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APPLICATION OF TIME SERIES ANALYSIS IN FORECASTING COAL PRODUCTION AND CONSUMPTION IN THE PHILIPPINES

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Abstract

Energy is the backbone of a country's economic and technological development. For a country to be competitive in the global market and secure sustainable development, energy must be efficiently used. The Philippines's main source of energy is coal. Historical data shows that the country's energy and coal consumption has been continuously increasing. With this, careful energy planning is required to develop policies that ensure sufficient energy supply in the future. This paper focuses on forecasting coal production and consumption in the Philippines. For the purpose of forecasting, the autoregressive integrated moving average (ARIMA) model is applied to reveal that ARIMA (1, 2, 0) is the best model to forecast coal production. For coal consumption, the best model identified was ARIMA (0, 2, 1). The models have undergone residual analyses and forecast evaluations to ensure that the 'best' models found are statistically appropriate models. The forecasts show that in the following years, Philippine coal production will decrease, while the coal consumption rate will increase. In addition, it is predicted that the Philippines will need to import a total of 133.1983 MMT of coal to meet the coal consumption from 2021 to 2025.

Keywords:

ARIMA, Coal Consumption, Coal Production, Data Mining, Energy Forecasting

1. INTRODUCTION

Energy has become a basic human necessity; it plays a role in practically every aspect of modern life. Countries need energy to support its industries, agriculture, transportation, and trade. To be competitive in the global market and secure sustainable development, countries must use energy efficiently. With this, efficient energy planning based on accurate forecasts is needed to provide the required energy for a given period of time, avoid economic losses, and build necessary energy structures.

In the Philippines, the current energy mix is composed of coal, natural gas, renewables, and oil. Coal is the most heavily used energy source in the country despite its environmental implications [1]. However, the country heavily relies on coal imports as its own coal production cannot support the demand. In recent years, most of the country's coal imports are from Indonesia and Australia. In 2020, 28.603 million metric tons (MMT) or 96.88 percent of imported coal were from Indonesia followed by Australia (1.82 percent), Russia (0.94 percent), and Vietnam (0.35 percent). Coal were mainly used in power plants (90.5 percent) for power generation while the remaining supply were used in cement plants (4.0 percent) and other industries (5.5 percent) [2]. Historical data shows that the Philippine coal production and consumption has been continuously increasing. However, since the country's consumption was greater than its production, the coal imports have also been growing. For these reasons, there is a need to forecast the future coal production and consumption to prepare for the country's future energy needs. Hence, in this paper, an attempt has been made to develop a model that can accurately forecast the production and consumption of coal in the Philippines.

This study utilizes the autoregressive integrated moving average (ARIMA) model for forecasting coal consumption and production in the Philippines. The study aims to: a) understand the features of the available historical data, b) develop an appropriate model that could accurately forecast the coal production and consumption, c) using the model, forecast the country's coal production and consumption, and d) based on the forecasts, predict the amount of coal needed to be imported to meet the country's future coal demands.

2. LITERATURE REVIEW

This section presents the studies related to the present study. In recent years, data-driven solutions from artificial intelligence and statistical methods have been used to address complex and practical problems in different fields. The ARIMA model is one of the forecasting techniques that can be used to better understand the time series data and predict future observations. It has better performance compared to other methods as it can identify the best-fitting, efficient and robust model from an orderly model searching procedure [3].

A study conducted by Parreño applied the ARIMA model in forecasting the electricity demand in Davao del Sur, Philippines. The historical time series has been transformed and first-differenced to make it stationary. Using the ACF and PACF plots, the order of the ARIMA (p, d, q) model was determined. The results revealed that the ARIMA (0, 1, 0) with drift outperformed ARIMA (0, 1, 0), ARIMA (0, 1, 1) with drift, ARIMA (1, 1, 0) with drift, and ARIMA (1, 1, 1) in forecasting the electricity demand. The study predicted that the electricity demand in the region would reach 505,246.4 MWh by 2026 [4]. Similarly, the method was applied in forecasting the electricity consumption of the Philippines for 2021-2030. The study applied data-splitting to test the resulting forecast errors of the 'best' model found. This step ensured that the 'best' model found was statistically appropriate. The study revealed that the 'best' model to forecast the electricity consumption of the Philippines was ARIMA (0, 2, 1) [5]. In addition, a project by Rupassara et al. analyzed the monthly average rainfall and temperature of Minot, USA and found that SARIMA (2, 0, 0) (2, 0, 1, 12) and SARIMA (1, 0, 1) (2, 0, 1, 12) could forecast the variables [6].

