to the seasonal components. m is the seasonal period.

The auto.arima function is applied to the data to make the computer automatically select the best model. However, the model should be further selected based on the evaluation indicators, and the PACF plots.

2.4 Evaluation

This paper focuses on Root Mean Squared Error (RMSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) as the evaluation indicators for prediction. RMSE calculates the average of the squares of the differences between predicted and actual values, which helps measure the model error. AIC is an indicator used to select the model, and it balances the goodness of fit and complexity of the model. BIC punishes more on the complex model compared to AIC. It tends to choose a simpler model.

This paper also focuses on the fitting ability of the SARIMA model. Considering that the SARIMA model has 6 parameters, this study will use an adjusted R square as the evaluation indicator. The adjusted R square can help avoid the situation that the R square will increase freely. as the complexity of the model increases. It can protect the model from overfitting.

3 EXPERIMENT RESULTS AND ANALYSIS

Sometimes, the auto.arima function cannot select the best model because it only focuses on minimizing the AIC and BIC values but not the RMSE values. Additionally, the auto.arima function may not try every combination of the six parameters. This paper further selected the model based on the values of AIC, BIC, and RMSE. The smaller the values of these indicators, the better the model is. Each combination of the six parameters is tested. The parameters p, P, q, and Q take the values 0, 1, and 2, the parameter d constantly equals 1, and the parameter D takes the values of 0 and 1. The results are shown in Tables 3, 4, and 5.

Table 3: SARIMA Models on Brent Oil Prices with Different Parameters.

(p, d, q)	(P, D, Q)	AIC	BIC	RMSE
(0,1,1)	(0,0,1)	-696.566	-684.683	0.0978
(0,1,1)	(1,0,0)	-696.489	-684.606	0.0978
(0,1,1)	(0,0,2)	-696.636	-680.792	0.0974
(0,1,1)	(2,0,0)	-696.365	-680.521	0.0975
(0,1,1)	(1,0,1)	-696.195	-680.351	0.0975
(1,1,2)	(1,0,0)	-697.365	-677.56	0.0971
(0,1,1)	**(2,0,2)**	**-698.882**	**-675.116**	**0.0947**

Table 4: SARIMA Models on Aluminum Prices with Different Parameters.

(p, d, q)	(P, D, Q)	AIC	BIC	RMSE
(1,1,0)	**(2,0,0)**	**-1268.17**	**-1252.33**	**0.0466**
(0,1,1)	(0,0,2)	-1268.16	-1252.32	0.0466
(0,1,1)	(2,0,0)	-1267.98	-1252.14	0.0466
(0,1,1)	(0,0,1)	-1263.53	-1251.65	0.0471
(2,1,0)	(0,0,2)	-1266.91	-1247.1	0.0466
(0,1,1)	(1,0,0)	-1262.94	-1251.06	0.0471
(1,1,1)	(0,0,2)	-1266.89	-1247.09	0.0466

Table 5: SARIMA Models on Wheat Prices with Different Parameters.

(p, d, q)	(P, D, Q)	AIC	BIC	RMSE
(0,1,1)	(0,0,1)	-1020.07	-1008.19	0.064
(0,1,1)	(1,0,0)	-1019.31	-1007.43	0.0645
(1,1,0)	(0,0,1)	-1019.14	-1007.26	0.0645
(1,1,0)	(1,0,0)	-1018.46	-1006.58	0.0645
(0,1,1)	(0,0,2)	-1020.44	-1004.6	0.0642
(2,1,1)	**(0,0,1)**	**-1022.3**	**-1002.49**	**0.0638**
(0, 1,1)	(1, 0,2)	- 1021.01	- 1001.21	0.0 638

Finally, the best model is selected for each commodity. For Brent oil, the best model is SARIMA (0, 1, 1) (2, 0, 2), and the AIC value equals -698.882, the BIC value equals -675.116 and the RMSE value equals 0.094708. For Aluminum, the best model is SARIMA (1, 1, 0) (2, 0, 0), and the AIC value equals -1268.17, the BIC value equals -1252.33 and the RMSE value equals 0.046628. For the wheat, the best model is SARIMA (2, 1, 1) (0, 0, 1), and the AIC value equals -1022.3, the BIC value equals -1002.49 and the RMSE value equals 0.063838.

