A TIME SERIES ARIMA MODEL FOR PREDICTING DEMAND FOR LPG IN BANGLADESH

Rafid Masrur Khan
North South University
Dhaka, Bangladesh
rafidkhan007@gmail.com

Abstract*— The work presented in this article constitutes a contribution to modeling and forecasting the demand for LPG gas (Liquefied Petroleum Gas) by using a time series approach. A time series modeling approach known as Box-Jenkins's ARIMA model has been used in this study to forecast LPG production in Bangladesh. The best order of the ARIMA model found here is (1, 2, 1). Later, the order ARIMA (1, 2, 1) is used to make the forecast, as accurate as possible, the future demand for LPG for up to five years in Bangladesh. The forecast results have shown that the demand for LPG gas will increase exponentially after the coronavirus pandemic, which affected the production and import of LPG gas. The demand will take a sharp increase in 2021 and subsequent years 2022 through 2026. The demand will continue to grow at approximately 30% year on year.

***Keywords*— forecasting, time series modeling, ARIMA, LPG (Liquefied Petroleum Gas), Bangladesh.**

I. INTRODUCTION

LPG which stands for Liquefied Petroleum Gas is an important factor in the Energy sector of Bangladesh. Bangladesh is the 32^{nd} highest consumer of natural gas in the world with over 6531 cubic feet of per capita gas consumption per year. With a growing population, it is hard to supply gas to households through pipeline-based infrastructure. To cope with the situation, Titas, the largest pipeline-based gas distributor in Bangladesh, stopped the piped connection, increasing the use of LPG in Bangladesh. The huge demand for gas supply cannot be met only by the piped gas alone, so the LPG market will become an effective as well as the cost-reducing solution in both households as well as industries. Although the sector is growing tremendously, this is a highly import-based sector. In 2021 the total demand was 1,348,968 metric tons and the total import was 1,331,207 metric tons. This implies more than 98% of the demand is met by importing from foreign countries and this is completely dependent on the international market.

The open source software 'Jupyter Notebook' using Python programming language, and various statistical and series packages like 'seasonal_decompose', 'adfuller', 'kpss' etc are used for this study purpose.

II. LITERATURE REVIEW

Manoj and Madhu built an ARIMA model to forecast sugarcane production in India. They used production data from 1950–51 to 2011–12 to forecast production for the next five years. This research shows how production will grow in the future using the ARIMA (2,1,0) model.

Abonzel and Ibrahim (2019) used the ARIMA model to observe the GDP of Egypt. An ARIMA(1,2,1) model is used here to forecast. They tried to minimize the out-of-sample forecast errors rather than maximize the in-sample goodness of fit.

Meyler et al. (1998) developed a framework for ARIMA time series models for forecasting Irish inflation. This research is also based on optimizing sample forecast errors. Their main aim was to minimize out-of-sample forecast errors to identify the Irish inflation rate.

Bhuiyan, Ahmed, and Jahan (2008) used the ARIMA model to model and forecast the GDP of the manufacturing industry in Bangladesh. This paper highlighted the performance of the manufacturing sector from 1979-80 to 2001-02. It also showed the future demand for the manufacturing industry in Bangladesh.

M. Salah Uddin and Nishat Tanzim built an ARIMA model to forecast the GDP of Bangladesh. We used the data from the World Bank and forecast the GDP from 2019 to 2025. According to their work, the GDP will steadily improve in upcoming years and it will remain expanding in the future.

Contreras et al (2003) in their study, used the ARIMA model to predict next-day electricity prices in mainland Spain and California. This model showed electricity prices for both spot markets and long-term contracts. This model could predict the next day's market clearing prices of 24 markets analyzing the data of these markets.

Awal, M., & Siddique, M. (2011) built an ARIMA model which predicted rice production in Bangladesh. They built separate ARIMA models for different variants of rice. The best models were ARIMA (4,1,4) for Australia, ARIMA (2,1,1) for Aman, and ARIMA (2,2,3) for Boro. It also showed that short-term forecasts were more efficient for their models compared to long-term deterministic models.