A paper by Yao and Zhang [7] applied the ARIMA model with Google Index as an exogenous variable in forecasting crude oil prices in China. It further tested the performance of ARMA-GARCH and ARMAX-GARCH models. The analysis found that the Google index negatively impacts the prices of crude oil. However, the Google Index was unhelpful for forecasting crude oil prices.

The study of Sen et al. [3] applied ARIMA for forecasting energy consumption and greenhouse gas emission from a pig iron manufacturing organization in India. The study has been carried out since the managers wanted to understand the present and future trends of the energy consumption and greenhouse gas emissions to formulate better policies leading to better practices for environmental management. The study found that ARIMA (1, 0, 0) (0, 1, 1, 12) was the 'best' model for forecasting energy consumption than ARIMA (0, 1, 0) (0, 1, 1, 12). On the other hand, the 'best' model to forecast greenhouse gas emissions was ARIMA (0, 1, 4) (0, 1, 1, 12) than ARIMA (1, 0, 0) (0, 1, 1, 12).

In terms of coal consumption forecasts, the ARIMA model was applied in forecasting coal consumption, price, and investment in China [9]. The paper by Jiang et al. found that the ARIMA model was effective in forecasting the future values of each variable. The results of the study showed that the rate of coal consumption and investment would decrease from 2016 to 2030 with exception to the coal price. It was predicted that by 2030, China's coal consumption would reach 1.4 billion tons Moreover, it was found that the coal consumption has a close relationship with coal investment.

In the paper of Li et al. [10] the metabolic grey model (MGM), back-propagation Network (BP), and the combinations of the said models with the ARIMA model were implemented to forecast the coal consumption in India by 2030. The annual data from 1995 to 2017 was used to train the models. According to the forecasted results, India's use of coal will increase at an average annual rate of 2.5% from 2018 to 2030. Furthermore, a regression model was built in the study of Wang [11]. It was based on the original and fitted sequences, and the ARIMA-BP combined model II which can precisely fit China's per capita coal consumption. The method further boosts the prediction accuracy and offered a fresh concept for time series prediction with both linear and nonlinear relations. The prediction statistics for per-capita coal consumption could aid relevant government agencies in understanding the state of the economy and could serve as a guide for developing sensible coal resource development strategies. It was found that while the growth rate of per capita coal consumption slows down, the consumption overall grows marginally. This information could serve as a guide for key government departments as they establish reasonable energy development strategies.

The grey model (GM) was also used to forecast coal consumption. In the study of Ma et al., the linear (Metabolic Grey Model), nonlinear (Non-linear Grey Model), and combined (Metabolic Grey Model-Autoregressive Integrated Moving Average Model) models have been implemented to forecast coal consumption of South Africa for the period of 2017 to 2030, based on the historical coal consumption data in 2000 to 2016. The results of the analysis indicated that the coal consumption of South Africa would decrease by 1.9% annually. The results showed that the South Africa is reducing its dependence on coal [12]. A similar study was conducted by Raheem et al. that aimed to forecast the energy consumption of Great 20 (G20) countries using the grey model. In their paper, an adjacent accumulation - discrete grey model was studied to enhance the prediction of the grey model and improve the use of up-to-date data. It was predicted that the coal consumption would show a downfall in its consumption by G20 countries excluding South Africa and France [13].

