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Jordan Energy Demand Forecast Using ARIMA Model Until 2030

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Abstract

After viewing Jordan energy sector development through the period (1996 – 2022), this paper used ARIMA model to forecast Energy Consumptions in Jordan up to 2030 by sector. Augmented Dicky Fuller test is used to test stationarity of each sector data set, followed by differencing when required. Additionally, ACF and PACF tests have been done to find p and q parameters of the ARIMA model for each sector, and finally mean absolute percentage error s MAPE were calculated to validate the forecasting results. Main findings were that total final consumption will reach (7045 ktoe) by 2030 with the expected values of [1548, 1112, 3431, 708 and 665] ktoe for Residential, Industrial, Transport, Commercial and Other consumption sectors respectively in the same year. MAPE results for the ARIMA model for total final consumption and the mentioned sectors is (10%, 4%, 4%, 22%, 21%, 6%) respectively.Haut du formulaire

Keywords: Jordan, Energy Balance, Energy Forecast, Auto-Regression, Final Energy Consumption.

1. Introduction

Ensuring a stable equilibrium between supply and demand of energy resources, alongside their consistent availability and relative price stability, holds paramount importance. The accessibility and affordability of energy exert the most significant influence on the overall energy security.[1]

Based on International Energy Agency (IEA) energy balance aids in comprehending the transformation of products into one another, elucidating the diverse relationships among these products, and demonstrating the ultimate utilization of all energy types.

Jordan Energy Sector is interconnected with economic growth, for instance figures 1 and 2 show Electricity per capita, Primary Energy per capita and GDP per capita based onJEBfor the period (1996 – 2022). Both figures represent a close behaviour, which confirm the proposed connection between economic growth and energy consumption as discussed in [2][3][4] , Where evidence shows that long-run and short-run causalities run from energy consumption to GDP, but not vice versa especially in developing countries.

However, after 2013 GDP per capita fall in a steady rate, while energy consumed per capita dropped dramatically after 2015.

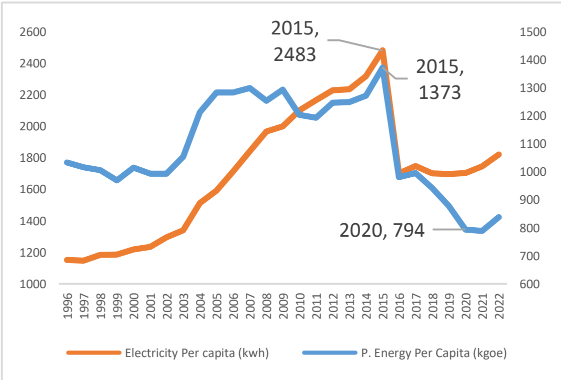

Figure 1. Electricity per capita and Primary energy per capita (1996-2022)

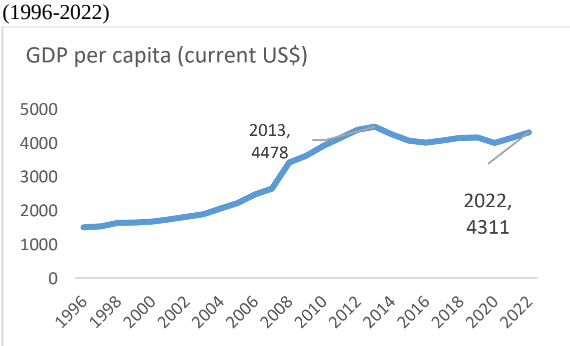

Figure 2. GDP per capita ($US) [2]

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[2] World bank open data

In 2022, Primary energy supply reached 10476 ktoe, where local production shares are 17%. In addition, energy intensity recorded as 217 kgoe/$1000 in GDP fixed prices. While primary energy per capita reached 838 kgoe. Renewable energy shares in primary energy were 15%. And Energy costs were 3.45 billion JD with a share in GDP of 10%. Meanwhile Final energy consumption is 6756 ktoe, with transport as the major contributor with 43% shares in final consumed energy. The following Sankey diagram represents the energy flows between primary supply, energy transformation and final consumers in Jordan for the same year.

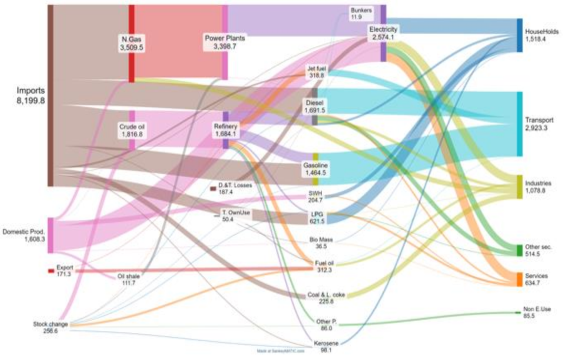

Figure 3. Sanki Diagram of Fuel transformations in Jordan 2022[3]

Between 1996 and 2022 main KPI's differ widely as shown in table1, for instant primary energy supply has a cumulative growth rate 3.2% increasing the value from 4.6 million-tons oil equivalent to 10.4 million tons oil equivalent in 1996 and 2022 respectively, indicating an economic growth during the whole period.

Table 1. Main sector KPI's between (1996 - 2022)[4]

Indicators	1996	2022	CAGR
Primary Energy Supply (ktoe)	4590	10476	3.2%
Imports share in PES	94%	83%	-0.5%
local resources share in PES	6%	17%	4.1%
Energy cost (MJD)	345	3450	9.3%
Energy Intensity (MJ\2017 $USD ppp)	4.73	3.54*	-1.1%
PES per capita	1033	838	-0.8%
*Latest year available 2020			

More details about the primary energy supply can be shown in Figure2, which views a peak in 2017 with PES of 10.1 ktoe followed by a bottom in 2020 regarding the pandemic.

Deeper understanding of primary energy supply can be reached by looking at the fuel mix, as described in table2. While crude oil has the highest share it has decreased with CAGR of (-2.6) through the years and this can be explained by the fact that many Jordan oil markets have liberalized and oil marketing companies (i.e. oil stations owners) have the permission to import oil products directly from global market, which lower the refinery sales and as a result their imports of crude oil has decreased.

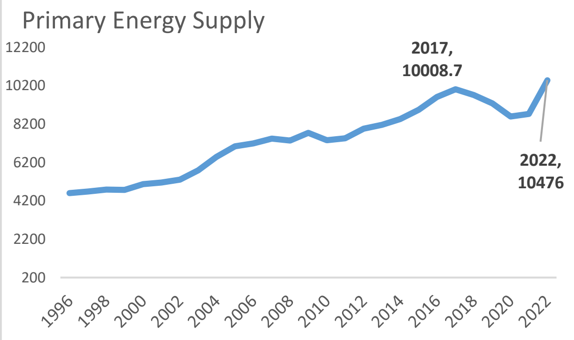

Figure 4. primary Energy Supply ktoe (1996 - 2022)[3]

Table 2. Primary Energy Supply by Fuel[4]

PES by Fuel	1996	2022	CAGR
Crude oil	3246	1631	-2.6%
Oil products	1070	2614	3.5%
N.gas	211	3509	11.4%
Renewable Energy	63	1,373	12.6%
Coal and Coke	0	226	-
Oil shale	0	1117	-

Market liberalization also can explain why oil products increased by 3.5% cumulative rates. Natural Gas has also increased dramatically because of the high dependency on this fuel in electricity production after shifting to use it in power plants instead of heavy fuel oil. On the other hand, the increase in renewable energy explains why local resources had increased after 2015 as mentioned previously.