Khan, S.Islam, and A.Khan made the first application of Long-Range Energy Alternative Planning (LEAP) in energy forecasting of the gas sector in Bangladesh. The data on gas consumption from the years 1993 to 2007 has been collected and a forecast has been made up to the year 2020. This used the 'Linear' and 'Exponential' time series wizards for a forecast.

III. RESEARCH METHODOLOGY

Limited which is the only government organization for LP Gas production and bottling started the first production in 1978-79. It made the first initiative to bottle LPG from refined gas and later many other private companies joined the league.

Table 1: Inland LPG Production in Bangladesh (in Metric Tons)

Sl No	Year	Production	Sl No	Year	Production
1	1978-79	93	23	2000-01	15037
2	1979-80	2692	24	2001-02	20190
3	1980-81	2692	25	2002-03	22258
4	1981-82	4585	26	2003-04	22707
5	1982-83	4874	27	2004-05	22926
6	1983-84	4370	28	2005-06	20902
7	1984-85	6228	29	2006-07	22430
8	1985-86	7116	30	2007-08	16778
9	1986-87	8935	31	2008-09	14911
10	1987-88	9062	32	2009-10	10753
11	1988-89	9185	33	2010-11	16741
12	1989-90	9259	34	2011-12	21269
13	1990-91	9485	35	2012-13	20942
14	1991-92	7869	36	2013-14	25165
15	1992-93	8108	37	2014-15	23831
16	1993-94	9885	38	2015-16	22874
17	1994-95	12632	39	2016-17	20440
18	1995-96	15756	40	2017-18	20682
19	1996-97	13448	41	2018-19	21197
20	1997-98	15948	42	2019-20	25560
21	1998-99	1362	43	2020-21	17805
22	1999-20	11750			

Table 2: Import LPG Production in Bangladesh (in Metric Tons)

Sl No	Year	Production	Sl No	Year	Production
1	1978-79	0	23	2000-01	6382
2	1979-80	0	24	2001-02	19532
3	1980-81	0	25	2002-03	24697
4	1981-82	0	26	2003-04	38098
5	1982-83	0	27	2004-05	30449
6	1983-84	0	28	2005-06	26104
7	1984-85	0	29	2006-07	32260
8	1985-86	0	30	2007-08	25311
9	1986-87	0	31	2008-09	34221
10	1987-88	0	32	2009-10	48409
11	1988-89	0	33	2010-11	58959
12	1989-90	0	34	2011-12	69364
13	1990-91	0	35	2012-13	85342
14	1991-92	0	36	2013-14	95779
15	1992-93	0	37	2014-15	162346
16	1993-94	0	38	2015-16	335906
17	1994-95	0	39	2016-17	547000
18	1995-96	0	40	2017-18	707175
19	1996-97	0	41	2018-19	917446
20	1997-98	0	42	2019-20	1065709
21	1998-99	0	43	2022-21	1331207
22	1999-20	2922			

The above table indicates the inland production of LPG in Bangladesh. This means these above-mentioned units are built inside Bangladesh by Bangladeshi companies. LP Gas

The above table shows the import of LPG in Bangladesh. Although LPG is highly dependent on imports from foreign countries, at first there was no initiative of import until 1998-

99. In the year 1999-20 the first import of LPG was done by a private company and later many other companies started importing refined LPG from foreign countries.