In the study of Jebaraj et al. [8], the performance of an artificial neural network model was compared to different forecasting methods in forecasting coal consumption in India. The coefficient correlation (R2), mean percentage error (MPE), root mean squared error (RMSE), and mean percentage error (MAPE) were the bases in choosing the appropriate model. The results of the study showed that the ANN-based forecasting model has lesser mean percentage error and higher R2 value compared to other forecasting models being considered. The results indicate that the artificial neural network model has minimum errors and thus, it can effectively forecast the long-term coal demand. Similarly, a study by Benalcazar et al. [14] proposed a Multilayer Perception neural network (MLP) to forecast the global coal consumption for the years 2020 to 2030. An exhaustive search method and comparison of individual RMSEs were implemented to identify the optimal number of hidden neurons. The results of the model search found that a two-layer MLP with a 4-5-1 architecture could forecast the global coal consumption. The results of the study showed a decrease in coal consumption for the years 2025 and 2030.

3. METHODOLOGY

3.1 DATASET

The dataset used in this paper was the Philippine coal production and consumption in million metric tons (MMT). It was taken from the website of the Philippine Department of Energy. There were 44 data points (from 1977 to 2020) where the first 39 (from 1977 to 2015) observations were used to determine the best model while the remaining 5 (from 2016 to 2020) observations were used to validate the model. The R statistical software was used to perform all the calculations.

3.2 AUTOREGRESSIVE INTEGRATED MOVING AVERAGE

The model of the form ARIMA (p, d, q) is

$$\phi(B)(1-B)^d \bar{z}_t = \theta(B)a_t \tag{1}$$

where $\phi(B)$ and $\theta(B)$ are the autoregressive and moving average in backshift notations, respectively. d is the number times differencing was applied on the original time series, $\bar{z}_t$ is the dependent variable, and a_t is the error term [15].

3.3 PROCEDURE

The Fig.1 summarizes the procedure that was followed to find the appropriate ARIMA models in forecasting the Philippine coal production and consumption.

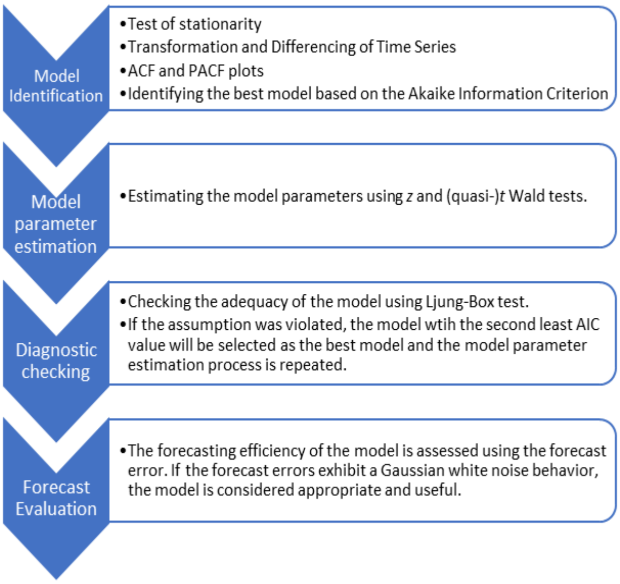


Fig.1. Box-Jenkin's ARIMA model procedure

4. RESULTS AND DISCUSSIONS

4.1 COAL PRODUCTION

Fig.2 displays the historical plot of annual coal production in the Philippines with 44 observations by the R statistical software. The plot showed a peak on 2019 with 15.273 MMT. And starting on 2009, the coal production has increased exponentially. Moreover, the coal production exhibits a general increase in its values.