Another important indicator about energy sector is the share of local resources in total primary energy supply, which started being 6% only and increased to reach 17% in 2022. This increase is visualized in Figure3, which records the progress of indigenous production in Jordan, this indicator is the summation of renewable energy produced in electricity forms and in heat too by solar water heater, in addition to the biomass produced locally as olive residuals.

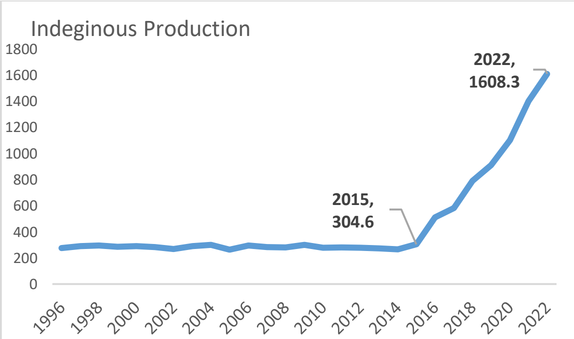

Figure 5. Indigenous Production ktoe [4]

The figure shows an exponential function with a turning point in 2015 when renewable energy projects were launched, reaching 1.6 million tons oil equivalent at the end of the period in 2022, which proves that renewables are a good alternative to existing conventional sources of energy in Jordan[5].

This significant reliance on renewables has been discussed in various literature,[6]found that until 2018, Jordan's transmission grid would face minor overloads,

[3]Available in large scale in the appendix.

[4]Resource: Ministry of Energy and Mineral resources Archive/ Website.

while most transmission lines would be overloaded by 2020. This was the reason for launching the Green Corridor project in 2019, aiming to reinforce the electric grid by increasing its capacity to accept more renewable energy.

Another important aspect of increasing renewable energy is the reduction of GHG emissions. As investigated in[7]the solar and wind projects launched under the implementation of Jordan Energy Strategy (2015 – 2025) will decrease GHG emissions by 1.9 – 3.2 megatons of CO2 annually.

Imports shares in PES are complementary to local production shares so the same period showed a decrease in imports. Although imports share declined, the imported amounts of oil and different oil products in addition to n. gas has increased significantly, as showed in Figure4, which indicates a peak of imports in 2017, with 9.4 million tons oil equivalent, followed by a decrease in the pandemic year in 2020. The increase in imports amounts can explain the reason why energy cost has increased dramatically through the whole period with cumulative annual growth rate of 9.3%, starting with no more than 345 million JOD and reaching 3.4 billion JOD as shown in Figure5.

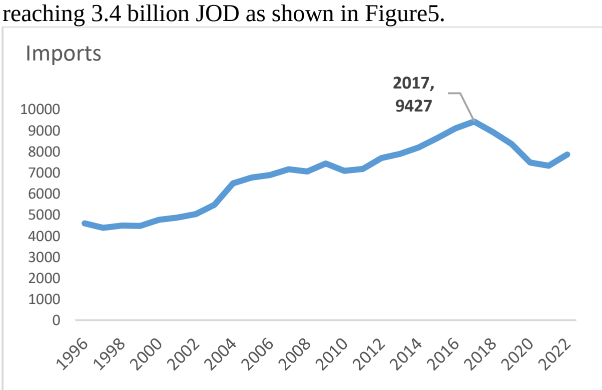

Figure 6. Imports amounts ktoe (1996 - 2022)[4]

Although Energy cost is highly dependent on Imports, it shows a spike in cost at 2012 all the way to 2014, which represents the years during which the N.gas imported from Egypt had cut-out and NEPCO started to import fuel oil as a supplement and that resulted in a huge loss to the company.

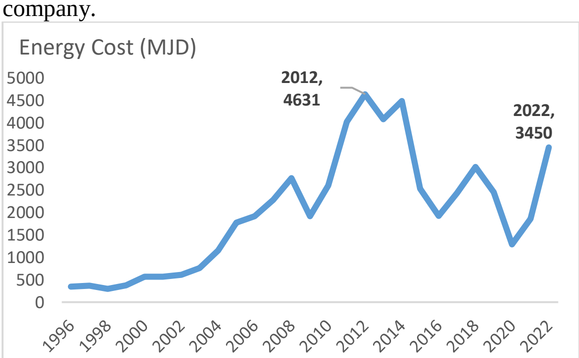

Figure 7. Energy Cost MJD[4]

While Imports were discussed briefly, Table3 describes the oil products imports during the study period. crude oil and fuel oil had negative growth rate for the reasons mentioned above. LPG, Gasoline, Jet fuel, and Diesel imports has all increased significantly, indicating the increase in demand for these products and one reason of this could be the economic growth during the period.

Table 3. Imports of Oil products kton (1996, 2022)[4]

Oil products Imports	1996	2022	CAGR
Crude oil	3272.4	1803.4	-2.3%
LPG	94.5	522.4	6.8%
Kerosene	0	32.6	-
Gasoline	20.7	974.8	16.0%
Jet fuel	0	77.7	-
Fuel oil	782.6	0	-100%
Pet coke	0	0	-
Diesel	281.2	1141.9	5.5%

Total final energy consumption has also increased through the whole period from 652.5 thousand tons oil equivalent in 1996 reaching 6.8 million tons oil equivalent in 2022, with a peak in 2017 reaching 7.1 million tons oil equivalent as shown in figure (8). Further research could take a place to discover the reasons behind having this peak in demand in 2017 which consequently lead to peak in imports and a peak in primary supply, as shown in Figures 3 and 6.

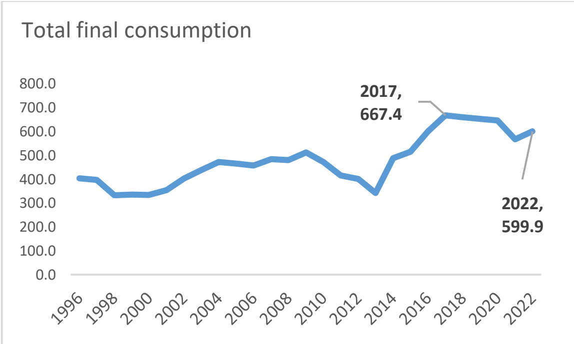

Figure 8. Total Final Energy Consumption ktoe (1996-2022)[4]

In addition to total final Energy Consumption, it is important for this paper to discuss the consumption of each sector, as they are the variables of interest and will be forecasted up to 2030. They are represented in figure(9) below:

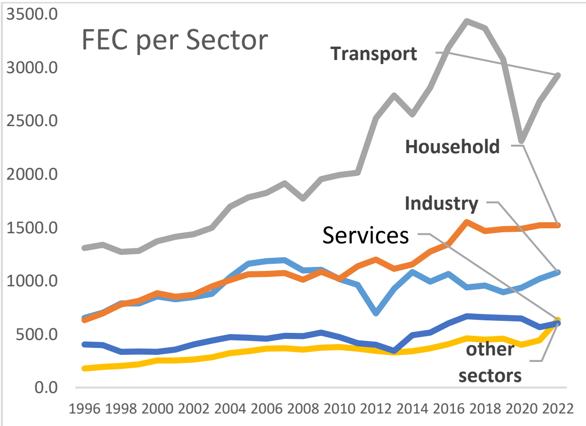

Figure 9. Final Energy Consumption by Sector for the period (1996 - 2022)

While transport dominate the highest consumption rates during the whole period, Household consumption rates increased significantly since 1996. Industrial sector in the other hand showed fluctuation during the period. Services sector in addition to the other sectors including [agriculture, water pumping and street lighting] increased slightly in different rates for each.

