Predicting the Sales and Revenues of four products of the REC Corp LTD company for 2023 and 2024

Steps:

1. **Project Proposal**
2. **Data Wrangling and Exploratory Data Analysis**
3. **Preprocessing and Modeling**

Source:
https://www.kaggle.com/datasets/ksabishek/product-sales-data/data

1. Project Proposal:

1.1 Predicting the sales and revenues for the year 2023 and 2024

REC Corp LTD. is small-scaled business venture established in India. They have been selling four products for over ten years.
They have collected data from their retail centers and organized it into a csv file, which has been given to you.
The excel file contains about 8 numerical parameters below and the time column:

Product Number	Total unit sales of product
1	Q1
2	Q2
3	Q3
4	Q4

Product Number	Total revenue from product
1	S1
2	S2
3	S3
4	S4

Now, REC Corp needs me to solve the following questions:
1) Is there any trend in the sales of all four products during certain months?
2) Out of all four products, which product has seen the highest sales in all the given years?
3) The CEO is considering an idea to drop the production of any one of the products. He wants you to analyze this data and suggest whether his idea would result in a massive setback for the company.
4) The CEO would also like to predict the sales and revenues for the year 2023 and 2024. He wants you to give a yearly estimate with the best possible accuracy.

I answer first three questions in Data Wrangling and Exploratory Data Analysis part. Last question is related to predict the model and I will answer it in Preprocessing and Modeling.

I will try to create a good model that it can perfectly predict sales and revenue in 2023 and 2024.

I will try to use AR| ARMA| ARIMA| SARIMA| SARIMAX concepts to predict data.

Data wrangling and EDA are the parts that I can get insights and watch their patterns that I can use later. Preprocessing and Modeling are the most important part that I have to create model and I will try to draw the best prediction, when I can compare actual data with my prediction.
In modeling part, I select the best P, Q, R that it has the lowest AIC and after that I will calculate RMSE. Then I will compare them, I select the specific P, Q, R with the lowest RMSE. Finally, I will draw the conclusions that I can compare them.

I will forecast the sales of product 1 (First Time Series), I will forecast others time series and other conclusion in Appendix part that you can check it if you are interested in.

2. Data Wrangling and Exploratory Data Analysis

- ## 2.1 Introduction

Data wrangling and EDA are the parts that I can get insights and watch their patterns that I can use later. Fortunately, the data is clean, and it doesn't have missing values.

In this part, I try to clean data and prepare it for EDA (Exploratory Data Analysis). I have 9 columns that are date, QP1, QP2, QP3, QP4, SP1, SP2, SP3, and SP4. The types of data are normal, but date column is object. After converting the date column, I found out I have 26 NA values. I delete them.

I will try to convert it to datetime. I will put date time as index later.

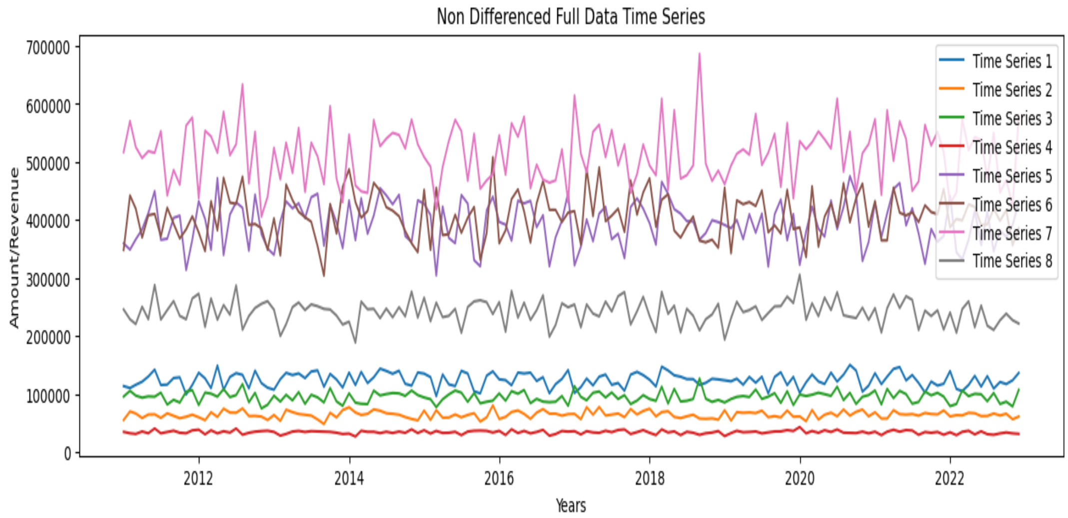
Our dates are between 2010-07 to 2023-12. When I compare all data, I will figure out the best data that I can use are between from 2011 to end of 2022. So, I can create a model that can predict the data in 2023 and 2024. I will explain it later.

The dates start from first day of month that it is easy to find out the trends. Our trends are continuous.

- ## 2.2 Data wrangling

Appendix 1) Distribution of our raw data. (You can check it at the end)

▪ 2.3 Exploratory Data Analysis (EDA)



Here is the question that CEO asked before:

Now, REC Corp needs you to solve the following questions:

1. Is there any trend in the sales of all four products during certain months?
2. Out of all four products, which product has seen the highest sales in all the given years?
3. The CEO is considering an idea to drop the production of any one of the products. He wants you to analyze this data and suggest whether his idea would result in a massive setback for the company.
4. The CEO would also like to predict the sales and revenues for the year 2024. He wants you to give a yearly estimate with the best possible accuracy.

Answers:

1. There is not any special trend in our data except that in 2010 and 2023 we have some specific trend for quantity and revenue sales. The reason is that our data in 2010 and 2023 are incomplete. I will remove them later.
2. Product 1 has the highest sales. Product 4 has the lowest sales. product 2 has greater quantity sales in comparing to product 3, however their revenues sales trend and amount are approximately equal.
3. If CEO decided to drop one product, I would suggest to drop product 4. because product 4 has the lowest quantity and revenue sales.
4. There is no answer in Data Wrangling and EDA. I will answer this question later. It needs to create a model for this question.

3 Preprocessing and Modeling

3.1 Introduction

There is a request that I have to answer it. This request needs to predict the data, so I have to create a model that can predict it.

The request is below (4th question):

4th) The CEO would also like to predict the sales and revenues for the year 2023 and 2024. He wants you to give a yearly estimate with the best possible accuracy.
I want to use AR, ARMA, ARIMA, and SARIMA model for prediction.

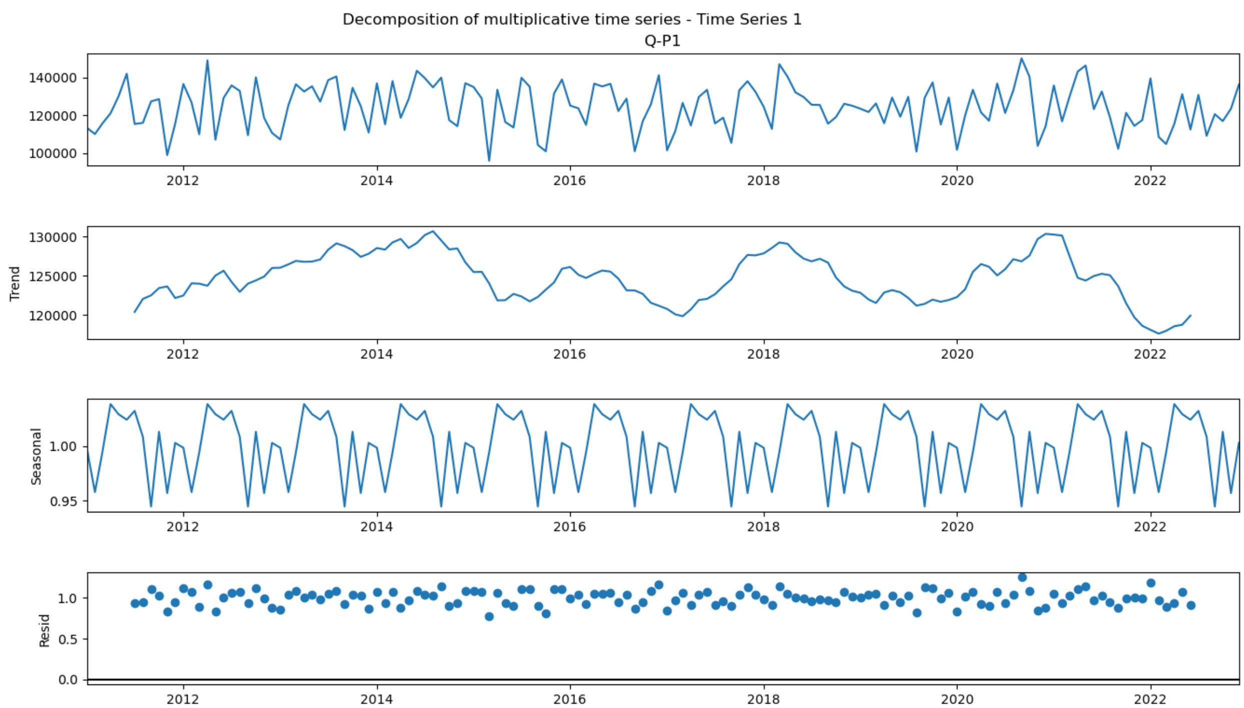
Select the Data

In previous part when I wanted to wrangle the data and explore data analysis, I found out the dates that are incomplete in 2010, 2023. Here, I decided to remove them. After that I will select the data between 2011 to 2019 as a train data. I will select the data between 2020 to 2022 as a test data. Test data size is 18% (2/11).

3.2 Time Series Decomposition

Here, I want to define the trend, seasonal, residual, and observed of changes to show what the data tell me.

I want to create the charts to find out these concepts of my data.



There are some differences in details, when I compare all 8-time series. But they look similar. The residuals for all time series don't have specific trend and pattern.

Observations of sales of product 1:

1.Trend: 12-months is a fairly straight line indicating a linear trend. Increasing at the first and decreasing at the end. But sales have the fixed average for all data.

are clear. As we notice before, we prefer to work on 2011-2022, because we have missing values in 2011, 2023, and 2024. and I decide to predict 2023 to 2024.

2.Seasonality: Changing seasonally of 12 months is clearly visible.

3 Irregular Remainder (random): The multiplicative model works as there are no patterns in the residuals.

How to Make a Time Series Stationary?

- Differencing 'd'
- Differencing 'd' is done on a non-stationary time series data one or more times to convert it into stationary.
- (d=1) 1st order differencing is done where the difference between the current and previous (1 lag before) series is taken and then checked for stationarity using the ADF (Augmented Dicky Fueller) test. If differenced time series is stationary, we proceed with AR modeling. Else we do (d=2) 2nd order differencing, and this process repeats till we get a stationary time series
- 1st order differencing equation is : $yt = yt - yt - 1yt = yt - yt - 1$
- 2nd order differencing equation is : $yt = (yt - yt - 1) - (yt - 1 - yt - 2) yt = (yt - yt - 1) - (yt - 1 - yt - 2)$ and so on…
- The variance of a time series may also not be the same over time. To remove this kind of non-stationarity, we can transform the data. If the variance is increasing over time, then a log transformation can stabilize the variance.

3.2.1 Non-Differenced Full Data Time Series

Appendix 3) Non-Differenced Full Data Time Series

3.2.2 Performing Differencing (d=1) as the Data is non-stationary

Appendix 4) Performing Differencing (d=1) as the Data is non-stationary for all-time series.

3.2.3 Performing differencing (d=2) as the data is non-stationary

Appendix 5) Performing differencing (d=2) as the data is non-stationary

We observe seasonality even after differencing. This suggests a log transformation of the data.

3.2.4 Log Transformed Time Series

Appendix 6) Log Transformed Time Series

3.2.5 Performing differencing (d=1) on the log transformed time series

Appendix 7) Performing differencing (d=1) on the log transformed time series

3.2.6 Performing differencing (d=2) on the log transformed time series

Appendix 8) Performing differencing (d=2) on the log transformed time series

3.3 Train Test Split

As I decided before I want to use AR, ARMA, ARIMA, and SARIMA model for prediction.

These models have some parameters that are below:

- p and seasonal P: indicate number of autoregressive terms (lags of the stationaries series)
- d and seasonal D: ...
- q and seasonal Q: indicate number of moving average terms (lags of the forecast errors)
- s: indicates seasonal length in the data.

I define these parameters here below:

p = 1, 2, 3

d = 0, 1

q = 1, 2, ,3

Here I try to select train data 2011 to 2020. I select test data 2020 to 2022.

P-values are approximately zero. We know it can't be zero, but it can be close to zero. Using the log transformed series as there is variance in the data.

3.4 Modeling for Q-P1 (The sales of product 1)

Here I want to select quantity sales of product 1 (Ignoring other columns). Then I will try to create and predict the data. If I wanted to work on all columns, the process will be too complicated.

As I selected, I will try AR, ARMA, ARIMA, and SARIMA for product 1 here.

3.4.1 AR Model for Q-P1 (The sales of product 1)

AR Model: Autoregressive

Use previous time period values to predict the current time period values AR Model building to estimate best 'p' (Lowest AIC Approach)

The best one with lowest AIC (Akaike Information Criteria) for quantity sales of product 1 is ARIMA (2, 0, 0).

3.4.1.1 Calculating RMSE with the best AR model for Q-P1 (The quantity of product 1)

The Root Mean Squared Error of our forecasts is 12674.089

3.4.1.2 Drawing Train, Test, and Forecasted data with Best AR Model for the Quantity of product 1 per Year:

Appendix 9) Drawing Train, Test, and Forecasted data with Best AR Model for the Quantity of product 1 per Year

3.4.2 ARMA Model for Q-P1 (The sales of product 1)

- Improving Autoregressive Models through Moving Average Forecasts.
- ARMA models consist of 2 components: -
- AR model: The data is modeled based on past observations.
- MA model: Previous forecast errors are incorporated into the model.

ARMA Model building to estimate best 'p', 'q' (Lowest AIC Approach)

The best one with lowest AIC for quantity sales of product 1 is ARMA (1, 0, 1).