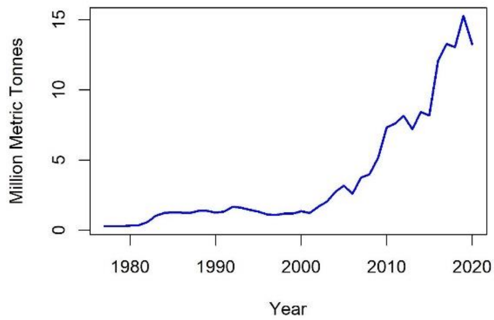


Fig.2. Philippine coal production from 1977 to 2020

The Fig.2 also tells that the series is nonstationary as the mean changes through time. To formally test the stationarity of the data series, the ADF test is performed. A large p-value is observed (0.9786), hence we cannot reject the null hypothesis that there exists a unit root in the data series. Hence, transformation and differencing are required to make the data series stationary. The Box-Cox transformation with lambda equal to zero is applied to the data series, and its stationarity is checked using the ADF test. The results indicate that the transformed data series is still nonstationary (p-value = 0.3892). Hence, first- and second differencing are applied to the data series to eliminate the unit root and achieve stationarity (p-value < 0.01).

The Fig.3 shows the ACF and PACF plots of the transformed and differenced series. It can be observed from the plots that both ACF and PACF are significant at lag 1. From the ACF and PACF plots, ARIMA (0, 2, 0), ARIMA (0, 2, 1), ARIMA (1, 2, 0), and ARIMA (1, 2, 1) are considered. To select the appropriate model, the individual Akaike information criterion values of each model are considered.

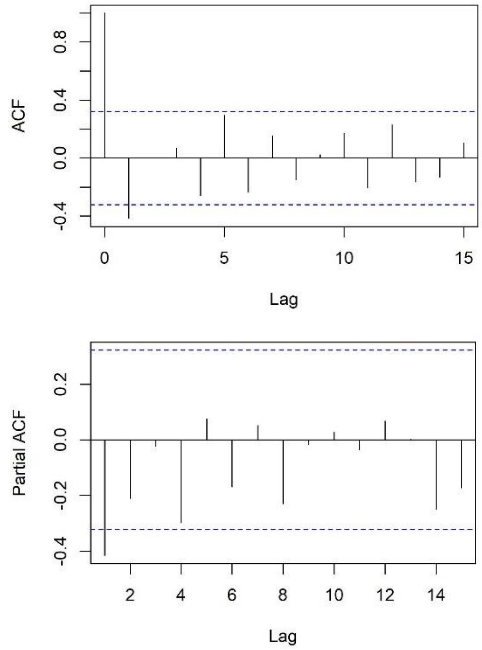


Fig.3. ACF and PACF plots of the transformed and differenced coal production data series

Table.1. Tentative models of Philippine coal production.

Model	AIC
ARIMA (0, 2, 0)	-2.822997
ARIMA (0, 2, 1)	-12.49512
ARIMA (1, 2, 0)	-7.924789
ARIMA (1, 2, 1)	-12.93893

It can be observed from Table.1 that ARIMA (1, 2, 1) has the most negative AIC value, this indicates that ARIMA (1, 2, 1) is the appropriate model. The z and (quasi-)t Wald tests of estimated coefficients are then performed to the model. The results reveal that the moving average estimate is significant (p-value < 0.05). However, the autoregressive estimate is not significant from zero (p-value = 0.1153). Hence, the model with the next most negative AIC value will be selected which is ARIMA (0, 2, 1). The results of the tests of estimated coefficients reveal that the p-value of MA(1) is less than 0.05 level of significance.

However, results of the residual analysis on ARIMA (0, 2, 1) reveal that the residuals are skewed. This implies that the model may be overestimating or underestimating the data. The ARIMA (1, 2, 0) is then selected. The p-value of the AR(1) component of the model is significant (p-value < 0.001). This indicates that the autoregressive parameter of the model is significantly different from zero. The next step is to validate the model by performing a residual analysis. Residuals from a well-fitted model are uncorrelated, normally distributed with a mean zero and meet the property of homoscedasticity [16].

The residual analysis plots are displayed in Fig.4. It can be observed that the residuals show no patterns and the lags in the

ACF plot are within the acceptable boundaries. In addition, the residuals are approximately normally distributed. The results reveal that the residuals behave like a white noise. The Ljung-Box test is also performed to test if the residuals of the model are not correlated. The results indicate that there is no autocorrelation between the residuals of the model and thus, the model is adequate (p-value = 0.5435).