Table 3: Total (Inland + Import) of LPG Production in Bangladesh (in Metric Tons)

Sl No	Year	Production	Sl No	Year	Production
1	1978-79	93	23	2000-01	26572
2	1979-80	2692	24	2001-02	41790
3	1980-81	4585	25	2002-03	47404
4	1981-82	4874	26	2003-04	61024
5	1982-83	4370	27	2004-05	51351
6	1983-84	6228	28	2005-06	48534
7	1984-85	7116	29	2006-07	49038
8	1985-86	8935	30	2007-08	40222
9	1986-87	9062	31	2008-09	44974
10	1987-88	9185	32	2009-10	65150
11	1988-89	9259	33	2010-11	80228
12	1989-90	9485	34	2011-12	90306
13	1990-91	7869	35	2012-13	110507
14	1991-92	8108	36	2013-14	119610
15	1992-93	9885	37	2014-15	185220
16	1993-94	12632	38	2015-16	356346
17	1994-95	15756	39	2016-17	567682
18	1995-96	13448	40	2017-18	728372
19	1996-97	15948	41	2018-19	943006
20	1997-98	13629	42	2019-20	1083514
21	1998-97	11750	43	2020-21	1348968
22	1999-20	17959			

Source: LP Gas Limited, North Patenga, Chittagong, Bangladesh. (Former Managing Director Mohammad Fazlur Rahman Khan).

This table is the sum of both inland and import production of LPG in Bangladesh. The total production which is a combination of both onshore production and offshore import of LPG gas is used in this project to predict the future assumption of LPG gas. The total consumption will be useful to identify the future demand for LPG gas in Bangladesh.

IV. Box-Jenkins (ARIMA) Model

ARIMA stands for "Auto Regressive Integrated Moving Average". It is a linear regression time series analysis model. It uses its own lags as predictors to forecast based on the description of historical data. It can only make a forecast on a single variable based on the historical information given to the model. The main difference between an ARMA (Auto Regressive Moving Average) and an ARIMA is the integrated difference order. An ARIMA model is characterized by three terms: ‘p’, ‘d’, and ‘q’, where ‘p’ is the order of the Auto Regressive (AR) term, ‘d’ is the number of differences which is required to make the data stationary (I), and ‘q’, which is the Moving Average (MA) term. Here a number of lags are used as predictors, and ‘p’ indicates the lag order of the model. The term ‘q’ determines the size of the moving average window. It refers to the lagged forecast error that should go into the ARIMA model.

A. *Analysis of Dataset*

The given set of data given in Table 3 is used in this model. Figure 1 below represents the line plot of given dataset.

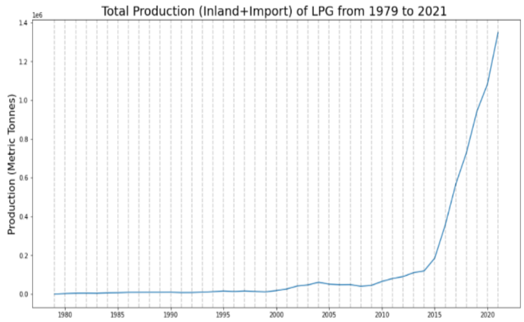

Figure 1: Total Production of LPG

The above picture shows the overall production of LPG over a certain period of time. . It shows that the production increased steadily from 1979 to 2015. Then, there was a sharp increase and upward trend with some fluctuations in the production numbers from the year 2015 to 2021. In order to get more insights from the graph, the statistical model of seasonal decomposition is used. Figure 2 below shows the trend, seasonality, and residuals of the given dataset.

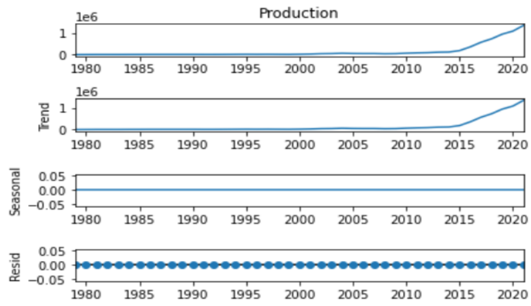

Figure 2: Seasonal Decompose of Data

The seasonal decomposition of data gives more insights into the dataset. According to Figure 2, there is no seasonality in the dataset. The residuals are also at zero, which means residuals do not have a significant effect on the dataset. But, there is a clear trend in the dataset from 2015 to 2021. This affects the stature of the dataset.