3.4.2.1 Calculating RMSE with best MA model for Q-P1 (The quantity of product 1)

The Root Mean Squared Error of our forecasts is 12634.902

3.4.2.2 Drawing Train, Test, and Forecasted data with Best ARMA Model for the Quantity of product 1 per Year:

Appendix 10) Drawing Train, Test, and Forecasted data with Best ARMA Model for the Quantity of product 1 per Year

3.4.3 ARIMA Model for Q-P1 (The sales of product 1)

Appendix 10) ARIMA Model Structure

- ARIMA: Auto Regressive Integrated Moving Average is a way of modeling time series data for forecasting or predicting future data points.
- Improving AR Models by making Time Series stationary through Moving Average Forecasts
- ARIMA models consist of 3 components
- AR model: The data is modeled based on past observations.
- Integrated component: Whether the data needs to be differenced/transformed.
- MA model: Previous forecast errors are incorporated into the model.

The best one with lowest AIC for quantity sales of product 1 is ARIMA (1, 0, 1). The results of ARMA and ARIMA are exactly the same. So, we predict the results of them for quantity sales of product 1 should be the same, as well.

3.4.3.1 Calculating RMSE with best ARIMA model for Q-P1 (The quantity of product 1)

The best parameter is ARIMA (1, 0, 1) that is the same as ARMA. So, the RMSE of ARIMA is RMSE of ARMA

The Root Mean Squared Error of our ARIMA forecasts is 12634.902

3.4.3.2 Drawing Train, Test, and Forecasted data with Best ARIMA Model for the Quantity of product 1 per Year:

Appendix 11) Drawing Train, Test, and Forecasted data with Best ARMA Model for the Quantity of product 1 per Year

3.4.4 SARIMA Model for Q-P1 (The sales of product 1)

- The ARIMA models can be extended/improved to handle seasonal components of a data series
- The seasonal autoregressive moving average model is given by

SARIMA (p, d, q) (P, D, Q) m non-seasonal seasonal

- The above model consists of:
- Autoregressive and moving average components (p, q)
- Seasonal autoregressive and moving average components (P, Q)
- The ordinary and seasonal difference components of order ‘d’ and ‘D’
- Seasonal frequency ‘F’
- The value for the parameters (p, d, q) and (P, D, Q) can be decided by comparing different values for each and taking the lowest AIC value for the model build.
- The value for F can be consolidated by ACF plot

Inference * Criteria to choose the best fit model is the lowest/minimum AIC value For ARIMA (p, d, q) × (P, D, Q) S, we got SARIMAX (3, 1, 3) x (3, 1, 3, 12) model with the least AIC of 3984.33757 Here,

- p = non-seasonal AR order = 3,
- d = non-seasonal differencing = 0,
- q = non-seasonal MA order = 3,
- P = seasonal AR order = 3,
- D = seasonal differencing = 1,
- Q = seasonal MA order = 3,
- S = time span of repeating seasonal pattern = 12 Building SARIMA model with the best parameters

3.4.4.1 RMSE with the best SARIMA Model for Q-P1 (The sales of product 1)

The Root Mean Squared Error of our forecasts SARIMA_0 is 12001.957

3.4.4.2 Drawing Train, Test, and Forecasted data with Best SARIMA Model for the sales of product 1 per Year

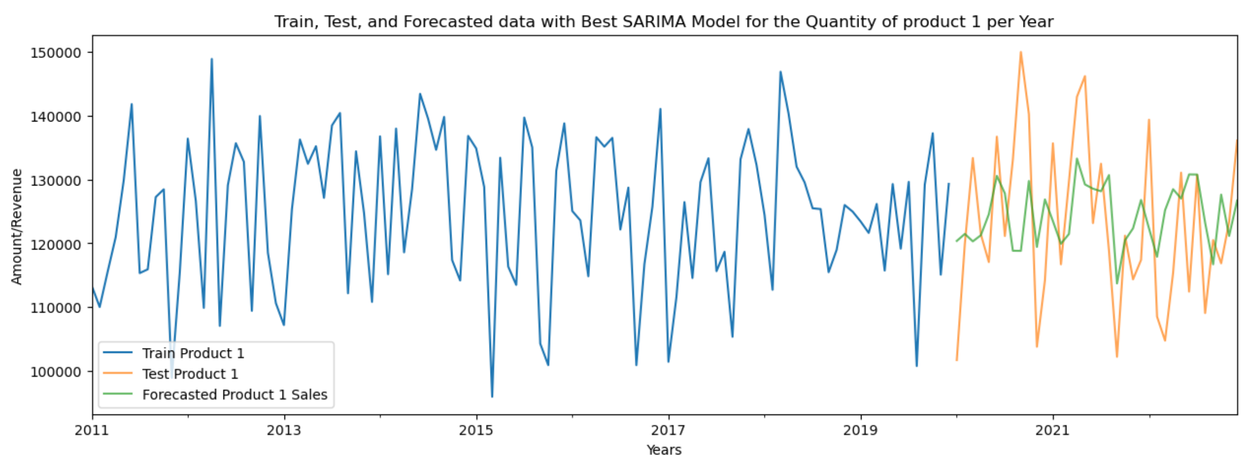
Appendix 12) Drawing Train, Test, and Forecasted data with Best SARIMA Model for the Quantity of product 1 per Year

3.4.5 Conclusion for Q-P1 (The sales of product 1):

Now we compare the RMSE for all models.

	RMSE
Best AR Model Product 1: AR (2,0,0)	12674.088666
Best ARMA Model Product 1: ARMA (1, 0, 1)	12634.901547
Best ARIMA Model Product 1: ARIMA (1,0,1)	12634.901547
Best SARIMA Model product 1: SARIMA (3, 1, 3) x (3, 1, 3, 12)	12001.956713

Here Sarima has the lowest RMSE (12001.95), so, It's the best model.



Appendix 13) All of these process for other time series

3.4.5.1 Forecast with the best model with the lowest RMSE

When plotting a forecast along with confidence bands of 99% and 95%, we're visualizing the uncertainty inherent in the prediction. The forecast itself represents the most likely outcome, while the confidence bands indicate the range within which we expect the actual outcomes to fall with a certain level of certainty. The 99% confidence band is wider than the 95% band, reflecting a higher level of confidence in capturing the true outcome within that range.

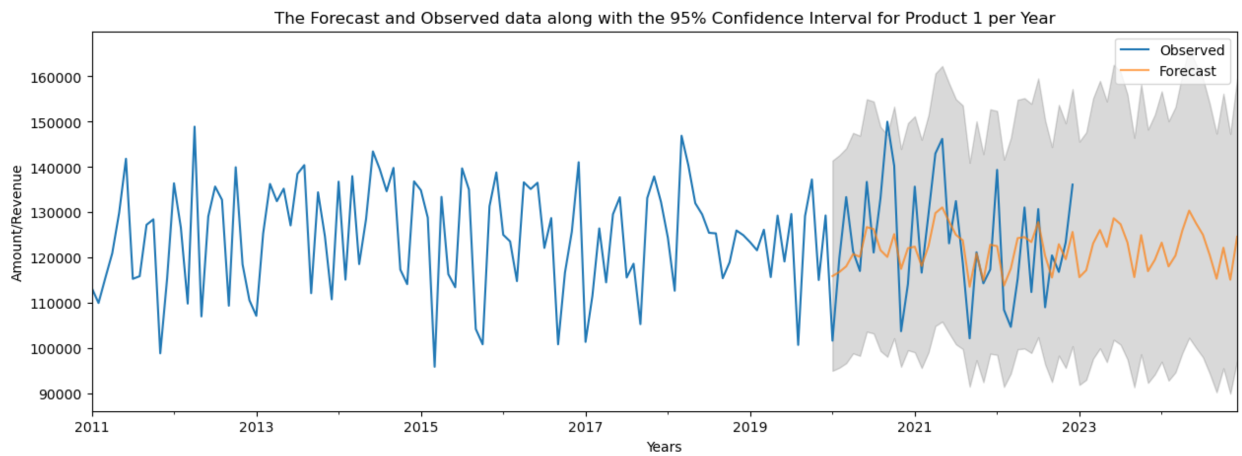
Essentially, if we were to repeat the forecasting process numerous times, we'd expect about 99% (or 95%) of the actual outcomes to fall within the respective confidence bands. This visualization is crucial for decision-makers, as it helps them understand the range of potential outcomes and make informed choices considering the associated uncertainty.

I decide to visualize with the 95% confidence band.

Appendix 13) Forecast table of the best model with the lowest RMSE 95% confidence interval

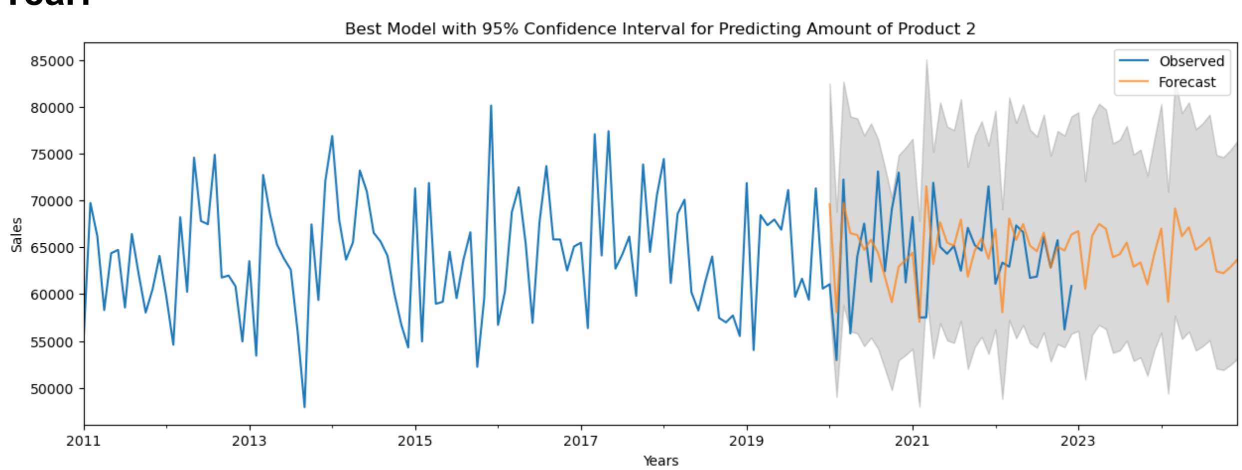
3.4.5.2 Draw the Forecast Observed data along with the 95% Confidence Interval for Sales of Product 1 per Year:

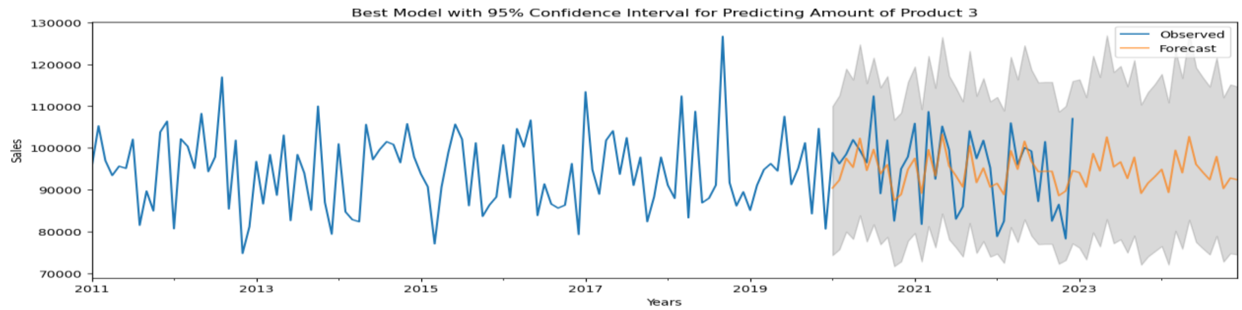
The final result of forecasting sales of product 1 is here.

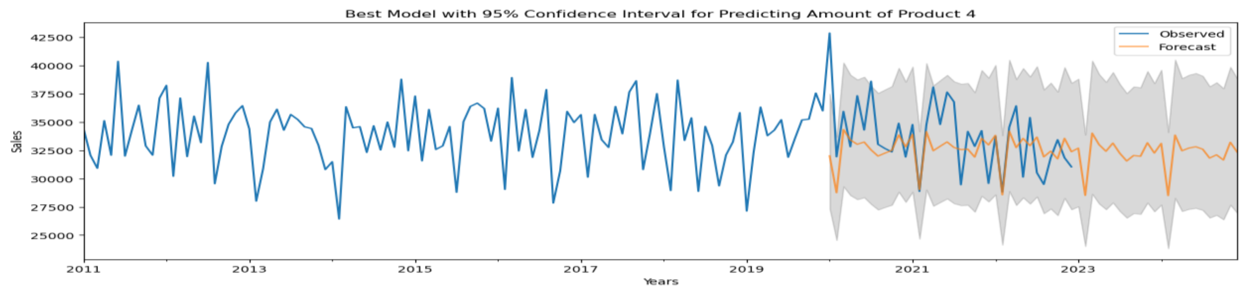


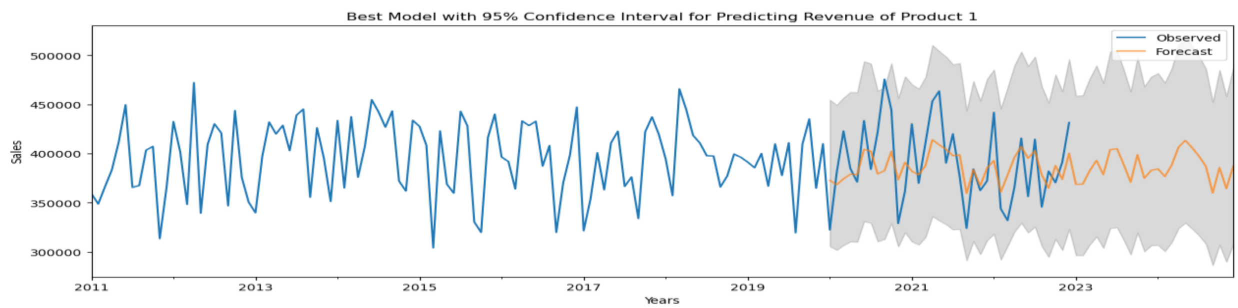
So, we can see the 4th request of the CEO. As we can see we can use the best model (SARIMAX (3, 1, 3) x (3, 1, 3, 12)) for product 1, and we can predict the sales of product 1 for 2023, 2024 and etc.