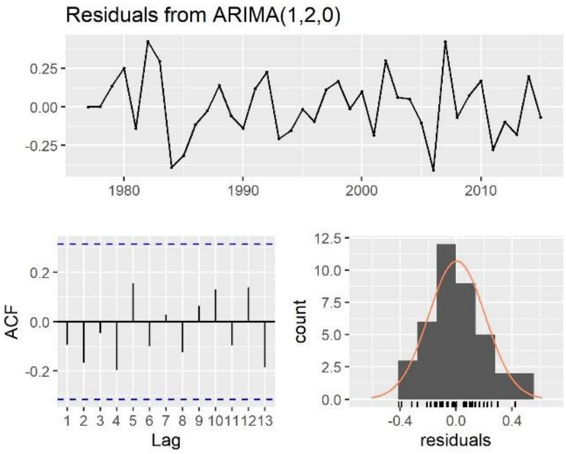


Fig.4. Residual analysis plots of ARIMA (1, 2, 0).

The Table.2 presents the one-step ahead forecast values, actual values, and forecast errors of ARIMA (1, 2, 0).

Table.2. Forecasted values, actual values, and forecast errors of Philippine coal production using ARIMA (1, 2, 0).

Year	One-step ahead forecasts	Actual values	Forecast Errors
2016	8.574465	12.0870	3 .512535
2017	14.991048	13.2830	-1.708048
2018	16.526595	13.0560	-3.470595
2019	13.445707	15.2730	1.827293
2020	16.612500	13.2671	-3.345402

The Fig.5 displays the plots of forecast errors of ARIMA (1, 2, 0). The values in the ACF and PACF plots are within the acceptable boundaries. Hence, the forecast errors can be considered white noise. Moreover, the forecast errors are close to the theoretical line, therefore we can consider that the forecast errors are approximately normally distributed. To formally test this, the Shapiro-Wilk test is performed. The resulting p-value of the test is 0.2726 which is significant indicating that the forecast errors are normally distributed. Therefore, the forecast errors behave like a Gaussian white noise.

The diagnostic checks performed yielded satisfactory results. Therefore, the ARIMA (1, 2, 0) is the statistically appropriate model to forecast the coal production in the Philippines.

4.2 COAL CONSUMPTION

The Fig.6 displays the historical plot of annual coal consumption in the Philippines. An upward trend is evident in the plot indicating that the coal consumption has been steadily increasing throughout the years. The consumption reached its highest on 2019 with 33.122 MMT.

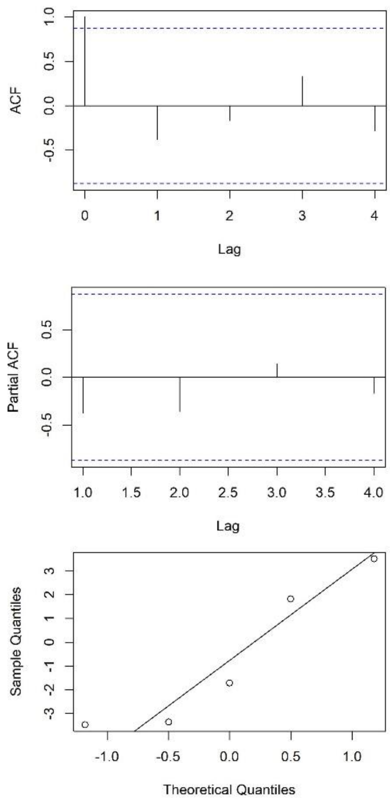


Fig.5. Plots of forecast errors of ARIMA (1, 2, 0).