B. Model Identification

The first step of the ARIMA model is to determine whether the dataset is stationary or not. The ARIMA model has the option of integrated differentiation. By stationary, we mean that the mean and variance of variable values remain constant over time. Figure 1 shows that the data is not stationary as there is an increasing trend from 2015 to 2021. The ARIMA (p, d, q) model is used because it will differentiate the data automatically to make it stationary. The difference order cannot be chosen at random as over-difference will increase the standard deviation rather than reduction. So it is practical to limit the order of difference to an order of two. Two tests have been used here to check whether the data is stationary. One is the Augmented Dicky-Fuller (ADF) test and the other one is the Kwiatkowski Phillips Schmidt Shin (KPSS) Test.

1) Check for stationary: Augmented Dicky-Fuller (ADF) Test

The Augmented Dicky-Fuller (ADF) test is used to determine whether the dataset is stationary or not. Two criteria need to be fulfilled to check whether data is stationary in the ADF test. The null hypothesis (H0) in this test is that the time series data is non-stationary while the alternative hypothesis (Ha) is that the series is stationary. This hypothesis is tested by differencing the data in d^{th} order, which gives a table of data. This table represents the current difference between the data and the immediately previous one. The main aim of this test is to find the appropriate critical p-value and ADF statistic. If the p-value is less than the threshold value of.05 and the ADF statistic is less than the critical values, then we can accept the alternate hypothesis and reject the null hypothesis. This means the p-value needs to be less than.05 to make the dataset stationary.

ADF Statistic: 2.710172
P value: 0.99
Critical Values:
    1%: -3.639
    5%: -2.951
    10%: -2.614

Here the ADF statistic is 2.710172, which is not less than any of the critical values. Again, the most important criterion, is that the P value is higher than the threshold value of 0.5. So we fail to accept the null hypothesis (H0) and the data is not stationary.

2) Check for stationary: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

Kwiatkowski-Phillips-Schmidt-Shin (KPSS) is another statistical test to find out whether the data is stationary or not over a deterministic trend, where the slope of the trend does not change permanently. The KPSS test is just the opposite of the ADF test. Here, the null hypothesis (H0) in this test is that the time series data is stationary while the alternative hypothesis (Ha) is that the series is not stationary. Like in the ADF test, there is also a p-value that determines the stationarity of the dataset but acts just the opposite of the p-value of the ADF test. In the KPSS test, the p-value needs to be higher than the threshold value of .05 to have stationary data. If the p-value is higher than the threshold value of .05, then we can accept the null hypothesis (H0) and reject the alternative hypothesis (Ha).

KPSS Statistic: 0.399673
P value: 0.077296
Number of Lags: 10.00
Critical Values:
    10%: 0.347
    5%: 0.463
    2.5%: 0.574
    1%: 0.739

Here, the KPSS statistic is greater than only 10% of the critical values and less than all other critical values. The most important criterion, the p-value, is slightly higher than the threshold value of .05, indicating that the data values are stationary over time.

Figure 1 gives a better understanding of this. The line graph shown in Figure 1 represents different values of the dataset. After observing the data, we find that the mean and variance of the data remain constant over 1979–2015 as there is no trend or outliers. If the mean and variance are measured around this period, then it provides around a constant value. Unfortunately, there is a massive upward trend in data from 2015 onwards, which makes data non-stationary for this time. If mean and variance are measured between two periods of this time, then it will not provide constant values.

Finally, according to the two above tests, it can be concluded that the dataset is nowhere near stationary according to the ADF test, but the data is stationary for a particular period of time in the KPSS test. The contradictory results of these two statistical tests make the dataset more complicated. That is why the difference, which is the order of the ARIMA model, is 2 here. Because more than twice the difference in the data can make the data less informative rather than reduce the trend. So now we can proceed to find the appropriate order of AR and MA for our ARIMA model.