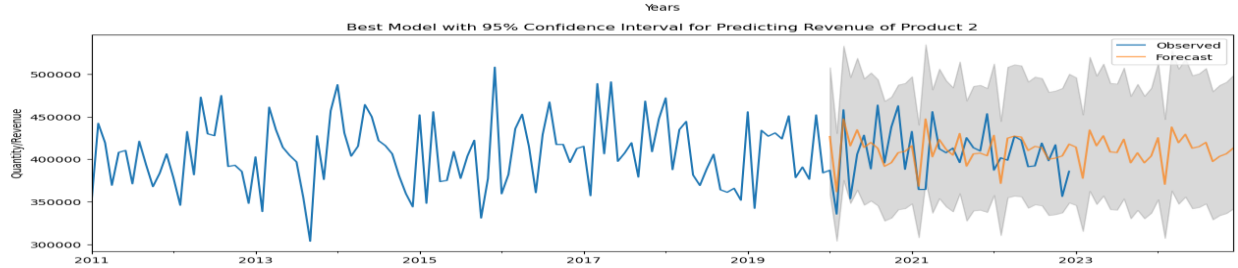
3.4.5.3 Draw the Forecast Observed data along with the 95% Confidence Interval for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4 per Year:

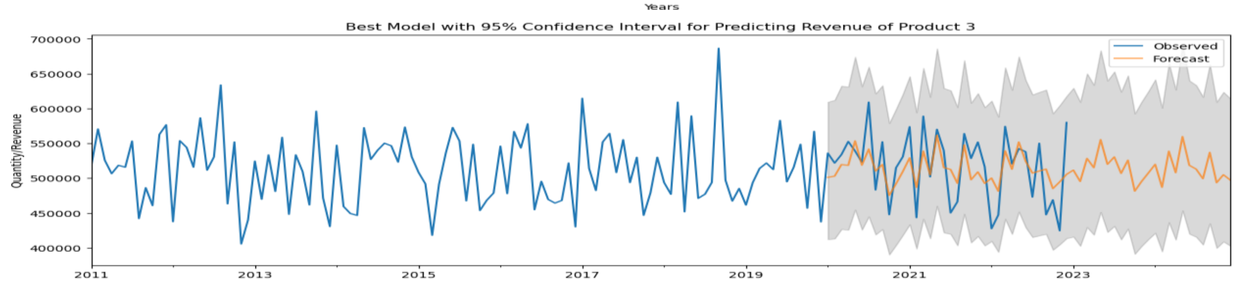


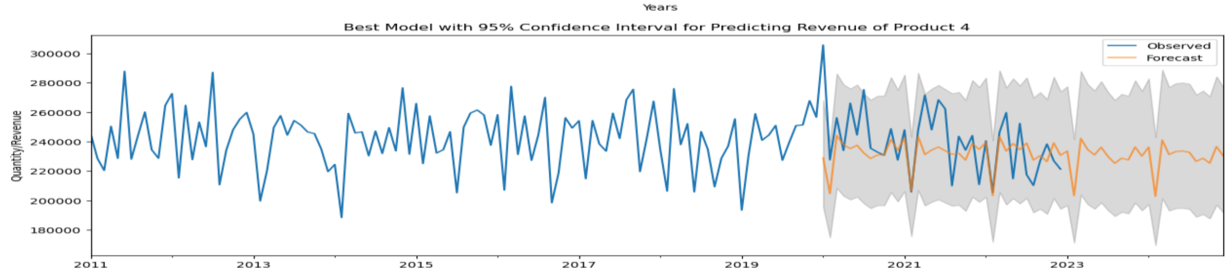

Best Model with 95% Confidence Interval for Predicting Amount of Product 3
Observed
Forecast
Sales
Years


Best Model with 95% Confidence Interval for Predicting Amount of Product 4
Observed
Forecast
Sales
Years


Best Model with 95% Confidence Interval for Predicting Revenue of Product 1
Observed
Forecast
Sales
Years


Best Model with 95% Confidence Interval for Predicting Revenue of Product 2
Observed
Forecast
Quantity/Revenue
Years


Best Model with 95% Confidence Interval for Predicting Revenue of Product 3
Observed
Forecast
Quantity/Revenue
Years


Best Model with 95% Confidence Interval for Predicting Revenue of Product 4
Observed
Forecast
Quantity/Revenue
Years

Finally, we can see the 5th question of the CEO. As we can use the best model of sales and revenue of product 1, 2, 3, and 4. And we can forecast them for 2023, 2024 and etc.

3.4.5.3 Other Conclusions:

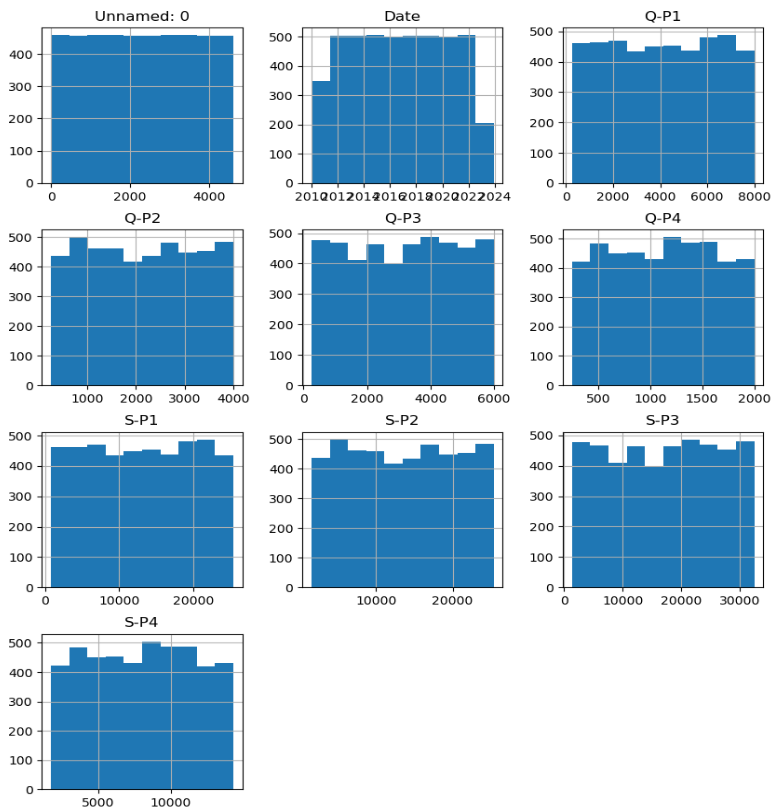
Appendix 14) Plot ACF and PACF for residuals of the best model to ensure no more information is left for extraction.

3.5 Summary:

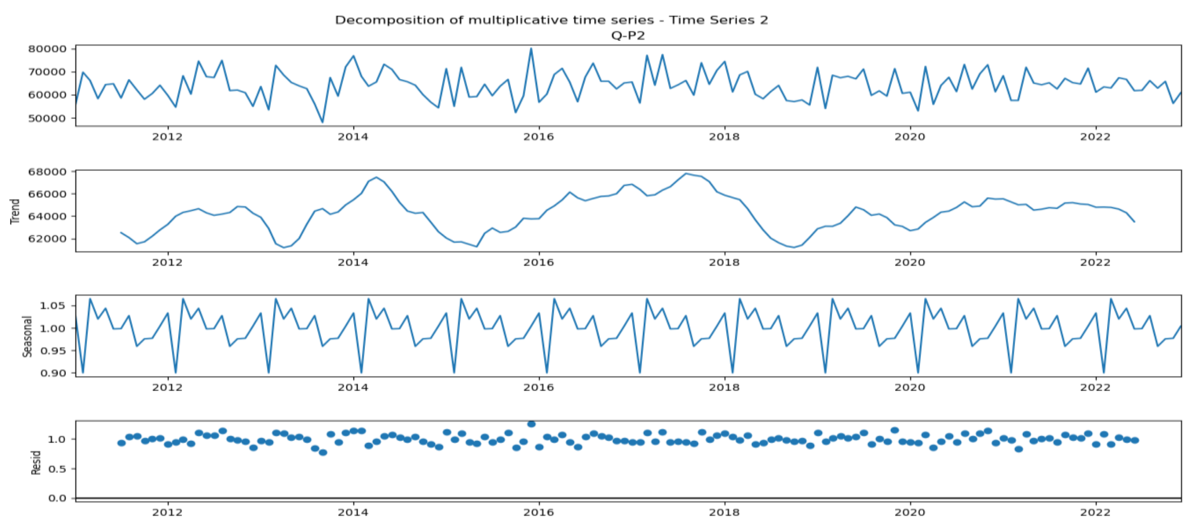
- There is not any special trend in our data except that in 2010 and 2023 we have some specific trend for quantity and revenue sales. The reason is that our data in 2010 and 2023 are incomplete. I will remove them later.
- Product 1 has the highest sales. Product 4 has the lowest sales. product 2 has greater quantity sales in comparing to product 3, however their revenues sales trend and amount for product 2 and 3 are approximately equal.
- If CEO decided to drop one product, I would suggest to drop product 4. because product 4 has the lowest quantity and revenue sales.
- I create AR, ARMA, ARIMA, and SARIMA models to forecast the data for 2023 and 2024. I select the best model based on the lowest RMSE, and at the end of my project, I visualize the forecasts with 95% confidence intervals.

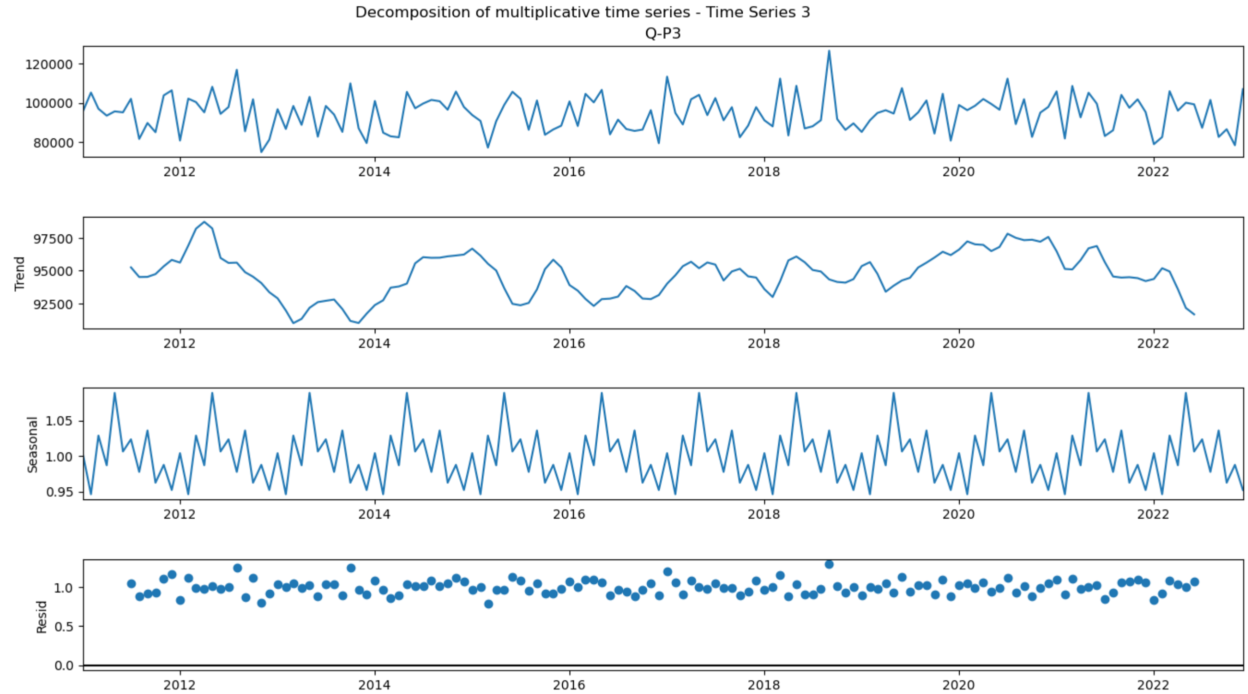
Appendix

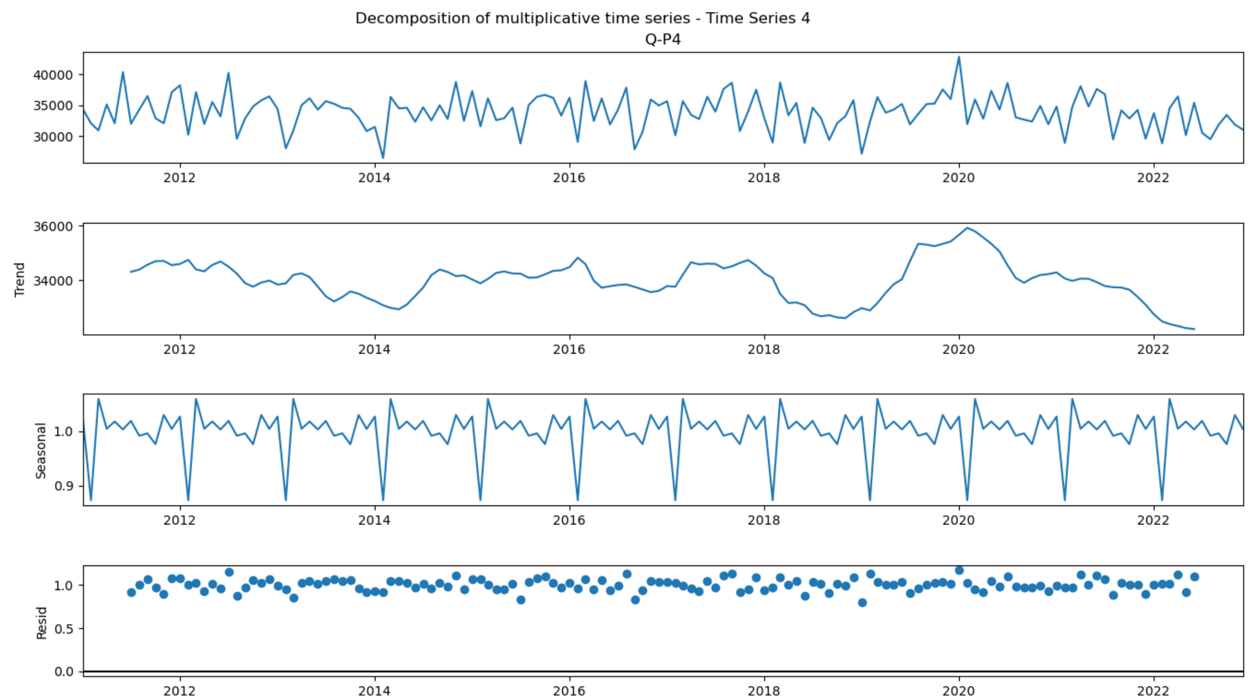
Appendix 1) Distribution of our raw data