Each of these sectors has its own energy consumption driver. For instance, industrial sector electricity consumption is highly dependent on production and capacity utilization based on[8] and [9]. On the other hand, energy efficiency measures like retrofit solutions can reduce consumption at various rates depending on the sector. Based on[10], applying measures such as replacing all single-glazed windows with double-glazed thermally broken windows, installing LED fixtures instead of the existing fluorescent fixtures, and separating the building's first-floor balcony terrace from the ground floor can lead to up to a 33% reduction in energy consumption of non-residential services buildings.

The following sections are described as follow: section2 will review literature among the past years that used ARIMA for energy forecast. section3 includes the forecasted model design, implementation and validation for each studied variable. Finally section4 views the conclusion of the study.

2. Energy Forecast Using ARIMA

Wide range of literature have used ARIMA or a hybrid model based on ARIMA for energy forecast. Others made comparison between different forecasting models where ARIMA showed superiority in some and wasn't the best in others.

Here literature were reviewed only if the forecasted variable is energy or energy product, the forecasting model is ARIMA, or a hybrid model based on ARIMA, in addition to forecast on the medium/ long range meaning (5-20) years, and results were concluded in the Tables 4,5, and 6 below.

Table 4. Literature used ARIMA in forecasting study variable

Reference	Country	Forecasted variable	Validation	Years
[11]	Afghanistan	Energy Consumption	Residuals analysis	2020-2024
[12]	China	Coal Price, Coal consumption, Coal Investments	NA	2016 - 2030
[13]	China	Energy Consumption	Relative Average Error	2013-2020
[14]	Greece	Oil consumption	(RMSE) (MAE)	2018-2023
[15]	Nigeria	electricity consumption	Residuals analysis	2012-2030
[16]	Pakistan	Gasoline consumption	NA	2015-2026
[17]	Pakistan	Hydroelectricity consumption	Goodness-of-fit (R2)	2018-2030
[18]	Philippines	Electricity consumption	Residuals analysis	2021-2030

It is clearly seen that variety of countries used ARIMA to forecast different types of energy variables, however none was conducted in Jordan which approves the novelty of this paper. However the main result of the papers shown in table4 is that the forecasted variable will probably increase in the forecasted years.

Table 5. Comparison between ARIMA and other methods used for Forecasting

Ref.	Country	Forecasted variable	models	Superiority	Validation
[19]	China	Energy Consumption	ARIMA, ANN	ANN	(RMSE) (MAPE)
[20]	Middle Africa	Energy Consumption	MGM, MECM, ARIMA, BP	BP	(MAPE)
[21]	Pakistan	Electricity consumption	ARIMA, HoltWinter	HoltWinter	(RMSE), (MAPE)
[22]	Pakistan	Electricity consumption	ARIMA, SARIMA, ARCH/ GARCH	ARIMA	(MAPE)
[23]	Sri Lankan	Energy Consumption	SSA, ETS, HW, TBATS, NN, ARIMA	SAA	(RMSE)
[24]	Taiwan	Energy Consumption	ARIMA, ANN	ARIMA for single variable	(MAPE)
[25]	Turkey	electricity consumption	ARIMA, GM, MAED	ARIMA, GM	(MAPE)

As shown in table 5 only [22][24], and [25] represented ARIMA superiority as a forecasting methodology. It is worth mentioning here that [26] reviewed conventional models and AI-based models and it concluded that Conventional models are preferred for the yearly energy consumption forecasting in the national level including ARIMA and other conventional models.

While based on table 5 mean absolute percentage error (MAPE) is the most common method used in validating the model. Future work in this regard could be comparing different methods used in forecasting energy demand for Jordan.

Table 6. Hybrid forecasting model based on ARIMA

Ref.	Country	Forecasted variable	models	Superiority	Validation
[27]	China	Energy Consumption	ARIMA, ANN, ARIMA-ANN	ARIMA-ANN	(RMSE), (MAE), (MAPE)
[28]	China	Energy Consumption	ARIMA, GM, ARIMA-GM	ARIMA-GM	Relative average error
[29]	China	Primary Energy consumption	ARIMA, GM, ARIMA-GM	ARIMA-GM	(MAPE)
[30]	East Africa	Energy Consumption	MGM, NMGM, MGM-ARIMA, NMGM-ARIMA	NMGM-ARIMA	Relative average error
[31]	India	Energy Consumption	MGM, ARIMA, MGM-ARIMA, BP	BP	Relative average error
[32]	India	Coal consumption	MGM, BP, MGM-ARIMA, BP-ARIMA	BP-ARIMA	Relative average error
[33]	Iran	Energy Consumption	ARIMA, ANFIS, ARIMA-ANFIS	ARIMA–ANFIS	MSE

While ARIMA models showed limited superiority, Hybrid models that are based on ARIMA are better than individual ones in almost all of the reviewed papers represented in table 6.

3. ARIMA model:

As referenced in [34], four essential stages required in ARIMA model, which are: model identification, parameter estimation, model diagnostics, and forecast verification and reasonableness. Accordingly, these steps involve:

1. **Model identification**: This entails using various tools such as graphs, statistics, autocorrelation function, partial autocorrelation functions, and transformations to make the data stationary and tentatively identify patterns and model components.
2. **Parameter estimation**: Here, the focus is on determining the model coefficients using methods like the method of least squares, maximum likelihood methods, and other applicable techniques.
3. **Model diagnostics**: This step involves assessing the validity of the model. If the model is deemed valid, it is utilized; otherwise, the process of identification, estimation, and diagnostics is repeated.
4. **Forecast verification and reasonableness**: After estimating an ARIMA model, it is crucial to reassess the identification process to enhance the selected model if possible. Various statistical techniques and confidence intervals are employed to validate forecasts and monitor model performance, detecting any instances where the model may be out of control.

Based on Box and Jenkins in 1970, ARIMA can be represented in the following mathematical equation:

$$Yt = u + \emptyset_1 Y_{t-1}, \dots, \emptyset_p T_{t-p}$$

where $\emptyset$ and u are ARIMA coefficients

3.1. Data Used

The Energy Balances of the period (1996 – 2022) were used, during which the years (1996 – 2017) used to build the model and the last 5 years (2018 – 2022) were used to validate the model using MAPE method. Finally, a forecast was made for the period (2023 – 2030). While the variables to forecast are final energy consumption of Jordan for each sector and the total final consumption, With 95% confidence interval levels. ARIMA model was built for each variable on its own using Python google colab, as it is a common tool used in past papers.

3.2. Design the model and Forecasting Results

Figures (8) and (9) previously mentioned, show the trend lines of the forecasting variables. The following sections will apply the 4 stages of the ARIMA model for each forecasting variable namely: 1. Total Final Energy consumption, 2.Residintial Sector Energy consumption, 3.Industrial Sector Energy Consumption, 4. Transport Sector Energy Consumption, 5. Services Sector Energy Consumption, 6. Other Sectors Energy Consumption.

3.2.1. Total final consumption

Sections 3.2.1.1 up to 3.2.1.4 represent the results of the stages described earlier to build and test the ARIMA model.

3.2.1.1. Model Identification

The results of the ADF test of the total final consumption data for the period (1996-2017), is as follows:

```
ADF Statistic: 2.9235271780219114
p-value: 1.0
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
Initial p-value: 1.0
```

Results conclude that the data is not stationary. So deferencing will take place, and the result is as follows:

```
ADF Statistic: -3.1900741209358237
p-value: 0.020566465245211121
Critical Values:
        1%: -3.8092091249999998
        5%: -3.0216450000000004
        10%: -2.6507125
```

Where the variable became stationary after **1 differencing**, with p-value of 0.02 and 5% significance level. Meaning that d in ARIMA parameter for this variable is 1.