3) Correlograms and Partial Correlograms

a) Auto Correlation Function (ACF)

The Autocorrelation Function (ACF) is a statistical technique to highlight the correlations between lags. It helps to identify how correlated the data points are in the time series. It uses lags to measure the correlation. It plots the correlation between the current time observations and previous time observations using the lagged version of itself. Below is the ACF plot of the model for lags 1 to 20.

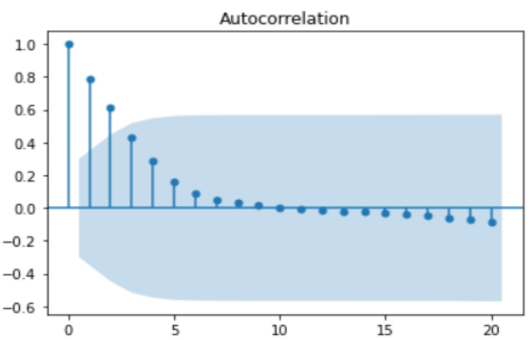

Figure 3: ACF Plot

We can identify the possible MA (Moving Average) from the autocorrelation function. The above graph shows that both lags 1 and 2 exceed the significant level, and correlations after two lags go towards zero. We can consider all the points inside the blue-shaded zone as zero and ignore the points for the order of MA. The ACF coefficient of lag-1 (0.8) and lag-2 (0.6) along with lag-0 are our possible candidates for the order of the MA model.

b) Partial Autocorrelations Function (PACF)

The partial autocorrelation function (PACF) acts like an ACF, but there is a slight difference. It only captures the correlation between two variables after ignoring the effect of all other variables. The PACF plot from lags 1 to 20 of the model is shown below.

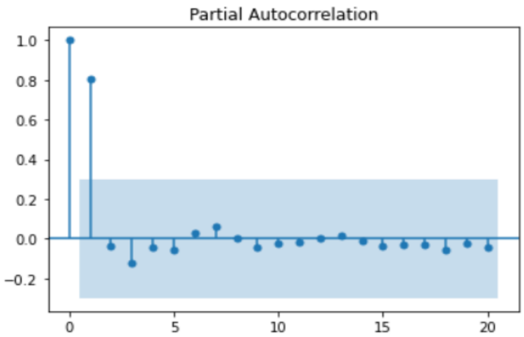

Figure 4: PACF Plot

We can identify the possible AR (Auto Regressive) from the partial autocorrelation function. The partial Correlograms shows that the autocorrelation coefficient at lag 1 exceeds the significant level. Only lag-1 (.8) exceeds the significance level, except for lag 0, which we can omit to have an AR order. All the other lags are well inside the blue-shaded region, and we can consider the partial coefficient values of these points to be equal to zero. So, the AR order of 1 is our possible candidate for the model.

According to both ACF and PACF, we achieved possible orders of AR of 1 and possible orders for MA of 1 and 2. In the ARIMA model, both AR and MA are denoted by p and q. So, we can define the ARIMA model from ARMA (Auto Regressive Moving Average) using these values of p and q.

(i) ARMA (1,0): This is an autoregressive model with order p = 1 and q = 0, as partial correlations of all subsequent lags are zero and autocorrelation is zero.

(ii) ARMA (1,1): This is a moving average model with order p = 0 and q = 1, as the autocorrelations of all other lags after lag-1 (except 2) trend to zero and partial autocorrelation is zero after lag-1.

(iii) ARMA (1,2): This is another moving average model of order p = 1 and q = 2, with zero autocorrelation after lag-2 and partial autocorrelation after lag-1.