Appendix 2) Decomposition of multiplicative for other time series



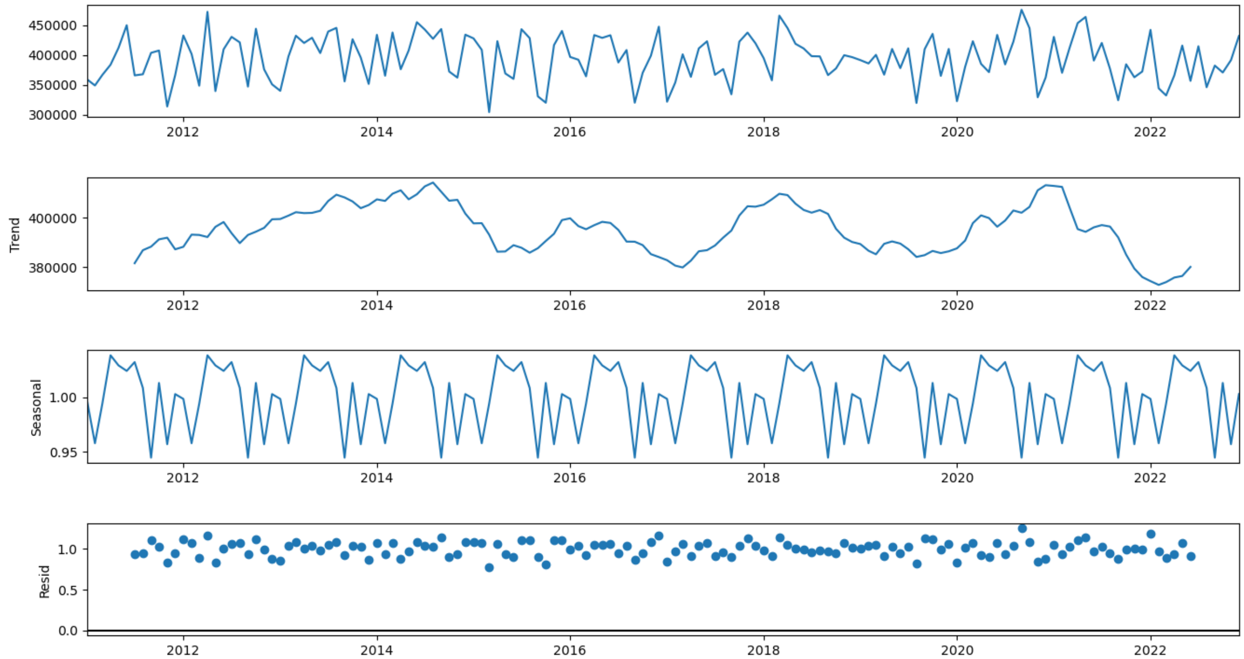




These are for quantity sales of product 1, 2, 3, and 4.

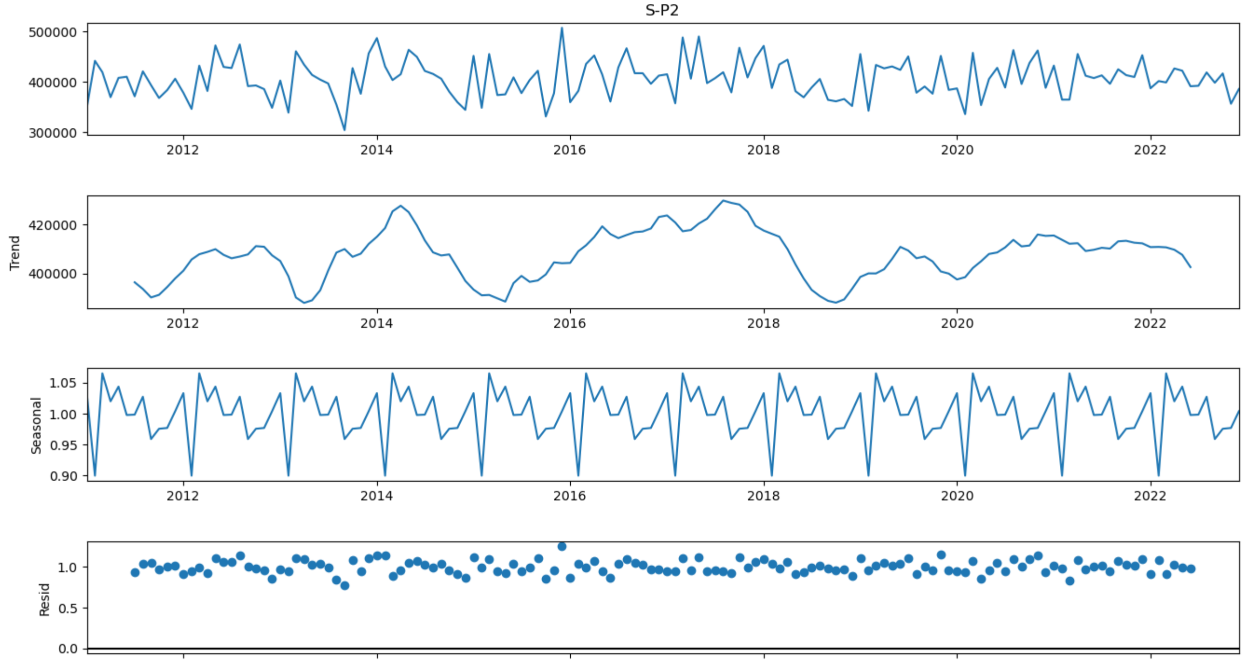
Decomposition of multiplicative time series - Time Series 5