This paper uses the checkresiduals function to check whether the residuals of the model are consistent with the white noise. If the residuals are not independent and are not consistent with normal distribution, the model selected may not be suitable for the study. Autocorrelation and time series plots of the residuals can be tested by the ACF plot and the Ljung-Box test in the function. The results of aluminum prices, wheat prices, and Brent oil prices are shown in Figures 13, 14, and 15 respectively. The results of the Ljung-Box tests are shown in Table 6.

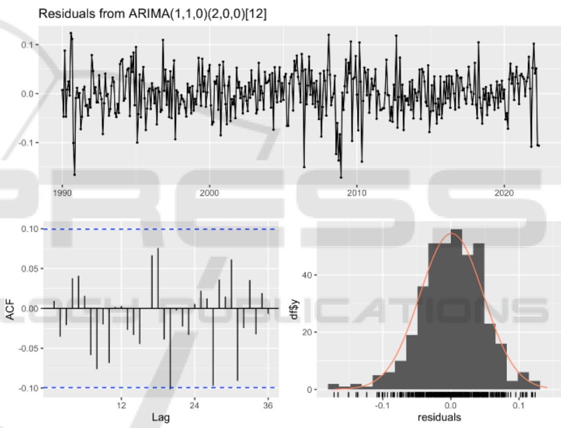

Figure 13: The Residuals Check on the SARIMA Model of Aluminum Prices. (Picture credit: Original)

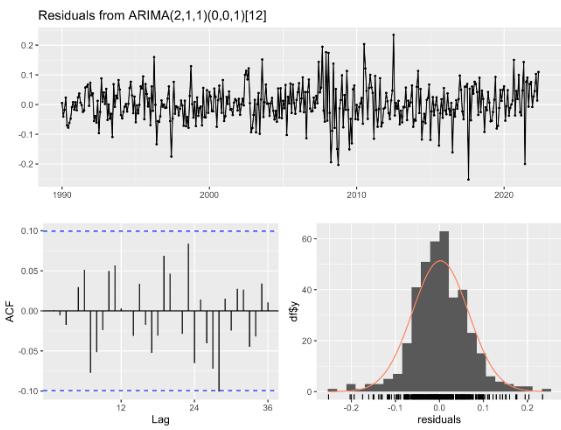

Figure 14: The Residuals Check on the SARIMA Model of Wheat Prices. (Picture credit: Original)

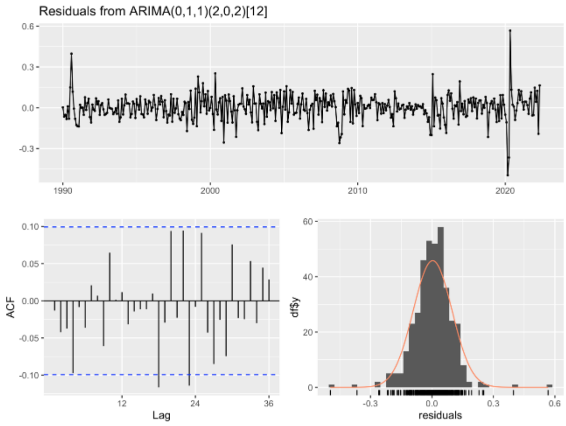

Figure 15: The Residuals Check on the SARIMA Model of Brent Oil Prices. (Picture credit: Original)

From the residuals plots, the residuals have random fluctuations around zero mean, which means that the model has a good fit. According to the ACF plots of the SARIMA models of the data, the autocorrelation values for most lags are within confidence intervals, which means the residuals of the SARIMA model are consistent with white noise. According to the histogram, the residuals are consistent with normal distribution. All the data pass the residuals check.

Table 6: Ljung-Box Test of Residuals of All SARIMA Models

Commodity	Ljung-Box test of Residuals
Oil	p-value = 0.08311
Wheat	p-value = 0.6398
Aluminum	p-value = 0.5808

All the p-values of the Ljung-Box test of residuals are larger than 0.05. This indicates that there is no significant autocorrelation in the residuals and that the residuals are white noise. The model has captured all the autocorrelation structures in the data, and the residuals do not contain any systematic patterns, which is the same as the conclusion from the ACF plots above.