The resulted stationary data is plotted below:

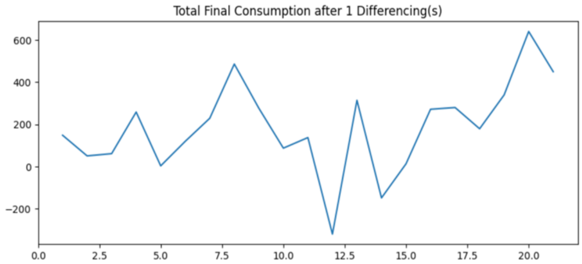

Figure 10. TFC stationary results

3.2.1.2. Parameter estimation

PACF test and ACF tests were applied with the following results for the total final consumption data with maximum number of lags 9 for each:

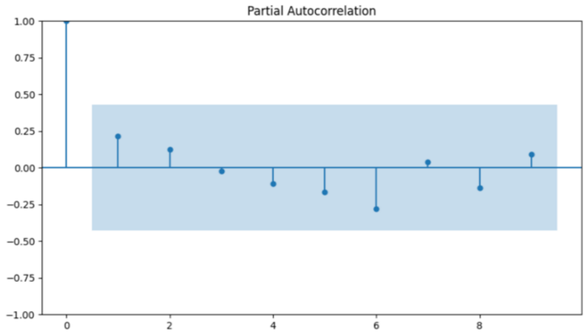

Figure 11. PACF results Total Final Consumption

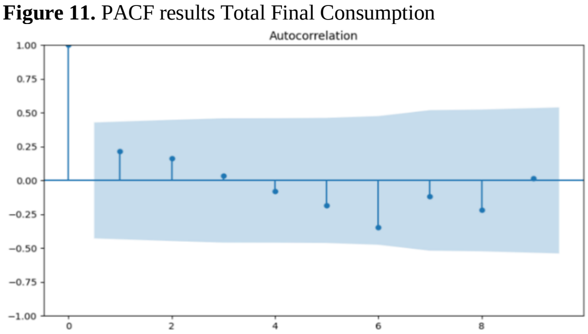

Figure 12. ACF test results Total Final Consumption

Based on these figures p and q are equals to (0). finally ARIMA (0,1,0) model were fitted with the following results:

```
==============================================================================
Dep. Variable:     total final consumption   No. Observations:                22
Model:                      ARIMA(0, 1, 0)   Log Likelihood             -148.054
Date:                     Tue, 11 Jun 2024   AIC                         298.108
Time:                             17:12:19   BIC                         299.153
Sample:                                  0   HQIC                        298.335
                                      - 22
Covariance Type:                       opg
==========================================================================
              coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------
sigma2   7.768e+04   2.71e+04      2.862      0.004    2.45e+04    1.31e+05
==============================================================================
Ljung-Box (L1) (Q):                   1.14   Jarque-Bera (JB):              0.24
Prob(Q):                              0.28   Prob(JB):                      0.89
Heteroskedasticity (H):               5.63   Skew:                         -0.17
Prob(H) (two-sided):                  0.04   Kurtosis:                      3.40
==============================================================================
```

Figure 13. ARIMA for FEC results

As a result the final equation is [$Y_t = Y_{t-1} + \varepsilon_t$] which is, in total final consumption case, a constant equals to [Y_t=7045.2].

3.2.1.3. Model diagnostics

The results of MAPE for the period (2018-2022), for the ARIMA model based on the parameters (0,1,0) are shown in the following table:

Table 7.MAPE results for FEC

Year	ARIMA results	Actual	Error	Absolute Error Percentage
2018	7045.2	6887.2	-158	0.02294
2019	7045.2	6557.6	-487.6	0.07435
2020	7045.2	5774.3	-1270.9	0.22009
2021	7045.2	6221.4	-823.8	0.13241
2022	7045.2	6755.7	-289.5	0.04285
Mean Absolute Error Percentage				10%

The MAPE result for the ARIMA of the total final energy consumption data of 10% is considered good and indicates that the forecasts are reasonably accurate.

3.2.1.4. Forecasting results

The following figure shows the results of the forecasting data through the years (2023-2030) in different color:

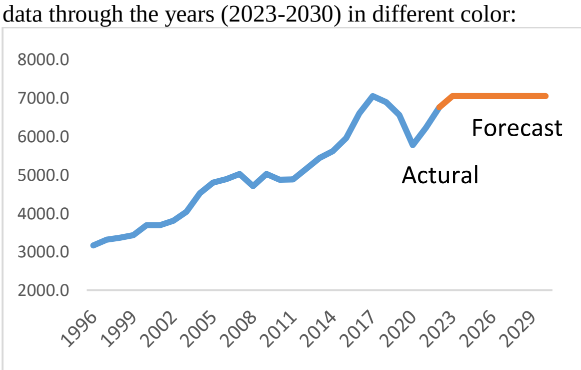

Figure 14. Forecasts of FEC for the period 2023-2030

This suggest that total final energy consumption could reach 7045 ktoe by 2030.

3.2.2. Transport Sector

Sections 3.2.2.1 up to 3.2.2.4 represent the results of the stages described arlier to build and test the ARIMA model for transport sector.

3.2.2.1. Model Identification

The results of the ADF test of the Transport sector consumption data for the period (1996-2017), is as follows:

```
ADF Statistic: 1.7148747968443367
p-value: 0.9981643585767268
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
Initial p-value: 0.9981643585767268
```

which means that the data needs differencing to become stationary. After 1 differencing, the ADF results are:

```
ADF Statistic: -3.8177447725967624
p-value: 0.002730892226109772
Critical Values:
        1%: -3.8326031418574136
        5%: -3.0312271701414204
        10%: -2.655519584487535
```

We can now reject the null hypotheses and be sure that data is not stationary by 95% confidence. And the resulted data after differencing is shown in the following figure:

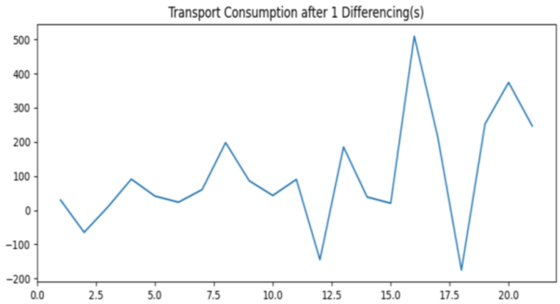

Figure 15. Transport consumption stationary data

3.2.2.2. Parameter estimation

While p, and q are required for fitting our ARIMA model the results of PACF and ACF is shown below:

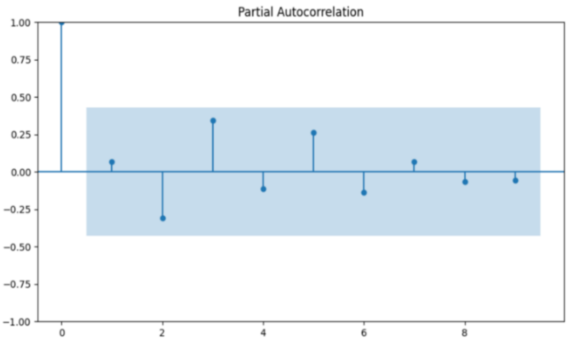

Figure 16. PACF test results for Transport Sector

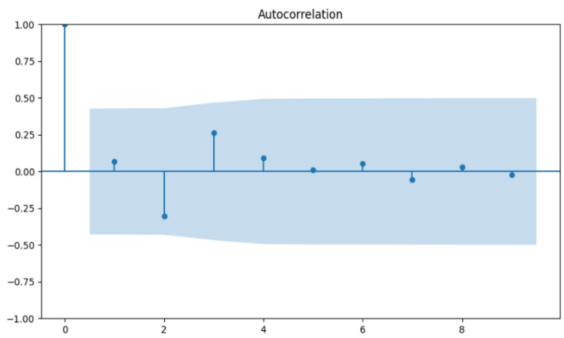

Figure 17. ACF results for Transport Sector

The PACF and ACF tests results suggest that p and q of the model is zero as there are no significant lags.