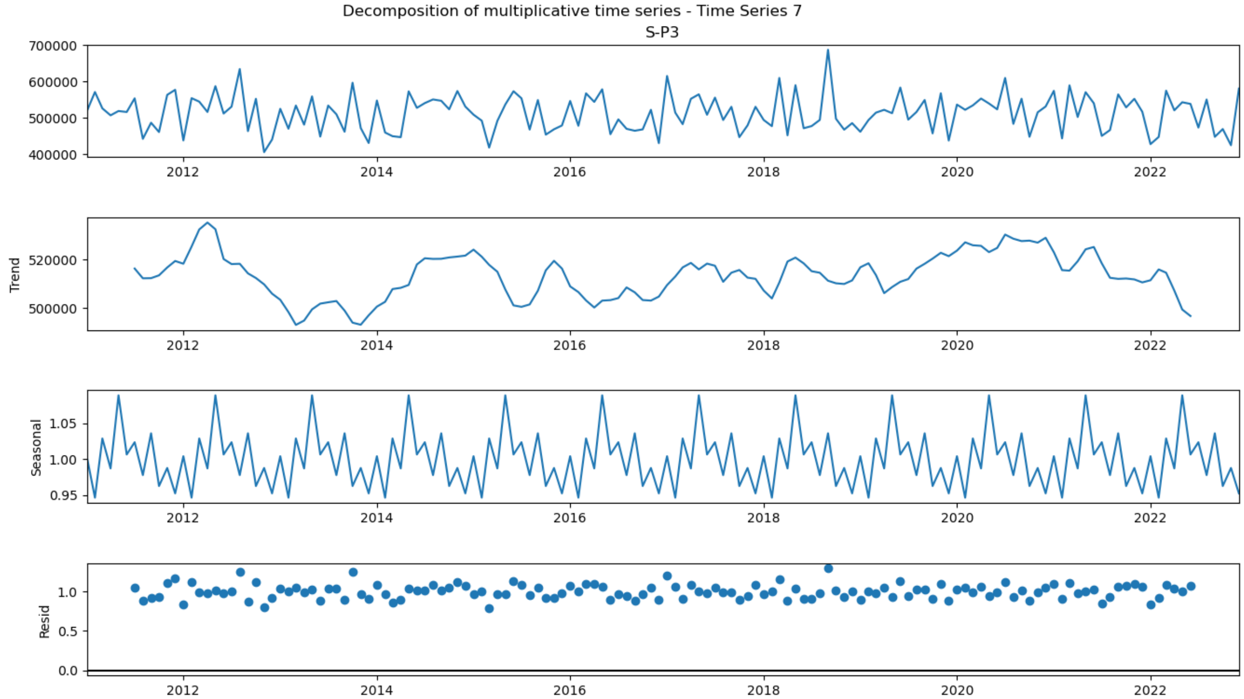
S-P1

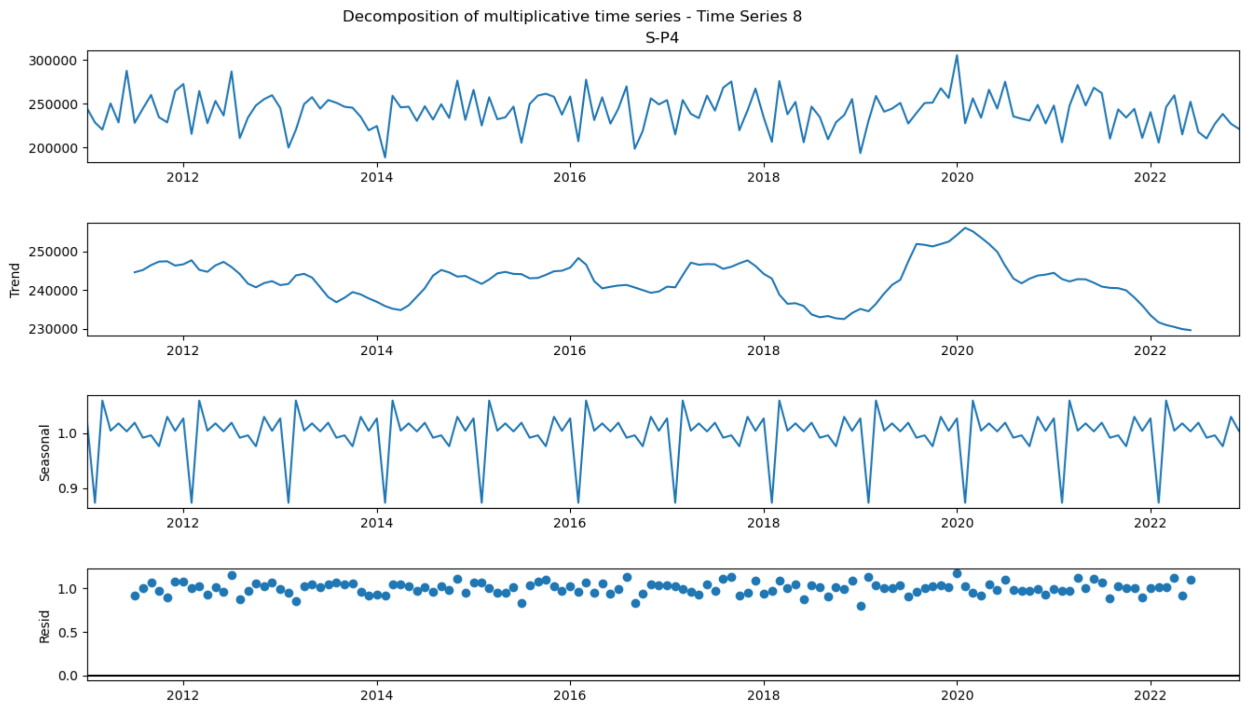


Decomposition of multiplicative time series - Time Series 6

S-P2

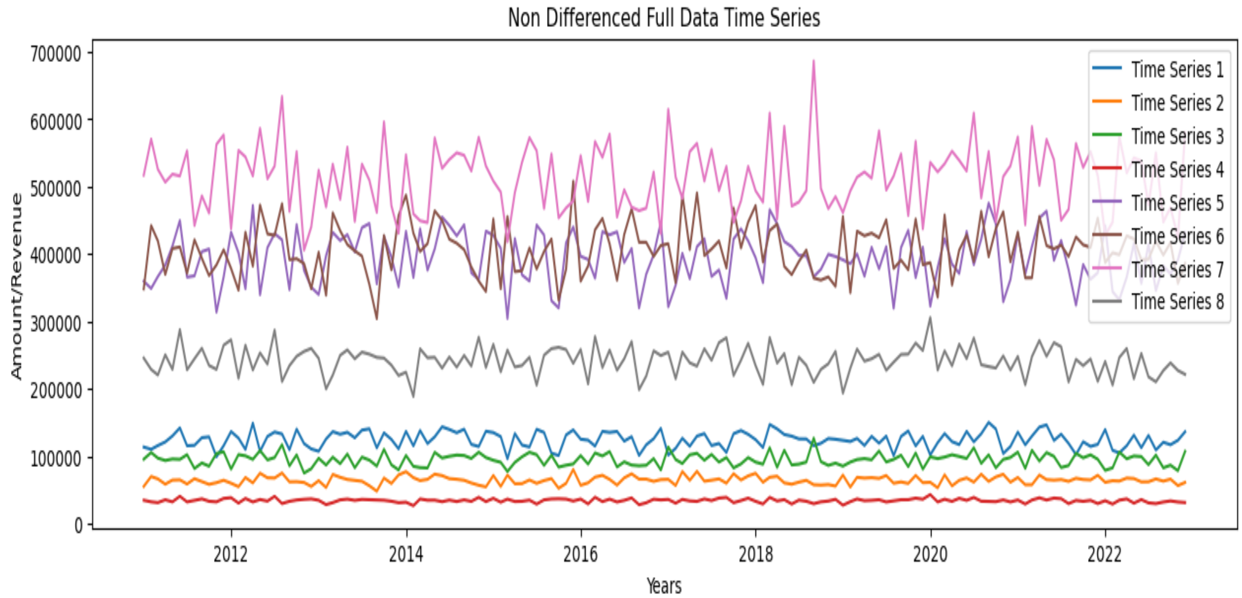




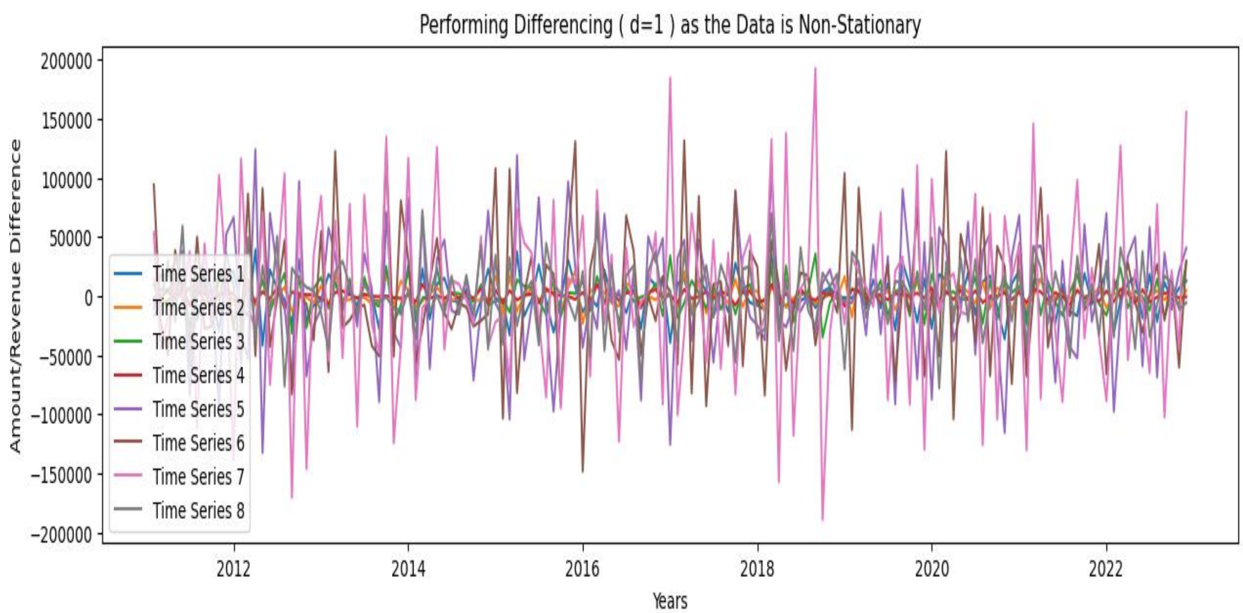


These are for revenue sales of product 1, 2, 3, and 4.

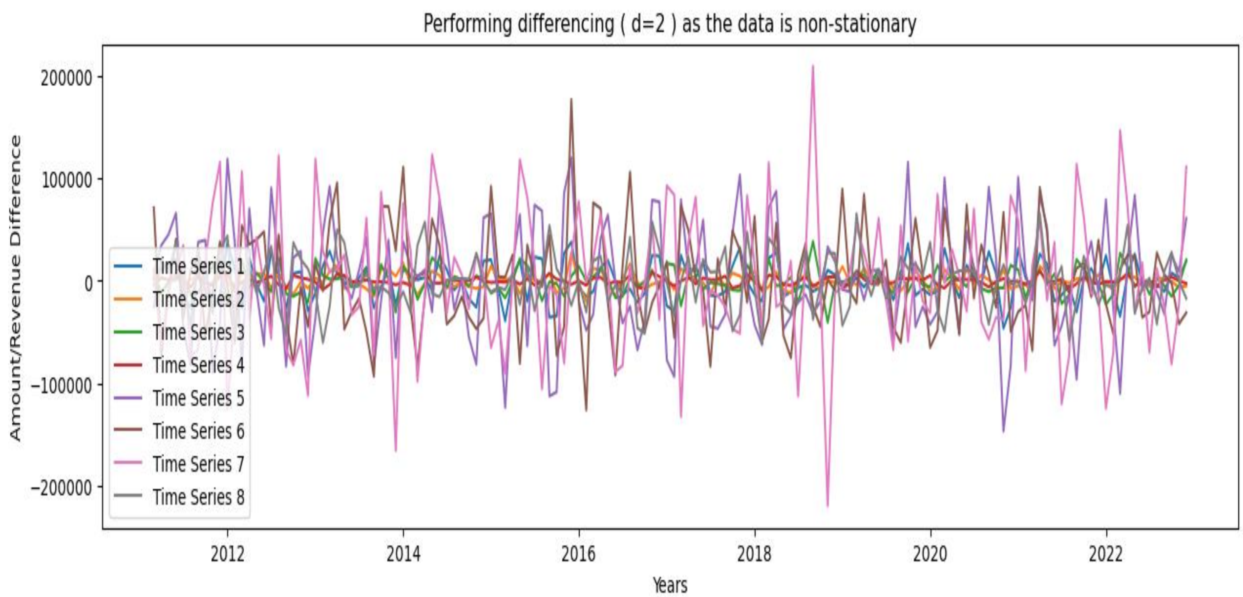
Appendix 3) Non-Differenced Full Data Time Series



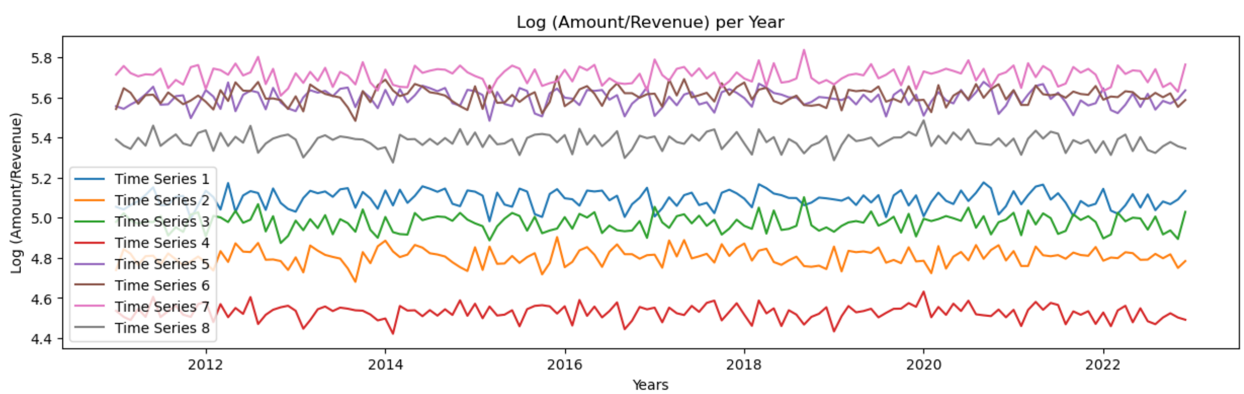
Appendix 4) Performing Differencing (d=1) as the Data is non-stationary for all-time series



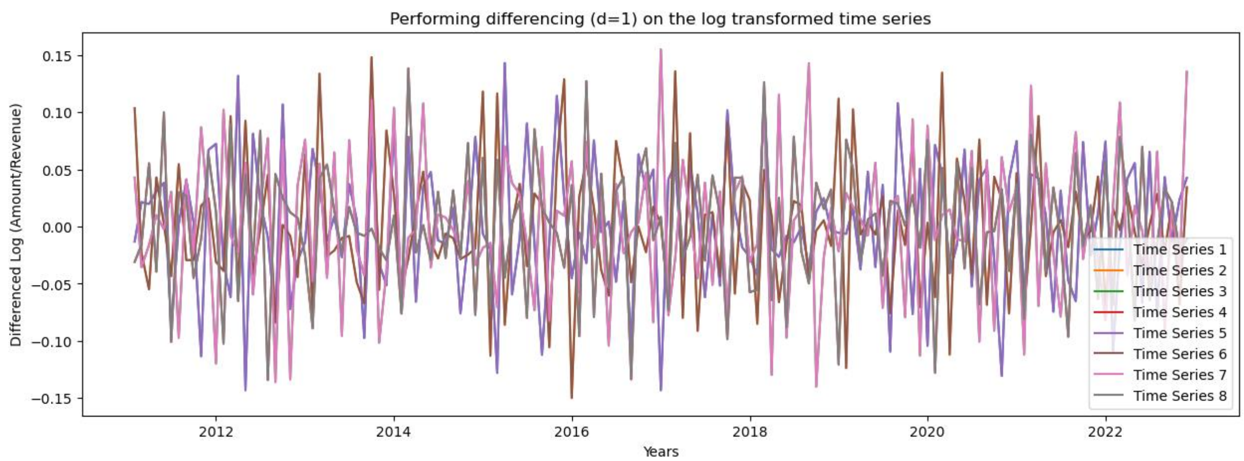
Appendix 5) Performing differencing (d=2) as the data is non-stationary



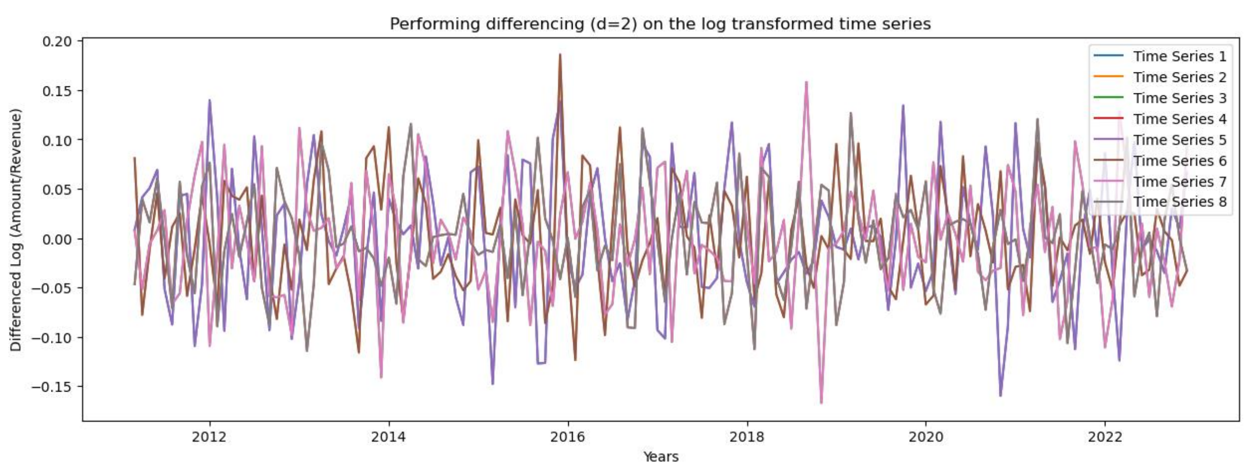
Appendix 6) Log Transformed Time Series



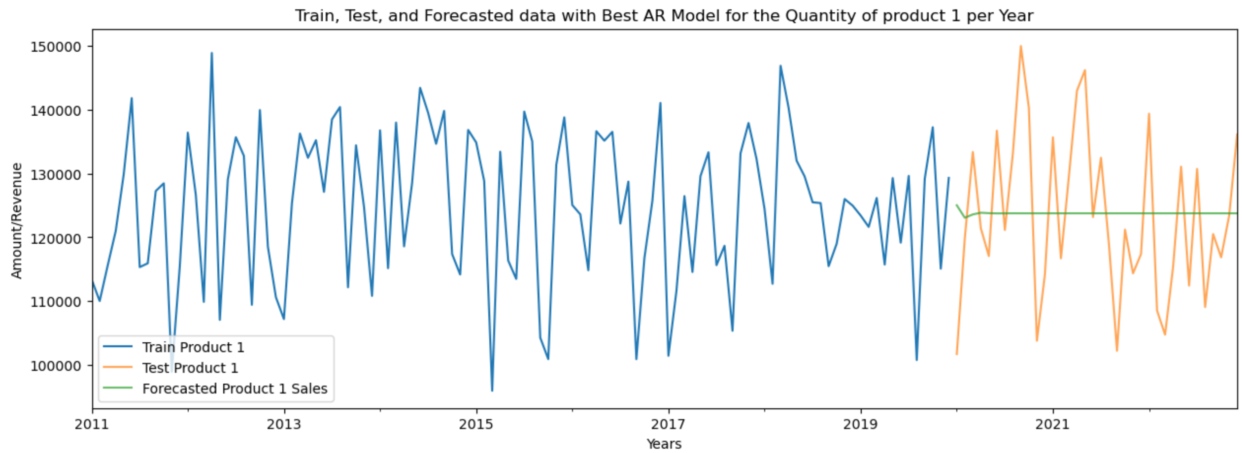
Appendix 7) Performing differencing (d=1) on the log transformed time series