In the forecasting part, this research generates the future movement of the prices of three commodities in the next 10 months. The confidence intervals are also generated. Finally, the real movement of the prices is shown in the same picture as the predicted movement to help offer some meaningful investing suggestions. In the forecasting plots below, the translucent black line indicates the historical data, the blue line is the predicted mean, and the light blue and dark blue areas indicate 80% and 95% confidence intervals, respectively. The results are shown in Figures 16, 17, and 18.

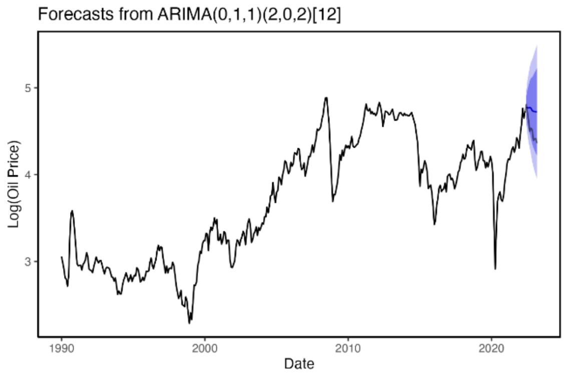

Figure 16: Brent Oil Prices Prediction Compared with Actual Values. (Picture credit: Original)

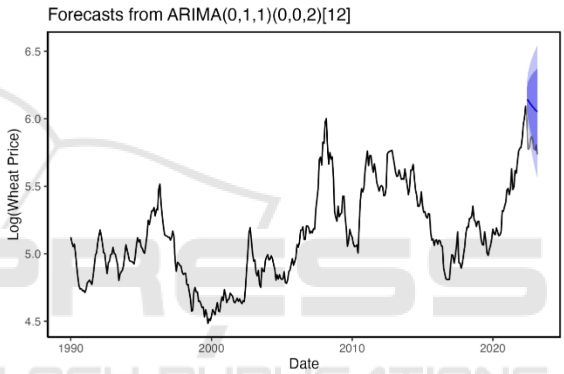

Figure 17: Wheat Prices Prediction Compared with Actual Values. (Picture credit: Original)

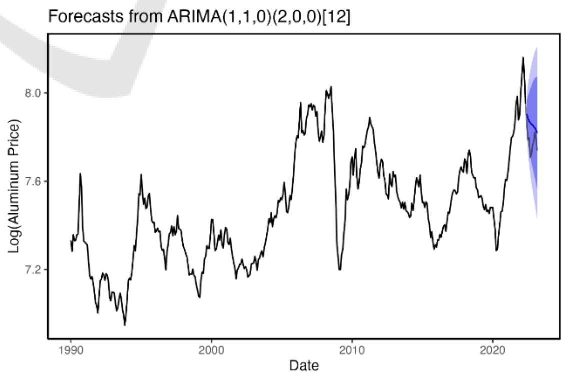

Figure 18: Aluminum Prices Prediction Compared with Actual Values. (Picture credit: Original)

From the three plots above, the Brent oil price will slightly go down in the next 10 months, and the prices of aluminum and wheat will experience a sharp decline in the next 10 months.

In the fitting part, this study calculated the adjusted R square to find out the fitting ability of the model. The results of the adjusted R square are shown in Table 7. The plots of the actual values and the fitted values of three commodities are shown in Figures 19, 20, and 21.

Table 7: Adjusted R2.

Commodity	Adjusted R square
Oil	0.9799
Wheat	0.9632
Aluminum	0.9631

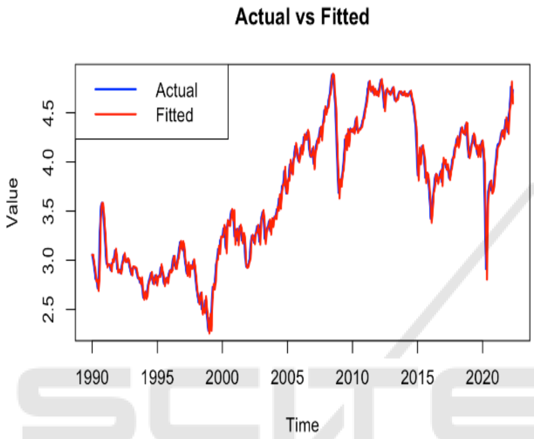

Figure 19: Fit Chart of Brent Oil Prices. (Picture credit: Original)