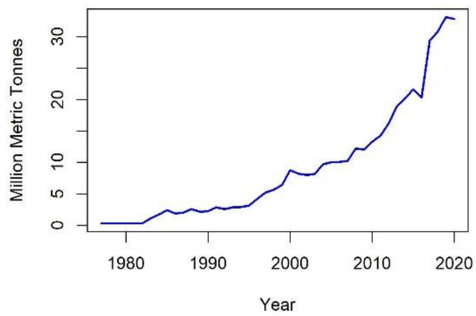


Fig.6. Philippine coal consumption from 1977 to 2020

A large p-value is observed when performing ADF test to the model building set of the coal consumption data (p-value > 0.99). This indicates that transformation and differencing is required to make the data series stationary. The Box-Cox transformation with optimal lambda equal to 0.6169712 is applied to the data series. However, the ADF test reveals a large p-value (0.9405), which indicates that the data series remain non-stationary. Hence, first-differencing and second-differencing are needed to be applied. After applying transformation and differencing, the data series have become stationary (p-value<0.01).

The Fig.7 presents the ACF and PACF plots of the data series after applying transformation and differencing. It can be observed that the ACF has significant lags at 0 and 1, indicating q=0,1. The PACF has significant lags at 1 and 2, indicating p=1,2. ARIMA (0, 2, 0), ARIMA (1, 2, 0), ARIMA (0, 2, 1), ARIMA (1, 2, 1), ARIMA (0, 2, 2), and ARIMA (1, 2, 2) are considered as tentative models. The Akaike information criterion is used to select the appropriate model among the tentative models.

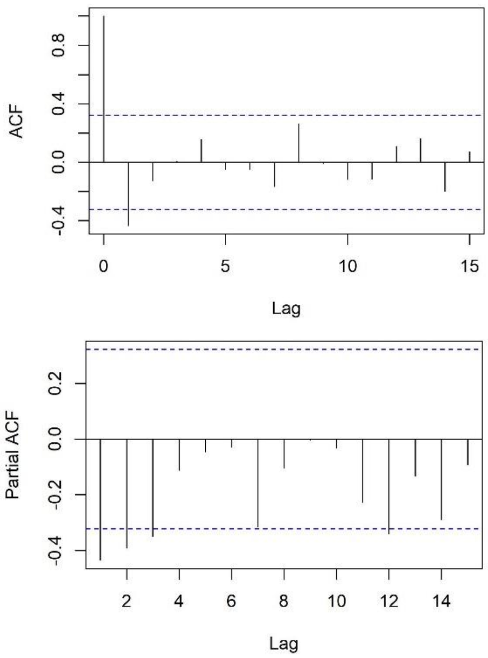


Fig.7. ACF and PACF plots of the transformed and differenced coal consumption data series.

Table.3. Tentative models of Philippine coal consumption.

Model	AIC
ARIMA (0, 2, 0)	53.15228
ARIMA (1, 2, 0)	47.55775
ARIMA (0, 2, 1)	35.43967
ARIMA (1, 2, 1)	37.36502
ARIMA (0, 2, 2)	37.34821
ARIMA (1, 2, 2)	39.2672

It can be observed from Table.3 that ARIMA (0, 2, 1) has the least AIC value. This indicates that ARIMA (0, 2, 1) is the appropriate model. To confirm this, the z and (quasi-)t Wald tests of estimated coefficients are performed. The analysis yields a significant p-value (p-value < 0.001) which indicates that the estimate of the moving average parameter is significantly different from zero.

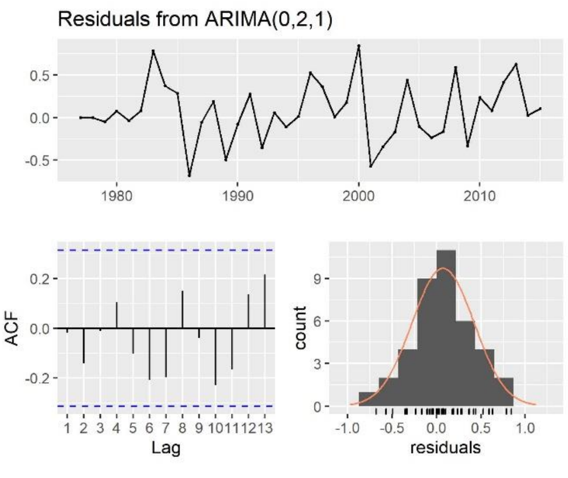


Fig.8. Residual analysis plots of ARIMA (0, 2, 1).