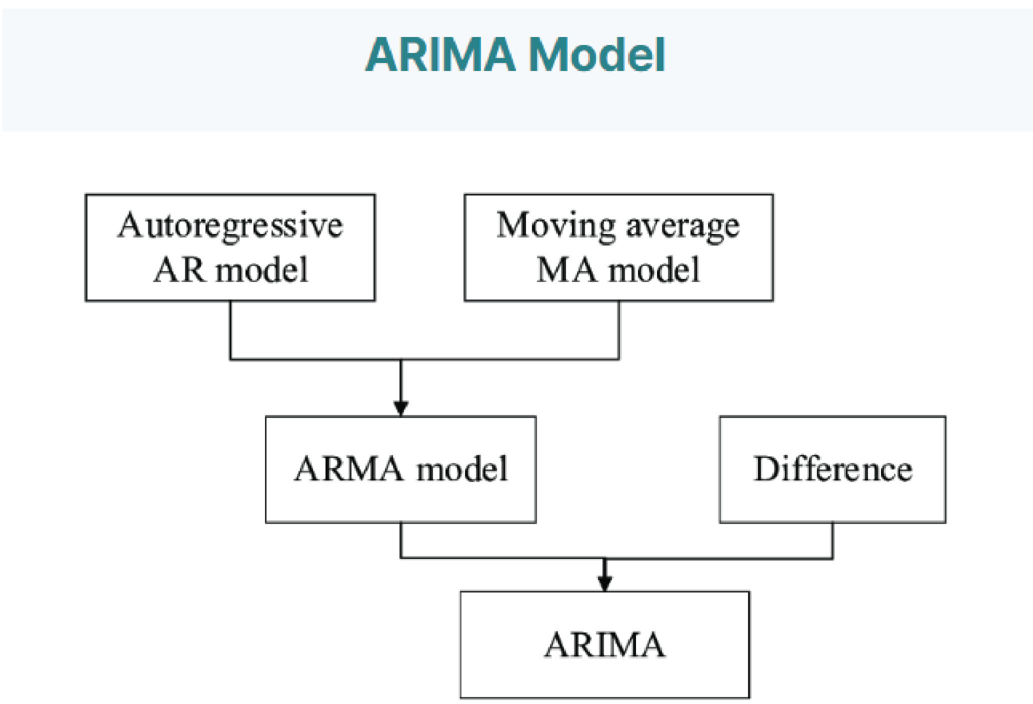
Appendix 8) Performing differencing (d=2) on the log transformed time series



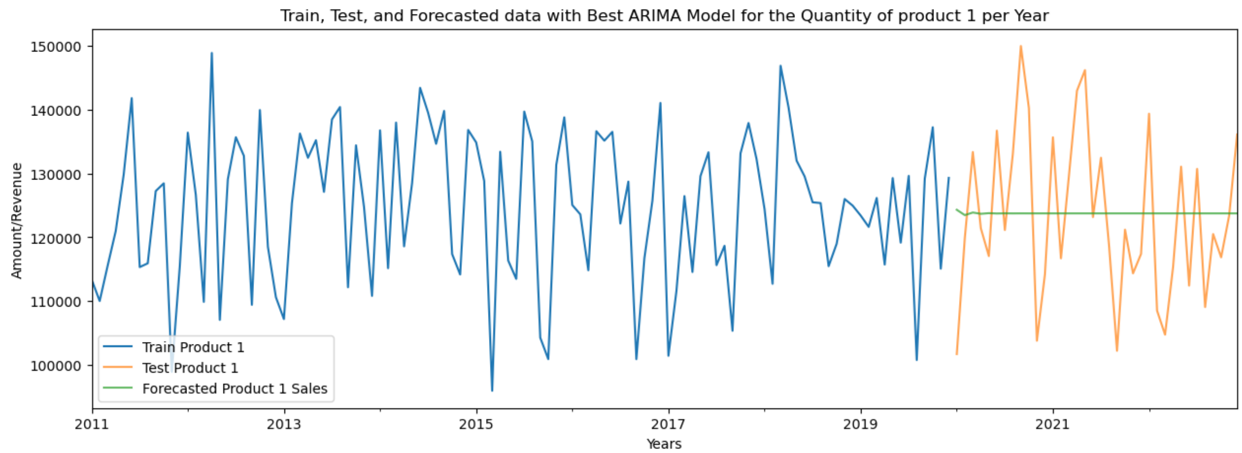
Appendix 9) Drawing Train, Test, and Forecasted data with Best AR Model for the Quantity of product 1 per Year



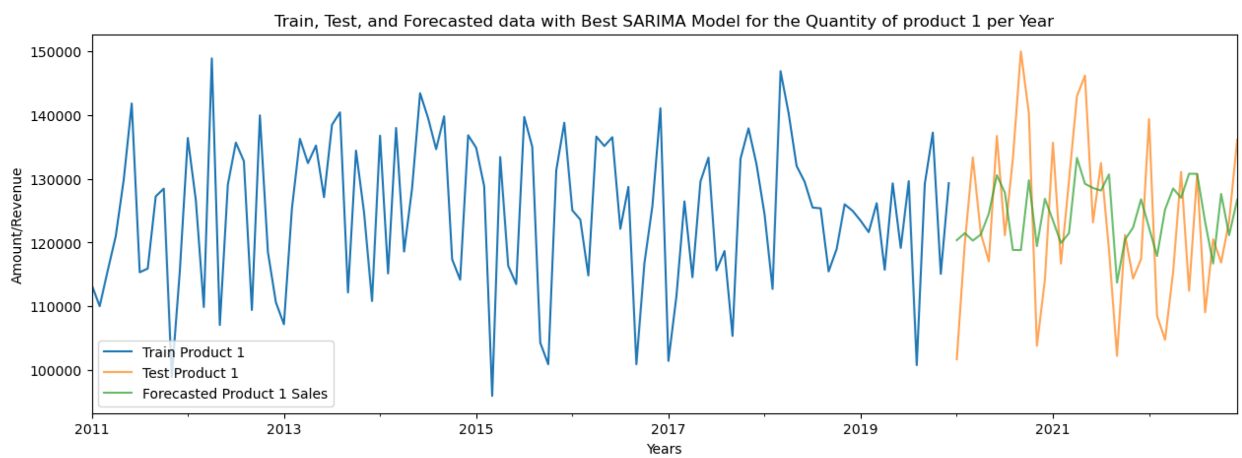
Appendix 10) ARIMA Model Structure



Appendix 11) Drawing Train, Test, and Forecasted data with Best ARMA Model for the Quantity of product 1 per Year



Appendix 12) Drawing Train, Test, and Forecasted data with Best SARIMA Model for the Quantity of product 1 per Year

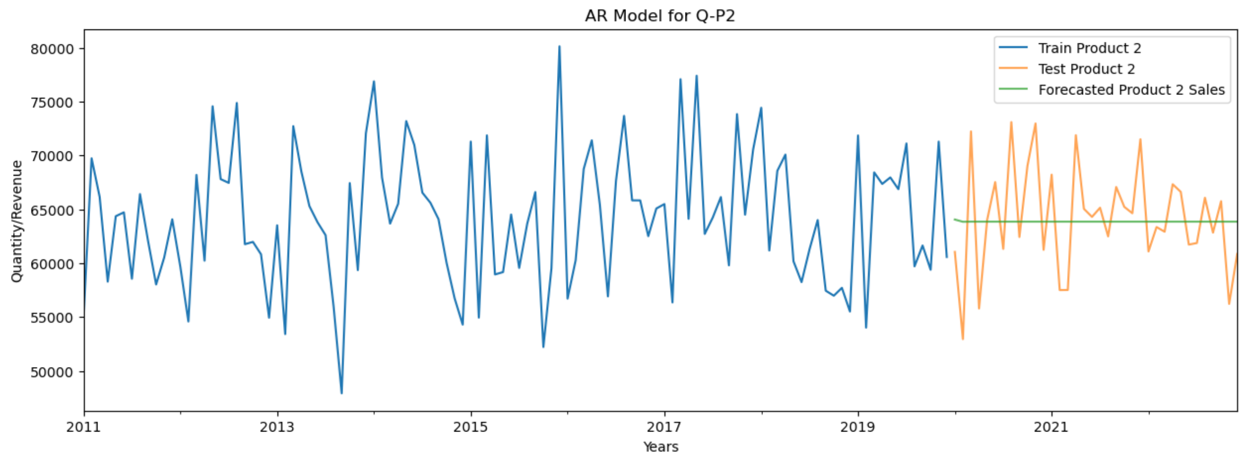


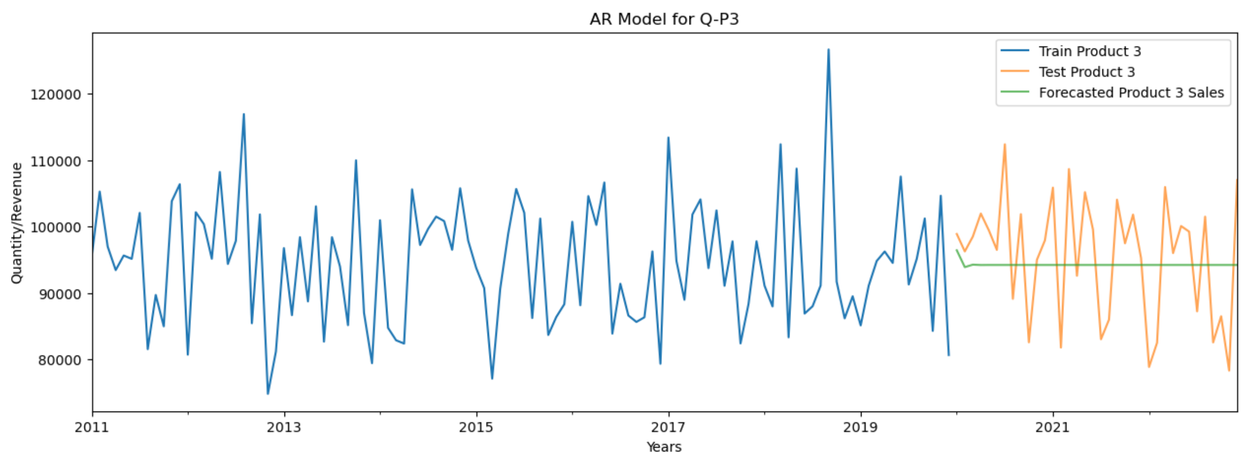
Appendix 13) All of these process for other time series

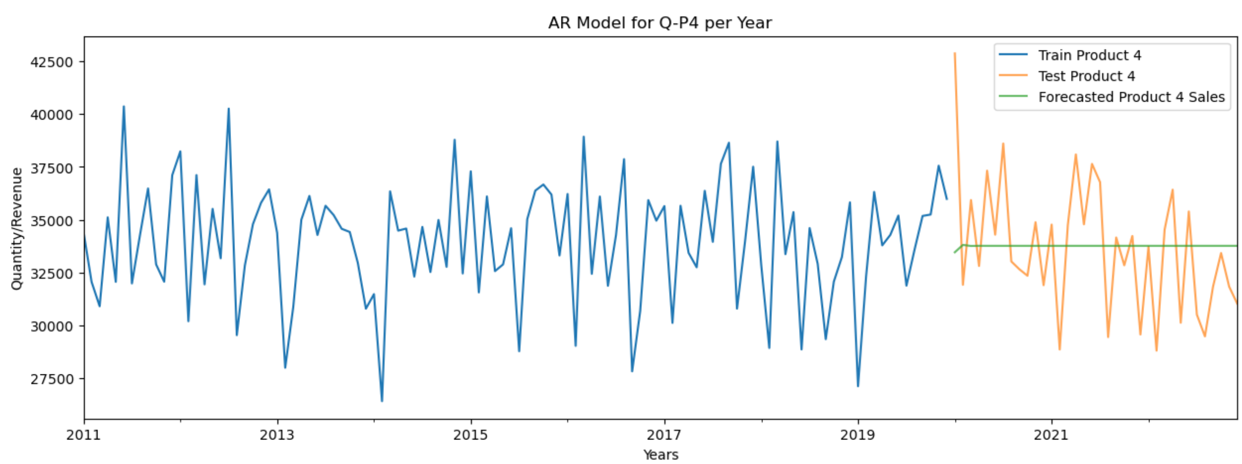
Modeling for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4

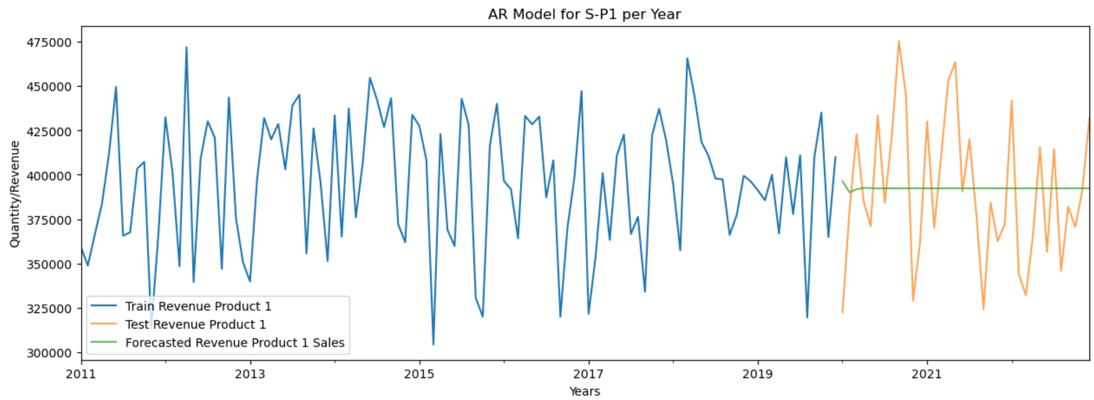
Here I will try to write main results (not details), because it becomes shorter.