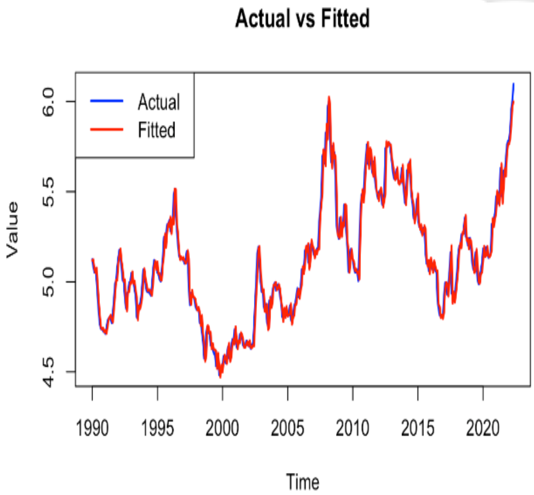

Figure 20: Fit Chart of Wheat Prices. (Picture credit: Original)

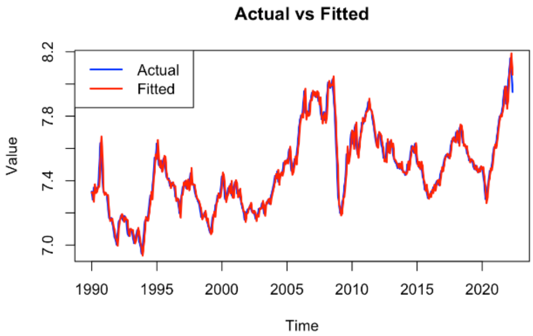

Figure 21: Fit Chart of Aluminum Prices. (Picture credit: Original)

It turns out that three SARIMA models fit well with the data. The values of the adjusted R square of Brent oil, wheat, and aluminum are 0.9799, 0.9632, and 0.9631 respectively.

Although the forecasting declines are not that serious compared with the actual fluctuation of the prices of the three commodities. The trends of the future movement are clear enough for investors to decide their next transaction.

The results from this study are not enough because the forecasting is not precise enough for investors to decide when to buy and when to sell. Therefore, investors need to combine some other factors such as some international events in politics and some news to make a reasonable transaction. In this study, considering the decline in demand and supply caused by the conflict in Ukraine, extreme weather, and geopolitical conflicts (Ji, 2023), the commodities prices are more likely to experience a downward trend (Liu, 2022). Therefore, short selling for all commodities mentioned above is a good choice.

In addition, some characteristics of the data may not be extracted completely. To make a more precise prediction and to help investors invest only by time series analysis, a more complex model or a combined model needs to be applied.

4 CONCLUSIONS

From the research, this paper discovers that the SARIMA model has a relatively excellent ability to predict the future prices of commodities. For aluminum, the prediction shows that its price will go down and the confidence interval is large, which means it is not wise to buy aluminum in May 2022 and the price of aluminum can fluctuate a lot. For wheat, the prediction also shows a decrease in price but the confidence interval is smaller, which means it is not wise to buy wheat in May 2022, and the fluctuation in wheat price will be smoother. For oil, the trend of the prediction is not obvious because there is only a slight decrease, and the confidence interval is also smaller, which means it may not be wise to buy oil in May 2022, and the price of the oil will not fluctuate a lot in the next 10 months. From the actual values, it turns out that the real movement of the prices of aluminum and wheat is almost the same as the prediction. On the contrary, the difference between the prediction of the Brent oil prices and the actual values is not neglectable. It indicates that the SARIMA model has a better forecasting ability in the agricultural industry and the manufacturing industry than in the energy industry. Overall, if investors make decisions based on the prediction, they will not lose money but can even earn some money by short selling. However, the prediction of the future prices of three commodities is not extremely precise, which means people are not able to do short-term trading and ultrashort-term trading because they will lose some opportunities to make profits. In the future, more complex models that can include more samples and some other factors such as international events, fundamental analysis, and investors' minds should be considered. In addition, the SARIMA model can be combined with other methods, such as BNPP to further make a more precise prediction.

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