Which conclude that ARIMA model parameters for Transport sector are (0,1,0). The following figure represents the results of the ARIMA (0,1,0) model:

```
==============================================================================
Dep. Variable:              Transport   No. Observations:                   22
Model:                 ARIMA(0, 1, 0)   Log Likelihood                -139.631
Date:                Thu, 13 Jun 2024   AIC                            281.261
Time:                        09:49:56   BIC                            282.306
Sample:                             0   HQIC                           281.488
                                 - 22
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2       3.49e+04   8867.982      3.935      0.000    1.75e+04    5.23e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.11   Jarque-Bera (JB):                 1.80
Prob(Q):                              0.74   Prob(JB):                         0.41
Heteroskedasticity (H):              31.07   Skew:                             0.67
Prob(H) (two-sided):                  0.00   Kurtosis:                         3.53
===================================================================================
```

As a result the final equation is [$Y_t = Y_{t-1} + \varepsilon_t$] which is in total Transport consumption case a constant equals [Y_t= 3431].

3.2.2.3. Model diagnostic

To calculate MAPE for the proposed model the following table finalize the results for the years (2018-2022) for transport sector consumption:

Table 8.MAPE results for Transport sector consumption

year	ARIMA results	Actual	absolute percentage error
2018	3431.3	3363.4	0.020187905
2019	3431.3	3074.1	0.11618164
2020	3431.3	2307.7	0.486910286
2021	3431.3	2676.8	0.281875353
2022	3431.3	2923.8	0.173575484
		MAPE	22%

As shown above the model considered moderately good fit for the forecasted variable as 22% result of MAPE means.

3.2.2.4. Forecast results

The following figure shows the predicted values for the period 2023 – 2030 in different color:

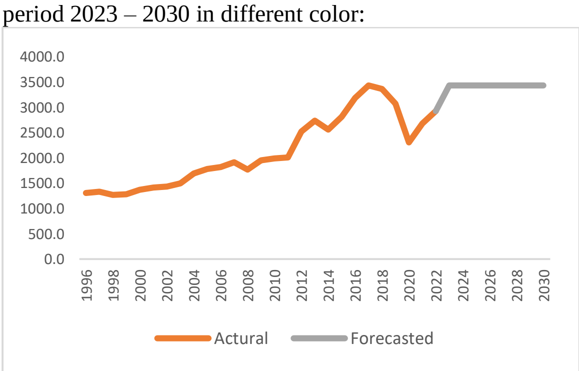

Figure 18. Forecasted results of Transport Sector (2023 - 2030)

The forecasted results suggest an increase in Transport sector final consumption reaching (3431.3 ktoe) in 2030.

3.2.3. Residential Sector

Sections 3.2.3.1 up to 3.2.3.4 represent the results of the stages described earlier to build and test the ARIMA model for residential sector.

3.2.3.1. Model Identification

The results of ADF are shown below where it is concluded that data are not stationary with positive ADF stat:

```
ADF Statistic: 0.4836029335207516
p-value: 0.9843661070442601
Critical Values:
        1%: -3.8092091249999998
        5%: -3.0216450000000004
        10%: -2.6507125
Initial p-value: 0.9843661070442601
```

After 1 differencing, results show that data become stationary with 99% confidence of the test results, as shown below:

```
ADF Statistic: -3.805347503927232
p-value: 0.0028530744600732904
Critical Values:
        1%: -3.8092091249999998
        5%: -3.0216450000000004
        10%: -2.6507125
```

Find below the representation of the data after differencing took place:

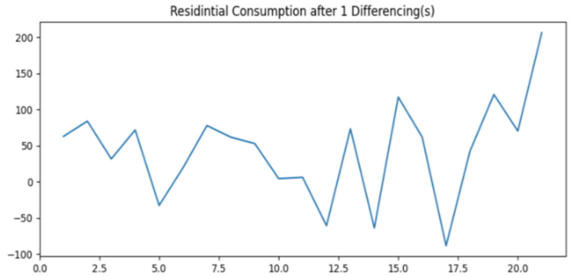

Figure 19. Residential Sector data after differencing

3.2.3.2. Parameter estimation

To find p and q the following PACF and ACF test occurred and the results are as shown:

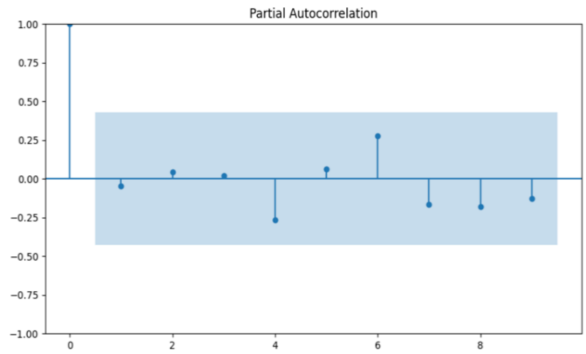

Figure 20. PACF results of Residential sector

PACF test shows no significant lags.

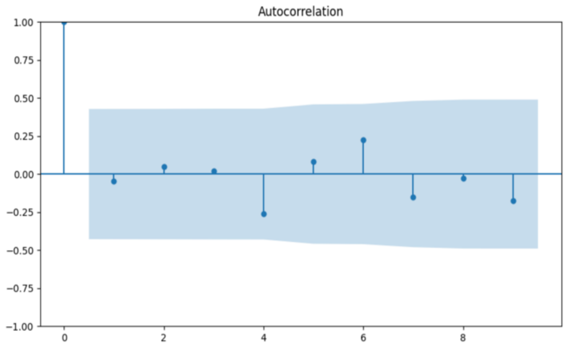

Figure 21. ACF test results for Residential sector

ACF test results shows no significant lags too. In conclusion p and q are zeros.

The results of the ARIMA (0,1,0) model for Residential sector is shown below:

```
==============================================================================
Dep. Variable:              Household   No. Observations:                   22
Model:                 ARIMA(0, 1, 0)   Log Likelihood                -121.746
Date:                Thu, 13 Jun 2024   AIC                            245.491
Time:                        10:54:41   BIC                            246.536
Sample:                             0   HQIC                           245.718
                                 - 22
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
sigma2      6354.5326   1975.781      3.216      0.001    2482.074    1.02e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.05   Jarque-Bera (JB):                 0.07
Prob(Q):                              0.83   Prob(JB):                         0.97
Heteroskedasticity (H):               3.63   Skew:                             0.01
Prob(H) (two-sided):                  0.11   Kurtosis:                         3.28
===================================================================================
```

these results suggest that transport sector energy consumption equation is $[Y_t = Y_{t-1} + \varepsilon_t]$ which is this case a constant equals $[Y_t = 1548.6]$.

3.2.3.3. Model diagnostic

The table below shows the MAPE calculations for the residential sector based on ARIMA (0,1,0) model results.

Table 9. MAPE results for Residential sector model

year	ARIMA results	Actual	absolute error percentage
2018	1548.6	1463.5	0.05814827
2019	1548.6	1484.1	0.0434876
2020	1548.6	1487.3	0.04121942
2021	1548.6	1520.2	0.01866238
2022	1548.6	1518.4	0.01988936
		MAPE	4%

With MAPE result of no more than 4% the proposed ARIMA model considered reasonably accepted.