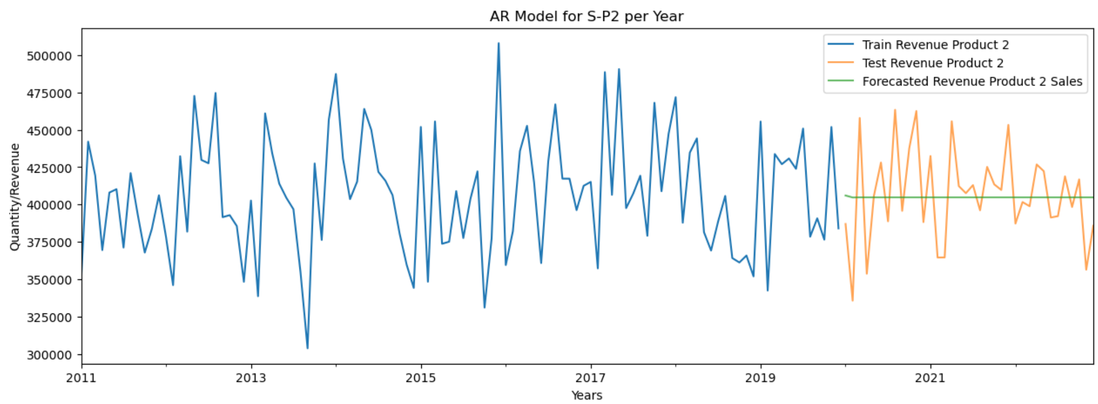
Drawing Train, Test, and Forecasted data with Best AR Model for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4 per Year

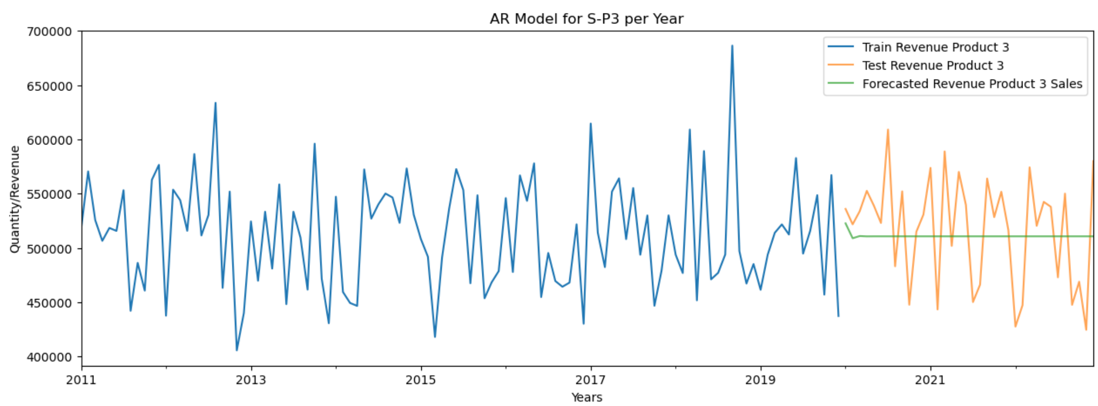


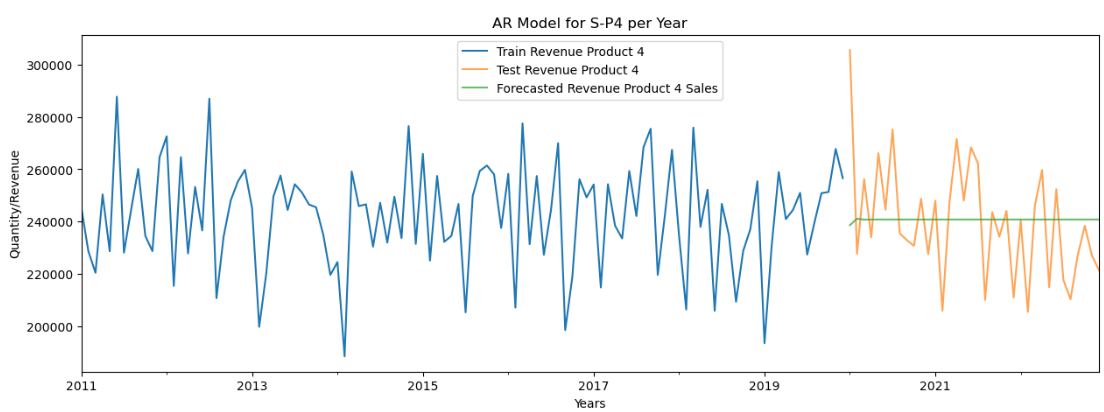




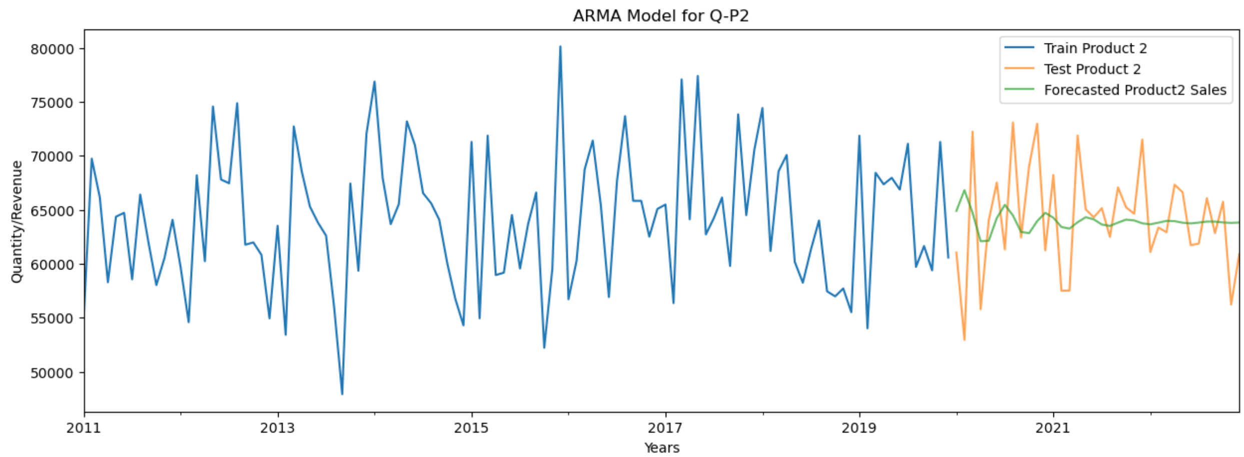

AR Model for S-P1 per Year
Quantity/Revenue
Years
475000
450000
425000
400000
375000
350000
325000
300000
2011
2013
2015
2017
2019
2021
Train Revenue Product 1
Test Revenue Product 1
Forecasted Revenue Product 1 Sales

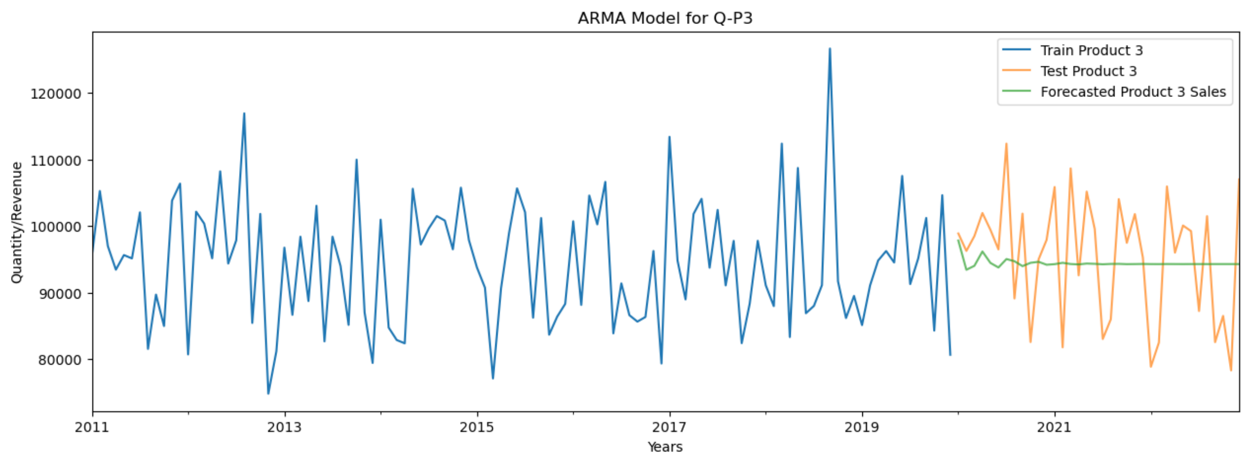

AR Model for S-P2 per Year
Quantity/Revenue
Years
500000
475000
450000
425000
400000
375000
350000
325000
300000
2011
2013
2015
2017
2019
2021
Train Revenue Product 2
Test Revenue Product 2
Forecasted Revenue Product 2 Sales

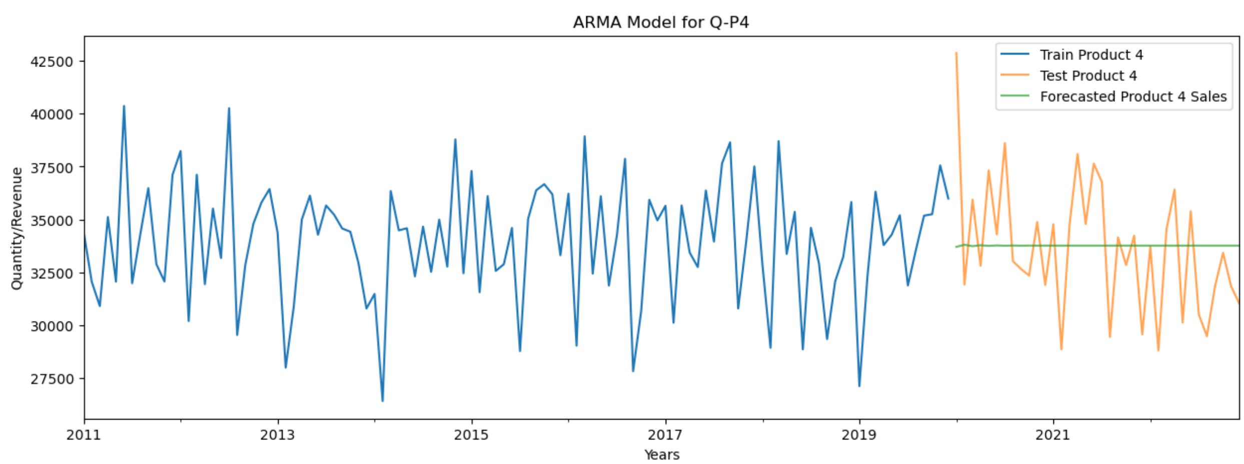

AR Model for S-P3 per Year
Quantity/Revenue
Years
700000
650000
600000
550000
500000
450000
400000
2011
2013
2015
2017
2019
2021
Train Revenue Product 3
Test Revenue Product 3
Forecasted Revenue Product 3 Sales

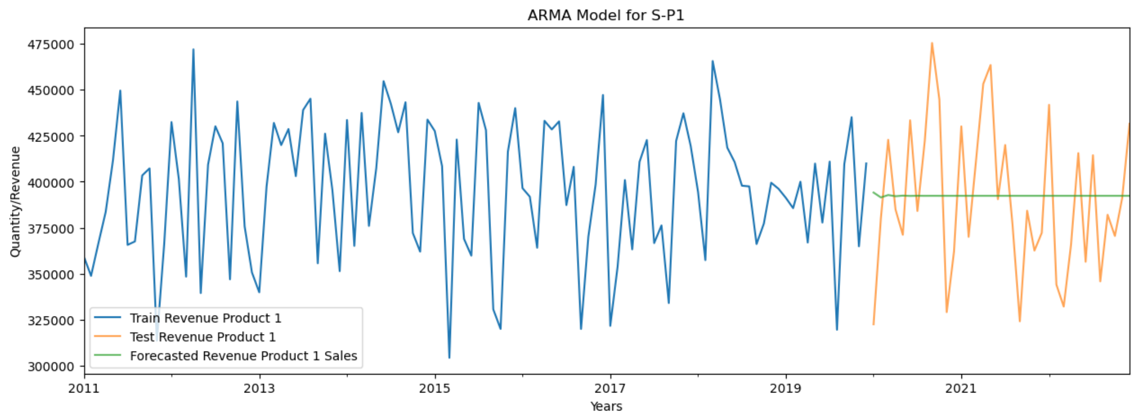

AR Model for S-P4 per Year
Quantity/Revenue
Years
300000
280000
260000
240000
220000
200000
2011
2013
2015
2017
2019
2021
Train Revenue Product 4
Test Revenue Product 4
Forecasted Revenue Product 4 Sales

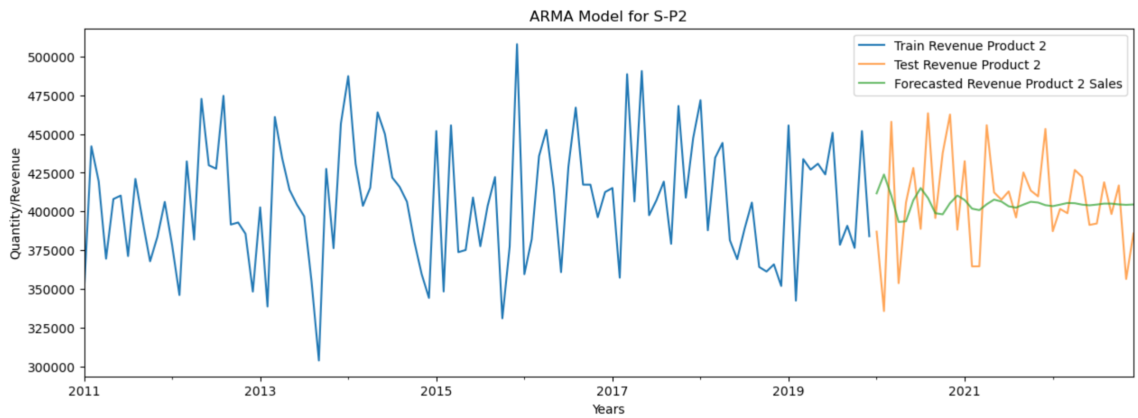
Drawing with best ARMA Model for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4