The residual analysis is then performed and resulting residual analysis plots are displayed in Fig.8. It can be observed that the residuals do not show any patterns and the lags in the ACF plot are within the acceptable boundaries. Moreover, the residuals closely resemble a normal distribution. To confirm this, the Shapiro-Wilk test is performed. The test yielded a p-value of 0.8627 which indicates that the residuals are approximately normally distributed. These results indicate that the residuals behave like a white noise. Then, the Ljung-Box test is performed. The test yielded a p-value of 0.9013, which indicates that there is no autocorrelation between the residuals of the model and thus, the model is adequate.

The Table.4 shows the one-step ahead forecast values, actual values, and forecast errors of ARIMA (0, 2, 1).

Table.4. Forecasted values, actual values, and forecast errors of Philippine coal consumption using ARIMA (0, 2, 1).

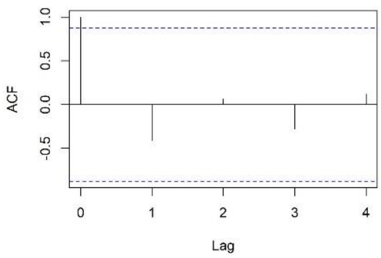
Year	One-step ahead forecasts	Actual values	Forecast Errors
2016	22.87939	20.29600	-2.5833881
2017	21.25074	29.38700	8.1362604
2018	31.29706	30.83700	-0.4600592
2019	32.73864	33.12200	0.3833620
2020	35.11163	32.84567	-2.2659657

The Fig.9 presents the plots of forecast errors of ARIMA (0, 2, 1). The values in the ACF and PACF plots are within the acceptable boundaries. Hence, the forecast errors can be considered white noise. Moreover, most of the forecast errors are close to the theoretical line, and we can consider that they are approximately normally distributed. To formally test this, the Shapiro-Wilk test is performed. The resulting p-value of the test is 0.06702 which is significant indicating that the forecast errors are normally distributed. However, since there is an outlier in the forecast errors, this model should be used with caution. However, we can still consider that the forecast errors behave like a Gaussian white noise.

The results of the diagnostic checks being performed are satisfactory. Therefore, the statistically appropriate model to forecast the coal consumption in the Philippines is ARIMA (0, 2, 1).

4.3 FORECASTS

The Fig.10 shows the forecasts for Philippine coal production computed using the ARIMA (1, 2, 0). The forecasted values for 2021 to 2025 are shown in Table.5. It shows that the coal production will decrease in the following years.



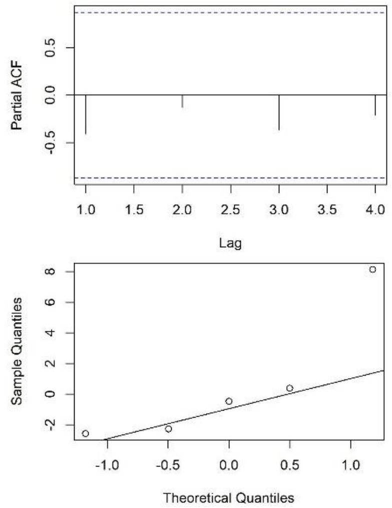


Fig.9. Plots of forecast errors of ARIMA (0, 2, 1)

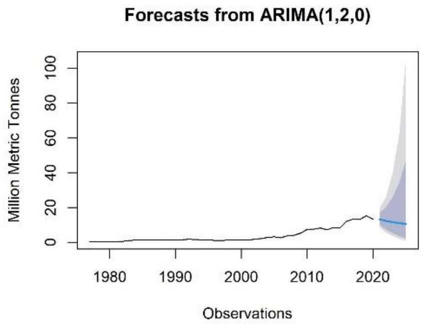


Fig.10. Forecast of coal production in the Philippines using ARIMA (1, 2, 0)