C. Best order for ARIMA(p,d,q)

In order to get the best order for ARIMA (p, d, q), the auto-arima library of Python is used. It provides the best order of the model based on the lowest AIC (Akaike Information Criteria) and BIC (Bayesian Information Criterion). At first, the best order is obtained using this library, and then the AIC and BIC values are checked manually

```
Performing stepwise search to minimize aic
 ARIMA(2,2,2)(0,0,0)[0]             : AIC=971.553, Time=0.47 sec
 ARIMA(0,2,0)(0,0,0)[0]             : AIC=971.212, Time=0.01 sec
 ARIMA(1,2,0)(0,0,0)[0]             : AIC=970.413, Time=0.01 sec
 ARIMA(0,2,1)(0,0,0)[0]             : AIC=971.797, Time=0.01 sec
 ARIMA(2,2,0)(0,0,0)[0]             : AIC=968.829, Time=0.01 sec
 ARIMA(3,2,0)(0,0,0)[0]             : AIC=inf, Time=0.06 sec
 ARIMA(2,2,1)(0,0,0)[0]             : AIC=968.877, Time=0.10 sec
 ARIMA(1,2,1)(0,0,0)[0]             : AIC=968.094, Time=0.08 sec
 ARIMA(1,2,2)(0,0,0)[0]             : AIC=969.314, Time=0.14 sec
 ARIMA(0,2,2)(0,0,0)[0]             : AIC=972.100, Time=0.02 sec
 ARIMA(1,2,1)(0,0,0)[0] intercept   : AIC=968.090, Time=0.06 sec
 ARIMA(0,2,1)(0,0,0)[0] intercept   : AIC=971.755, Time=0.01 sec
 ARIMA(1,2,0)(0,0,0)[0] intercept   : AIC=970.023, Time=0.01 sec
 ARIMA(2,2,1)(0,0,0)[0] intercept   : AIC=969.244, Time=0.11 sec
 ARIMA(1,2,2)(0,0,0)[0] intercept   : AIC=969.839, Time=0.11 sec
 ARIMA(0,2,0)(0,0,0)[0] intercept   : AIC=971.574, Time=0.01 sec
 ARIMA(0,2,2)(0,0,0)[0] intercept   : AIC=973.101, Time=0.03 sec
 ARIMA(2,2,0)(0,0,0)[0] intercept   : AIC=969.384, Time=0.02 sec
 ARIMA(2,2,2)(0,0,0)[0] intercept   : AIC=inf, Time=nan sec

Best model:  ARIMA(1,2,1)(0,0,0)[0] intercept
Total fit time: 1.512 seconds
```

Figure 5: Search for best fitted ARIMA model

This shows us the lowest AIC value is for ARIMA (1,2,1) where p = 1, d = 2, q = 1. The order of the d is used for integrated differencing of the dataset. Our data was stationary over a certain period and that is why the order of d=2 is used and gives the lowest AIC with p=1 and q=1. The minimum order of differentiation is 1, and if d> 2, then it may deduce valuable information from the data points. Now we will check manually using p = 1 and q = 0,1,2 along with d = 2. This will verify our findings.

Table-4: AIC and BIC values of the best ARIMA model

Arima Model	**Coefficients**				**Log Likelihood**	**AIC**	**BIC**	**HQIC**
	AR1	**AR2**	**MA1**	**MA2**				
(1,2,0)	-0.3173				-480.045	968.090	974.944	970.586
(2,2,0)	-0.3196	0.3888			-481.414	968.829	973.970	970.701
(1,2,1)	-0.9995		0.6303		-480.045	968.090	974.944	970.586
(1,2,2)	-1.0000		0.7360	0.2318	-480.657	969.314	976.168	971.810

It is observable from the table-4 that ARIMA (1,2,1) provides the lowest AIC and BIC values. Further, we have used ARIMA (2,2,0) to find out whether any other order, except what we found from ACF and PACF, can give the lowest AIC and BIC values. But, the ARIMA (2,2,0) provides higher AIC and BIC values than our optimal ARIMA (1,2,1). So, it is evident that the order ARIMA (1,2,1), which is found through the automated process of order choosing, is accurate. So, the p=1, d=2 and q=2 orders of ARIMA (p, d, q) is used for further validation and forecast of the model.