3.2.3.4. Forecasting results

The following figure represent the forecasted results for the period (2023 – 2030):

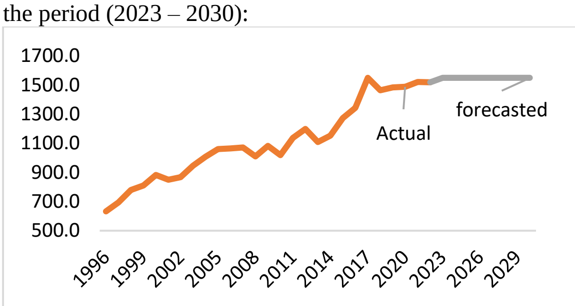

Figure 22. Forecasted results of Residential (2023 - 2030)

The main result suggest that Residential sector energy consumption will reach 1548.6 in 2030.

3.2.4. Industrial Sector

Sections 3.2.4.1 up to 3.2.4.4 represent the results of the stages described earlier to build and test the ARIMA model for Industrial sector.

3.2.4.1. Model Identification

The results of ADF are shown below where it is concluded that data are not stationary with relatively high ADF statvalue:

```
ADF Statistic: -0.41411082361806095
p-value: 0.9077159821908853
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
Initial p-value: 0.9077159821908853
```

After 2 differencing results shows that data became stationary with 99% confidence of the test results, as shown below:

```
ADF Statistic: 0.5067175538874819
p-value: 0.9850758471450277
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
ADF Statistic: -11.873731153987052
p-value: 6.413374996017888e-22
Critical Values:
        1%: -4.223238279489106
        5%: -3.189368925619835
        10%: -2.729839421487603
```

Find below the representation of the data after deferencing took place:

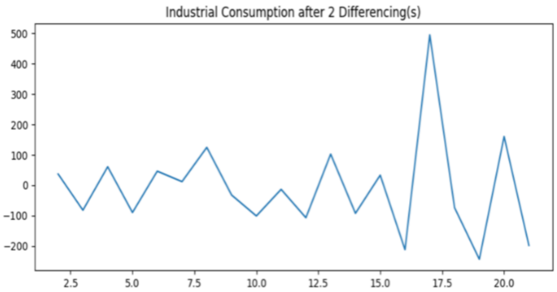

Figure 23. Industrial consumption data after differencing

3.2.4.2. Parameter estimation

To find p and q the following PACF and ACF test occurred and the results are as shown:

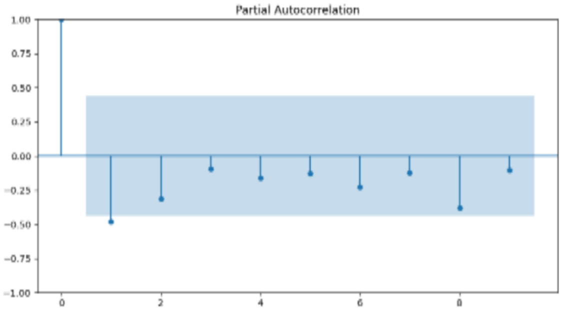

Figure 24. PACF results for Industrial Sector

PACF test shows one significant lags.

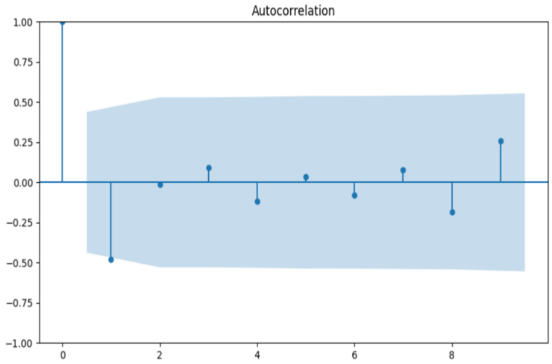

Figure 25. ACF test results for Industrial Sector

ACF test results shows one significant lag. In conclusion p is zero and q is one.

The results of the ARIMA (0,2,1) model for Industrial sector is shown below:

```
==============================================================================
Dep. Variable:               Industry   No. Observations:                   22
Model:                 ARIMA(0, 2, 1)   Log Likelihood                -124.165
Date:                Thu, 13 Jun 2024   AIC                            252.330
Time:                        11:40:22   BIC                            254.322
Sample:                             0   HQIC                           252.719
                                 - 22
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.9813      0.471     -2.085      0.037      -1.904      -0.059
sigma2      1.264e+04   6166.882      2.050      0.040     557.619    2.47e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.15   Jarque-Bera (JB):                 0.09
Prob(Q):                              0.70   Prob(JB):                         0.96
Heteroskedasticity (H):               8.36   Skew:                             0.06
Prob(H) (two-sided):                  0.01   Kurtosis:                         3.30
===================================================================================
```

3.2.4.3. Model diagnostic

The table below shows the MAPE calculations for the Industrial sector based on ARIMA (0,2,1) model results.

Table 10. MAPE results for Industrial sector

year	ARIMA results	Actual	absolute error percentage
2018	951.6	953.5	0.001988835
2019	965.0	890.8	0.083253549
2020	978.4	934.7	0.046758585
2021	991.8	1016.6	0.024366707
2022	1005.2	1078.9	0.06829342
		MAPE	4%

With MAPE result of no more than 4% the proposed ARIMA model considered reasonably accepted.

3.2.4.4. Forecasting results

The following figure represent the forecasted results for the period (2023 – 2030):

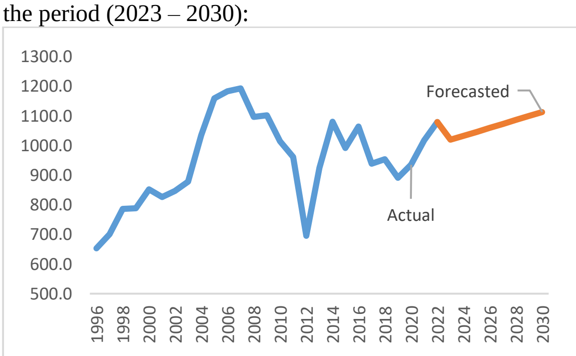

Figure 26. Industrial Sector Forecast (2023-2030)

Average annual increasing rate between 2023 and 2030 could reach (3%) and with suggested value for 2030 of (1112.4 ktoe)

3.2.5. Services Sector

Sections 3.2.5.1 up to 3.2.5.4 represent the results of the stages described earlier to build and test the ARIMA model for Services sector.

3.2.5.1. Model Identification

The results of ADF are shown below where it is concluded that data are not stationary with relatively high ADF statvalue:

```
ADF Statistic: -0.3937641599368771
p-value: 0.9111347445707949
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
Initial p-value: 0.9111347445707949
```

After 2 differencing, results show that data became stationary with 99% confidence of the test results, as shown below:

```
ADF Statistic: -1.898559081858967
p-value: 0.3327392674378773
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
ADF Statistic: -4.2982453456120915
p-value: 0.00044733053801577734
Critical Values:
        1%: -3.8326031418574136
        5%: -3.0312271701414204
        10%: -2.655519584487535
```

Find below the representation of the data after differencing took place:

Figure 27. Services sector data after differencing

3.2.5.2. Parameter estimation

To find p and q the following PACF and ACF test occurred and the results are as shown:

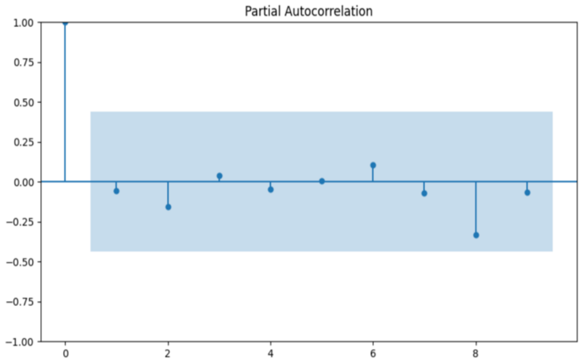

Figure 28. PACF test results for Services sector

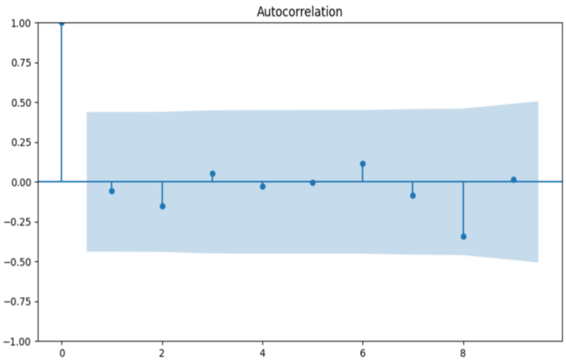

Figure 29. ACF results for Services sector

ACF test results shows no significant lags too. In conclusion p is zero, however, the model suggests the value of q to be 8. But after reviewing the MAPE for the ARIMA(0,2,8) model it was 36% so using trial and error ARIMA(0,2,5) has lower MAPE so the latest were used in the forecasting.

The results of the ARIMA (0,2,5) model for Services sector is shown below:

```
==============================================================================
Dep. Variable:               Services   No. Observations:                   22
Model:                 ARIMA(0, 2, 5)   Log Likelihood                 -84.134
Date:                Thu, 13 Jun 2024   AIC                            180.267
Time:                        12:35:13   BIC                            186.242
Sample:                             0   HQIC                           181.433
                                 - 22
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.2380    174.385     -0.001      0.999    -342.026     341.550
ma.L2         -0.2921    132.936     -0.002      0.998    -260.843     260.258
ma.L3         -0.1186     81.950     -0.001      0.999    -160.737     160.500
ma.L4         -0.3090     61.271     -0.005      0.996    -120.398     119.780
ma.L5         -0.0418      7.481     -0.006      0.996     -14.705      14.621
sigma2       238.6091   4.16e+04      0.006      0.995   -8.13e+04    8.18e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 1.68
Prob(Q):                              0.96   Prob(JB):                         0.43
Heteroskedasticity (H):               1.08   Skew:                            -0.35
Prob(H) (two-sided):                  0.92   Kurtosis:                         1.77
===================================================================================
```

3.2.5.3. odel diagnostic

The table below shows the MAPE calculations for the Services sector based on ARIMA (0,2,5) model results.

Table 11. MAPE results for Services sector

year	ARIMA results	Actual	Absolute percentage error
2018	500.9	448.0	0.118080357
2019	530.6	456.1	0.163389228
2020	554.2	399.0	0.388988041
2021	570.6	441.7	0.291942575
2022	585.9	634.7	0.076886718
		MAPE	21%

With MAPE result of about 21% the proposed ARIMA model considered reasonably accepted.

3.2.5.4. Forecasting results

The following figure represent the forecasted results for the period (2023 – 2030):

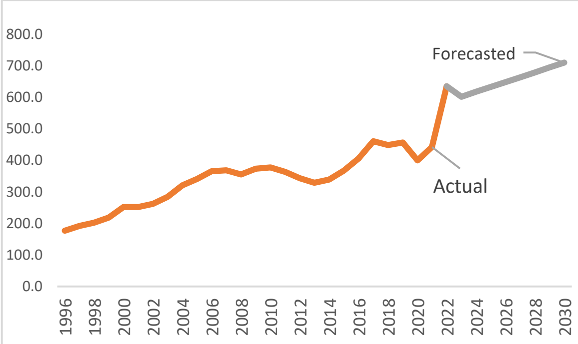

Figure 30.forecasted results of Services Sector (2023 - 2030)

As forecasting results suggest average annual increasing rate between 2023 and 2030 of about 12%. reaching 709 ktoe in 2030.

3.2.6. Other Sectors Energy Consumption

Sections 3.2.6.1 up to 3.2.6.4 represent the results of the stages described earlier to build and test the ARIMA model for Other sectors consumption.

3.2.6.1. Model Identification

The results of ADF are shown below where it is concluded that data are not stationary with relatively high ADF statvalue:

```
ADF Statistic: 0.6039663425237817
p-value: 0.9877129857601531
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
Initial p-value: 0.9877129857601531
```

After 1 differencing, results show that data became stationary with 90% confidence of the test results, as shown below:

```
ADF Statistic: -3.4469796887437725
p-value: 0.009457865640567142
Critical Values:
        1%: -4.137829282407408
        5%: -3.1549724074074077
        10%: -2.7144769444444443
```

Find below the representation of the data after differencing took place:

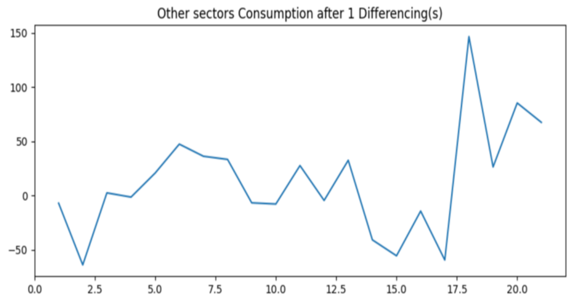

Figure 31. Other sectors data after differencing

3.2.6.2. Parameter estimation

To find p and q the following PACF and ACF test occurred and the results are as shown:

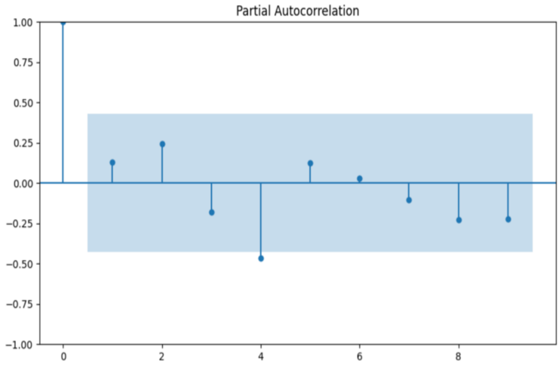

Figure 32. PACF test results for other sectors

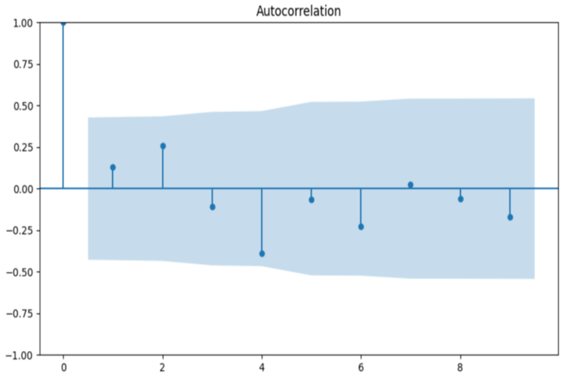

Figure 33. ACF results for other sectors

PACF, and ACF test results shows one significant lag. In conclusion p is zero, however, the model suggests the value of q to be 4.