Table.5. Forecasted coal production in the Philippines using ARIMA (1, 2, 0) with 95% confidence interval

Year	Point Forecasts	Lower 95% Confidence Interval	Upper 95% Confidence Interval
2021	13.05160	8.677502	19.63058
2022	12.18885	5.678044	26.16536
2023	11.63334	3.425497	39.50806
2024	11.00269	1.937247	62.49033
2025	10.44584	1.035346	105.39047

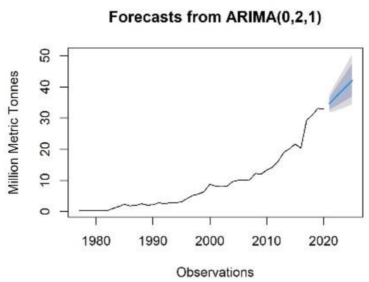


Fig.11. Forecast of coal consumption in the Philippines using ARIMA (0, 2, 1)

The Fig.11 displays the computed coal consumption forecasts using ARIMA (0, 2, 1). Table 6 shows that the rate of Philippine coal consumption for 2021 to 2025 will be increasing. Table 6 shows that the Philippine coal consumption for 2021 to 2025 will increase with an average rate of 5.06% per year. The growing trend of coal consumption found in this study is similar to the forecasts of Li et al. [10] and Wang [11]. This trend is particularly true to countries that heavily rely on coal and has no concrete policies for renewable energy.

Table.6. Forecasted coal consumption in the Philippines using ARIMA (0, 2, 1) with 95% confidence interval.

Year	Point Forecasts	Lower 95% Confidence Interval	Upper 95% Confidence Interval
2021	34.61827	31.86984	37.45295
2022	36.42635	32.30488	40.73474
2023	38.26947	32.92121	43.92077
2024	40.14724	33.61290	47.11712
2025	42.05927	34.34122	50.36271

The Table.7 displays the forecast of coal importation for 2021 to 2025. The coal importation forecast is computed using the coal production and consumption forecasts. An increasing coal importation can be observed in Table.6. It is predicted that for 2021 to 2025, the Philippines will need to import a total of 133.1983 MMT of coal to meet the coal consumption.

Table.7. Forecasted coal imports in the Philippines based on coal production and coal consumption forecasts

Year	Forecasts
2021	21.56667
2022	24.23750
2023	26.63613
2024	29.14455
2025	31.61343

5. CONCLUSIONS AND RECOMMENDATIONS

In this paper, the Box-Jenkin's method was implemented to develop appropriate forecasting models for coal production and consumption in the Philippines. The actual historical time series were nonstationary. Hence, Box-Cox transformation with optimal lambda and differencing were applied to make them stationary. The order of ARIMA (p, d, q) models were determined using ACF and PACF plots. From the set of tentative models, the best models were selected using the Akaike Information Criterion. The parameters of the best models were tested using the z and (quasi-)t Wald test. The parameters of the model with the least AIC value for coal production was found to be not significant. Hence, the model with the second least AIC value was considered. However, when running residual analysis to the model, it was found that its residuals were autocorrelated. Thus, the model with the next least AIC value was considered. On the other hand, the best model found for coal consumption has significant parameters. Once the best models with significant parameters were found, the residual analysis were performed. The results of the respective residual analyses showed that the residuals of each model were not autocorrelated and were normally distributed. After this, forecast evaluations were performed. It was found that the forecasts errors were satisfactory. The results of the analyses showed that ARIMA (1, 2, 0) was the best model to forecast the coal production in the Philippines. For the Philippine coal consumption, the best model identified was ARIMA (0, 2, 1). Forecasts showed that in the following years, Philippine coal production will decrease, while the rate of coal consumption will be increasing. In addition, it was predicted that the Philippines will need to import a total of 133.1983 MMT of coal to meet the coal consumption for 2021 to 2025.

Future researchers may consider the Philippine monthly coal production and consumption time series data to detect its seasonality and better understand its behavior.

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