V. Model Validation and Forecast

The optimal order of our ARIMA is (1,2,1) and then use walk-forward validation to find out how our model works on training and testing data. This is why the dataset is divided into a training and a testing set. Train data consists of 66% of the total dataset, and the rest (33%) is reserved for testing. The training set is used for training the model, and then walk-forward validation generates predictions on each of the test data. The rolling forecast is obtained by re-creating the ARIMA model after each new observation is received. A list is used to track down all the observations, and this list is seeded with new observations to see forecast performance on new observations. Below are the predicted values of 15 test datasets, where expected values are the demand of the last 15 years of datasets.

Predicted	Expected
35943.05	49038.00
48209.70	40222.00
36338.02	44974.00
41708.08	65150.00
72268.65	80228.00
87931.87	90306.00
96207.96	110507.00
124048.54	119610.00
127522.76	185220.00
210376.13	356346.00
627153.41	567682.00
780120.04	728372.00
855007.82	943006.00
1189869.50	1083514.00
1222547.91	1348968.00

Figure 6: Evaluation using walk-forward validation

The figure below shows the fitted ARIMA (1,2,1) model using walk-forward validation.

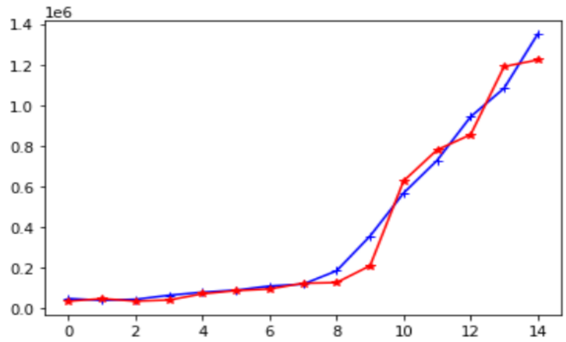

Figure 7: Forecast fitted with ARIMA (1,2,1)

Now the prediction is made using the predict function. This uses the last instances of the predicted feature and predicts the upcoming target. Based on the last value obtained from the validation, future demand will be generated.

Year	Demand (Metric Tons)
2022	1361059.68
2023	1499386.18
2024	1775885.08
2025	1914114.70
2026	2052341.39

Figure 8: Demand in upcoming years (2022-2026)

In order to further investigate, we will plot the forecast errors (residuals) of the model. The residual error indicates how far a value is from its original one. Here it indicates the deviation between predicted and actual values of the model.

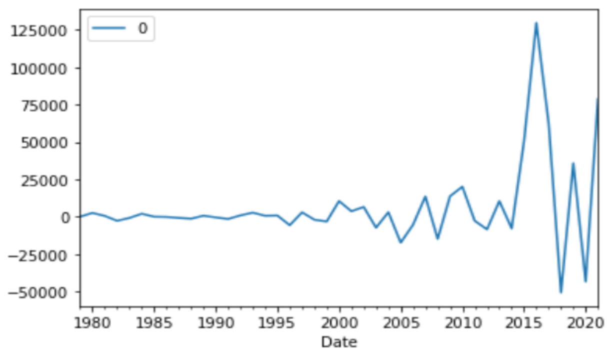

Figure 9: Residual Error

Above is the line graph of the residuals of the fitted models. Residuals are the errors that are the difference between observed and predicted values of data. The fewer residual errors make the model more accurate. From Figure-9, it is obtained that at the beginning there are fewer residual errors, but over time, there is a huge variance. This indicates that mean and variance do not stay constant at the end of the time series.