The results of the ARIMA (0,1,4) model for Other sectors is shown below:

```
==============================================================================
Dep. Variable:          other sectors   No. Observations:                   22
Model:                 ARIMA(0, 1, 4)   Log Likelihood                -107.476
Date:                Thu, 13 Jun 2024   AIC                            224.951
Time:                        13:09:13   BIC                            230.174
Sample:                             0   HQIC                           226.085
                                 - 22
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1          0.1237      3.810      0.032      0.974      -7.345       7.592
ma.L2          0.7349    192.876      0.004      0.997    -377.295     378.765
ma.L3          0.1706     31.823      0.005      0.996     -62.201      62.542
ma.L4         -0.2586     50.399     -0.005      0.996     -99.039      98.522
sigma2      1336.6861   2.59e+05      0.005      0.996   -5.07e+05    5.09e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.02   Jarque-Bera (JB):                11.79
Prob(Q):                              0.90   Prob(JB):                         0.00
Heteroskedasticity (H):               4.63   Skew:                             1.10
Prob(H) (two-sided):                  0.06   Kurtosis:                         5.94
===================================================================================
```

3.2.6.3. Model diagnostic

The table below shows the MAPE calculations for the Services sector based on ARIMA (0,1,4) model results.

Table 12. MAPE results for Services sector

year	ARIMA results	Actual	Absolute percentage error
2018	650.5	658.8	0.012598664
2019	668.6	652.4	0.024759635
2020	670.7	645.7	0.038784396
2021	663.5	566.1	0.17196504
2022	663.5	599.9	0.10601767
		MAPE	6%

With MAPE, no more than 6% of the proposed ARIMA model is considered reasonably accepted.

3.2.6.4. Forecasting results

The following figure represent the forecasted results for the period (2023 – 2030):

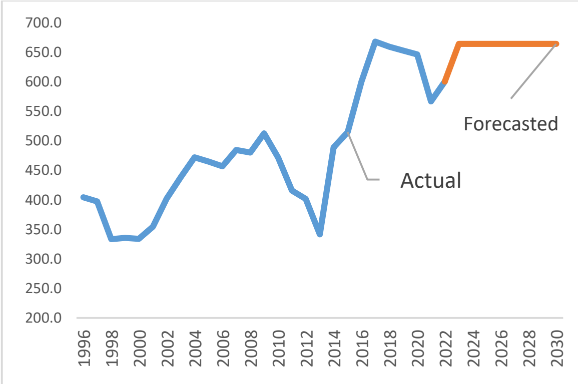

Figure 34. forecasted results of Services Sector (2023 - 2030)

As forecasting results suggest, average annual increasing rate between 2023 and 2030 of about 11% will be expected, reaching 663 ktoe in 2030.

4. Conclusion

ARIMA model is an effective way to predict time series data future trends. Augmented Dicky-fullr test, ACF and PACF tests were conducted in the design process of the model for each sector. Total final energy consumption is expected to reach 7045 ktoe based on ARIMA(0,1,0) model forecast with 10% MAPE. Transport sector is estimated to reach 3431.3 ktoe based on ARIMA (0,1,0) model with MAPE of (22%). In addition, Residential sector is estimated to reach 1548 ktoe based on the result of ARIMA (0,1,0) model with MAPE of (4%). Finally Industrial, Services and Other sectors energy consumptions were forecasted to reach 1112 , 709 , and 665 ktoe respectively with (4%) , (21%) and (6%) MAPE results for ARIMA(0,2,1) , ARIMA(0,2,5) and ARIMA(0,1,4) models for these sectors respectively.

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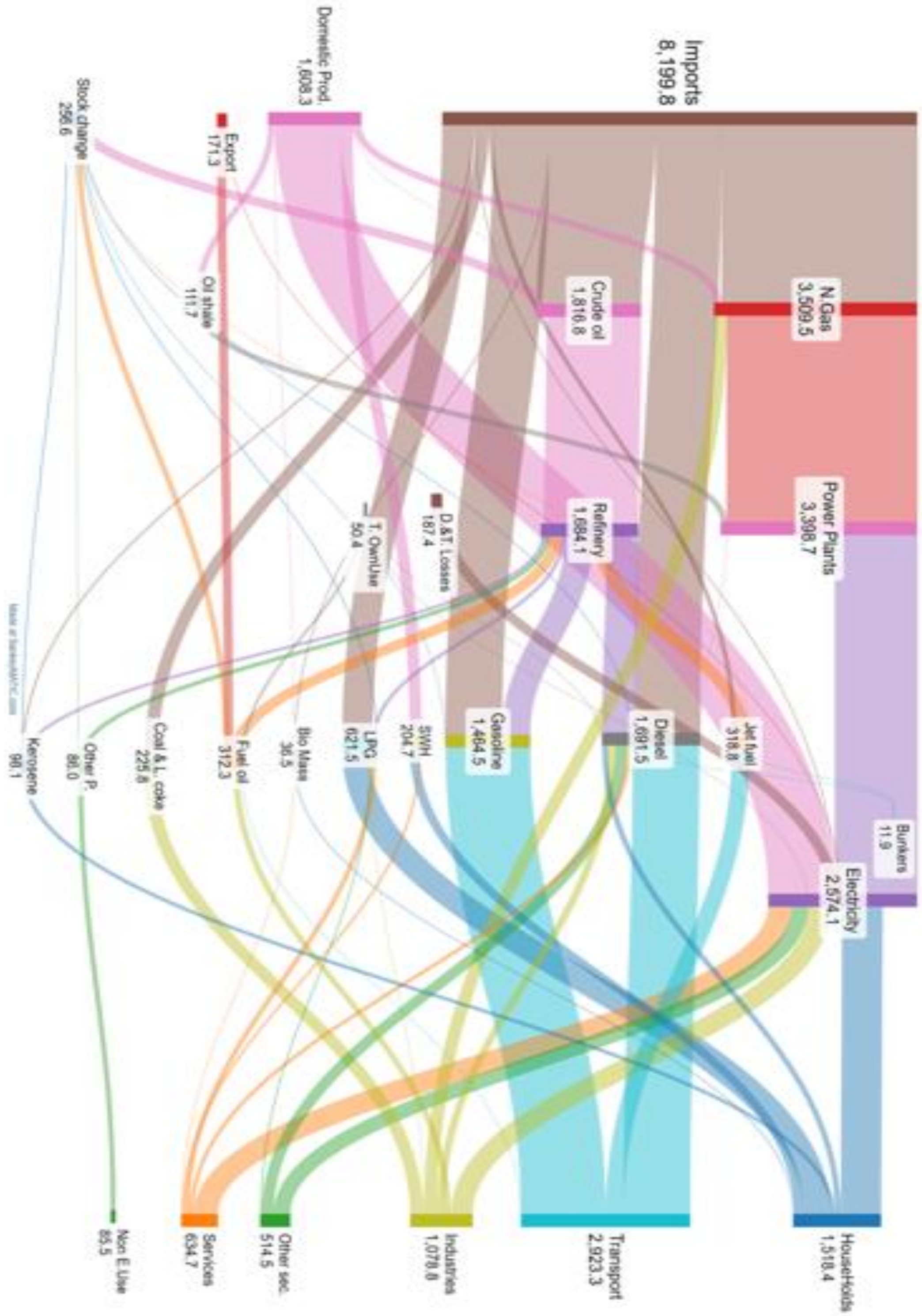
Appendix


Imports
8,199.8
Domestic Prod.
1,608.3
Stock change
256.6
Export
171.3
Oil shale
111.7
Crude oil
1,816.8
N.Gas
3,509.5
Power Plants
3,398.7
Refinery
1,684.1
D.&T. Losses
187.4
T. OwnUse
50.4
Kerosene
98.1
Other P.
86.0
Coal & L. coke
225.8
Fuel oil
312.3
Bio Mass
36.5
LPG
621.5
SWH
204.7
Gasoline
1,464.5
Diesel
1,691.5
Jet fuel
318.8
Bunkers
11.9
Electricity
2,574.1
Non E.Use
85.5
Services
634.7
Other sec.
514.5
Industries
1,078.8
Transport
2,923.3
HouseHolds
1,518.4