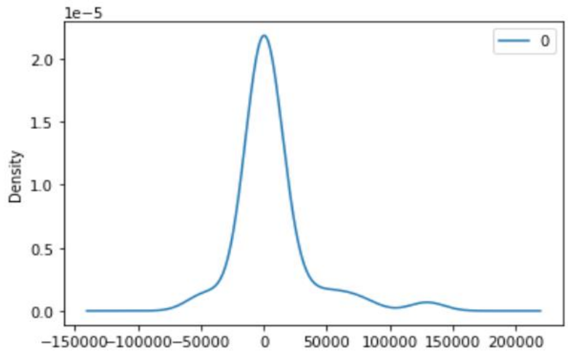

Figure 10: Density of Residual Error

Above is the density of the residual errors. The errors represent the Gaussian distribution. This indicates that the errors are following a Gaussian distribution and the mean of the error distribution is around zero.

VI. CONCLUSION

The study shows that ARIMA(1,2,1) is the best candidate for the prediction of the future demand for LPG in Bangladesh. ARIMA was used because it is capable to highlight the autocorrelations between the successive values to make future predictions. The model predicted an increase in the demand for LP gas in Bangladesh throughout the next five years. There will be a sharp increase in the demand for LPG throughout the next five years. The prediction for 2022 is approximately 1.3 million metric tons and this will continue to increase exponentially over the next five years at a 30% increase year to year. The rise (root mean squared error) of the model is 66583.38. This high-rise value happens because of the high scale of the data values.

The biggest drawback of my model is the complexity of the dataset. The data remains stationary at the beginning of the time series. But in the end, there is a sharp increase in production and it keeps rising dramatically. This upward trend leads the dataset to become non-stationary and affects the overall prediction of the model. Because of the coronavirus pandemic in the year 2020, overall onshore and offshore production was hampered a lot, and overall production declined. The moving average part of the model memorizes this decline and fails to give an expected result in the year 2021. Thus, it can be concluded that the overall production will be higher than the expected outcome of the model.

REFERENCES

[1] Kumar, Manoj & Anand, Madhu. (2014). An Application Of Time Series Arima Forecasting Model For Predicting Sugarcane Production In India. Studies in Business and Economics. 9. 81 - 94.

[2] Abonazel, M. R., and A. I. Abd-Elftah, "Forecasting Egyptian GDP Using ARIMA Models", Reports on Economics and Finance, vol. 5, issue 1, pp. 35 - 47, 2019.

[3] Meyler, Aidan; Kenny, Geoff and Quinn, Terry (1998), Forecasting Irish inflation using ARIMA models, Central Bank and Financial Services Authority of Ireland Technical Paper Series, Vol. 1998, No. 3/RT/98 (December 1998), pp. 1-48.

[4] M. N. A. Bhuiyan, K. S. Ahmed and R. Jahan, Study on Modeling and Forecasting of the GDP of Manufacturing Industries in Bangladesh, Chiang Mai University Journal of Social Science and Humanities, 2 (2008), 143-157.

[5] Uddin K.M. Salah,Tanzim Nishat (2021), ”Forecasting GDP of Bangladesh Using ARIMA Model”, Canadian Center of Science and Education, International Journal of Business and Management; Vol. 16, No. 6; 2021.

[6] Contreras, J., Espinola, R., Nogales, F.J., Conejo, A.J., (2003), ARIMA Models to Predict Next- day Electricity Prices, IEEE Transactions on Power Systems, Vol. 18, No. 3, pp. 1014- 1020.

[7] Awal, M & Siddique, And. (2011). Rice Production In Bangladesh Employing By Arima Model. Bangladesh Journal of Agricultural Research. 36. 10.3329/bjar.v36i1.9229.

[8] Khan, S. Islam, A., Khan, H.I. (2011), Energy Forecasting of Bangladesh in Gas Sector Using LEAP Software. Global Journal of Research in Engineering 11(1-1), 14-20.

[9] G. E. P. Box, G. M. Jenkins, *Times Series Analysis Forecasting and Control*, Holden-Day San Francisco, 1970.

[10] C. W. Granger, P. Newbold, *Forecasting Economic Time Series*, Academic Press, 1986.

[11] J. Frain, Lecture Notes on Univariate Time Series Analysis and Box Jenkins Forecasting, Economic Analysis, Research and Publications, 1992.