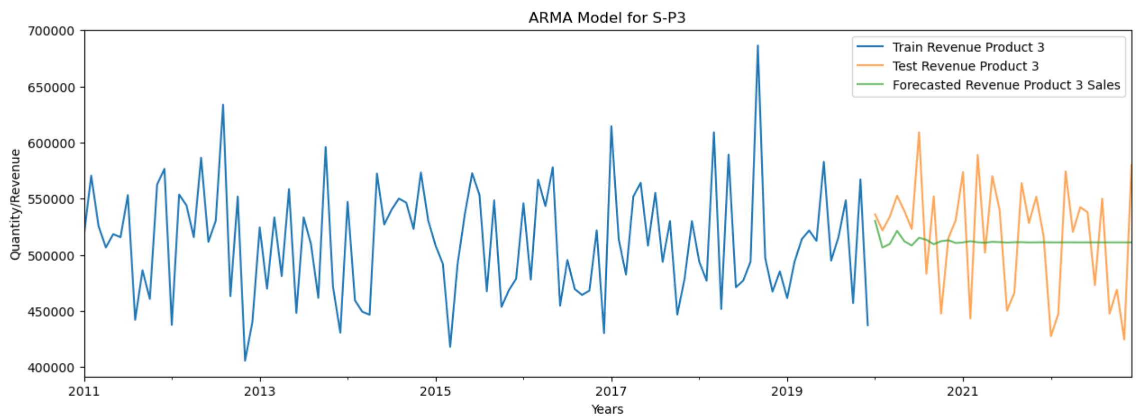


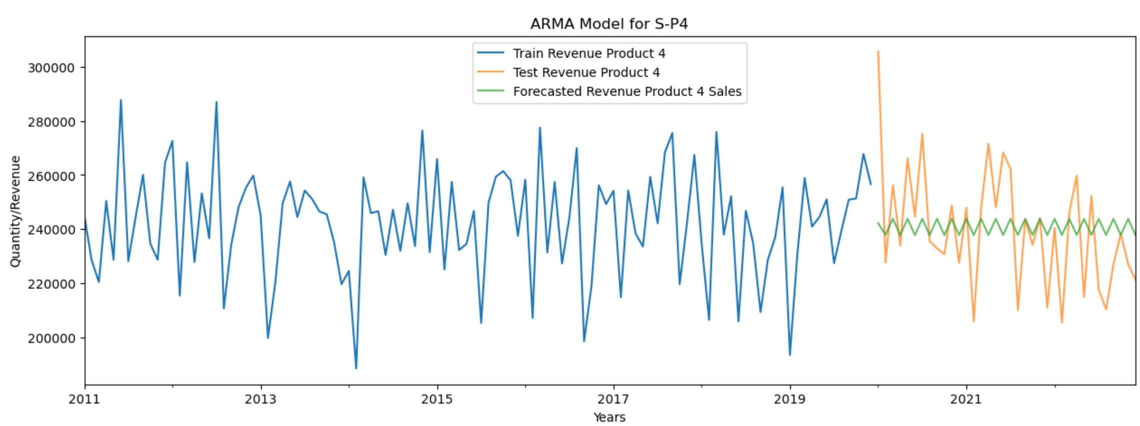




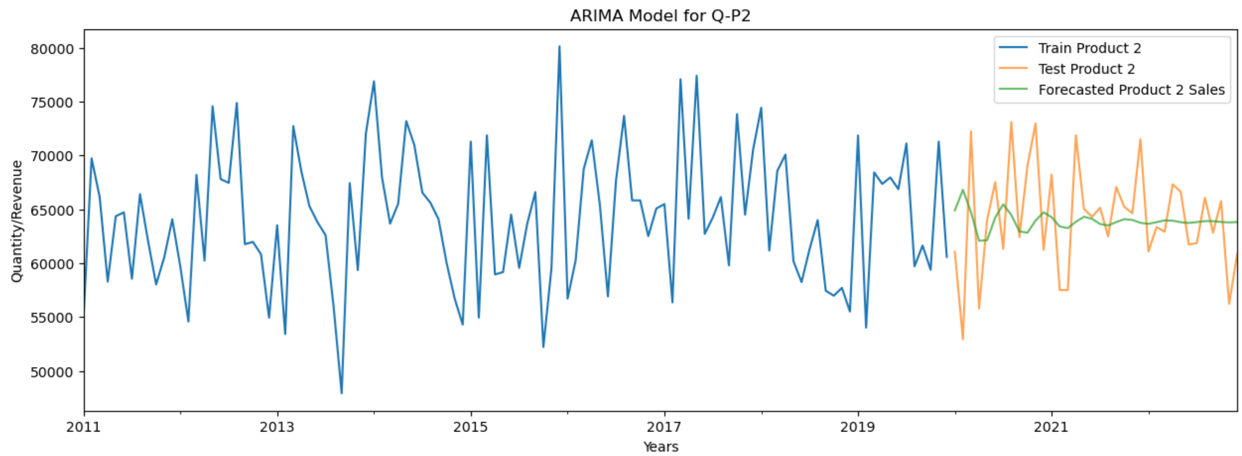

ARMA Model for S-P1
Quantity/Revenue
Years
475000
450000
425000
400000
375000
350000
325000
300000
2011
2013
2015
2017
2019
2021
Train Revenue Product 1
Test Revenue Product 1
Forecasted Revenue Product 1 Sales

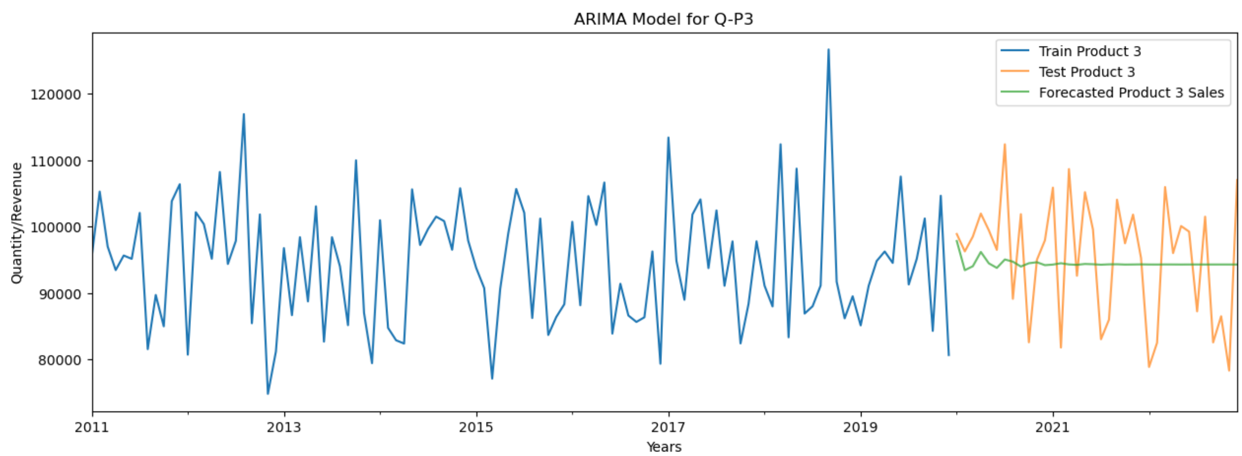

ARMA Model for S-P2
Quantity/Revenue
Years
500000
475000
450000
425000
400000
375000
350000
325000
300000
2011
2013
2015
2017
2019
2021
Train Revenue Product 2
Test Revenue Product 2
Forecasted Revenue Product 2 Sales

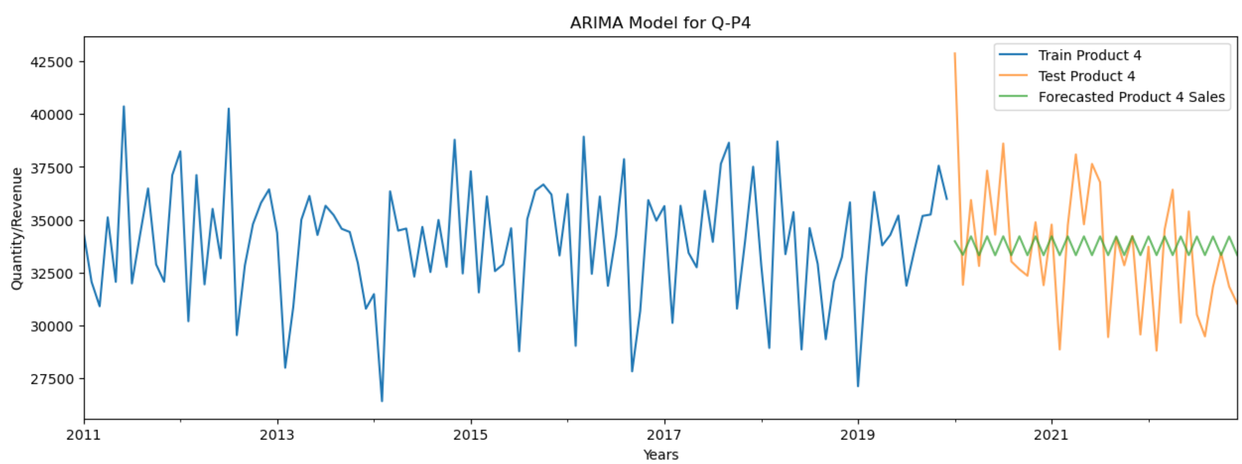

ARMA Model for S-P3
Quantity/Revenue
Years
700000
650000
600000
550000
500000
450000
400000
2011
2013
2015
2017
2019
2021
Train Revenue Product 3
Test Revenue Product 3
Forecasted Revenue Product 3 Sales

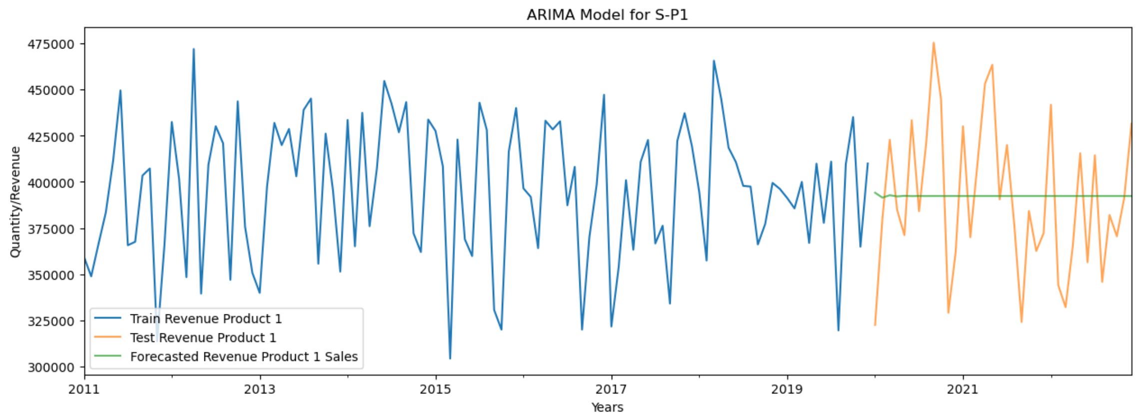

ARMA Model for S-P4
Quantity/Revenue
Years
300000
280000
260000
240000
220000
200000
2011
2013
2015
2017
2019
2021
Train Revenue Product 4
Test Revenue Product 4
Forecasted Revenue Product 4 Sales

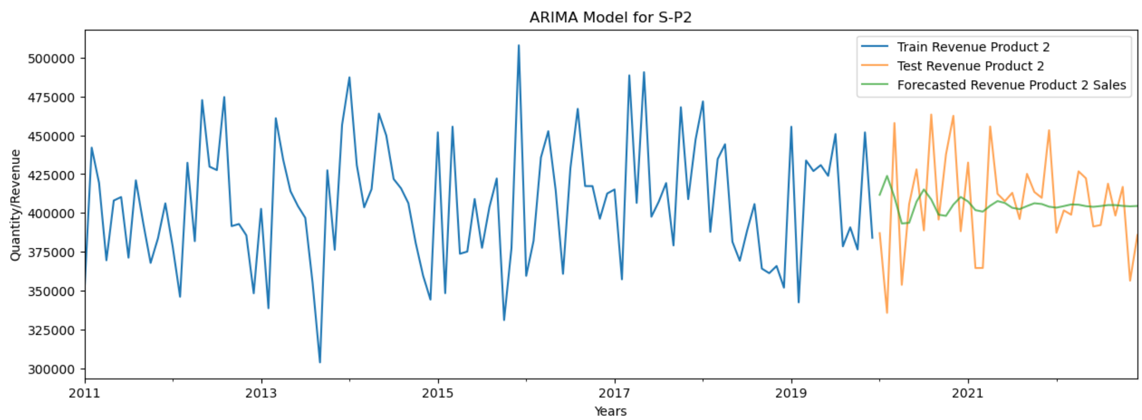
Drawing with best ARIMA Model for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4

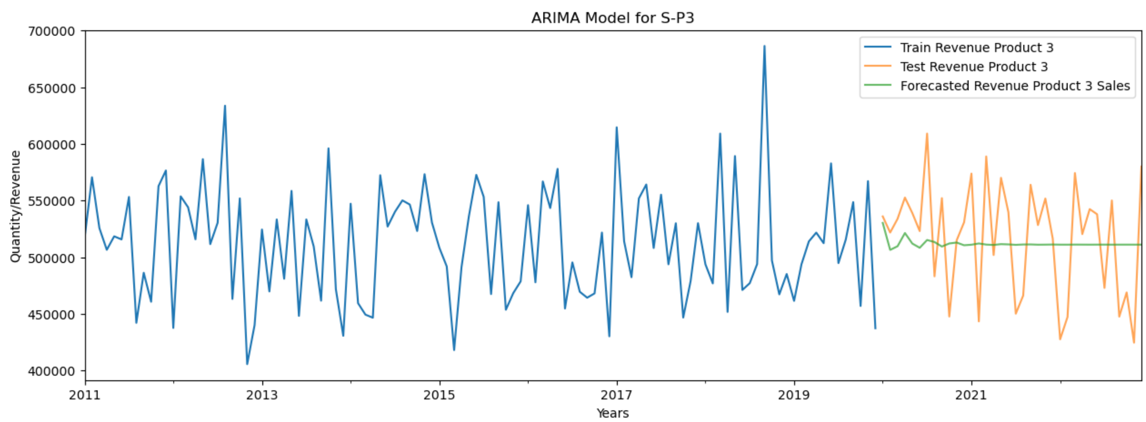


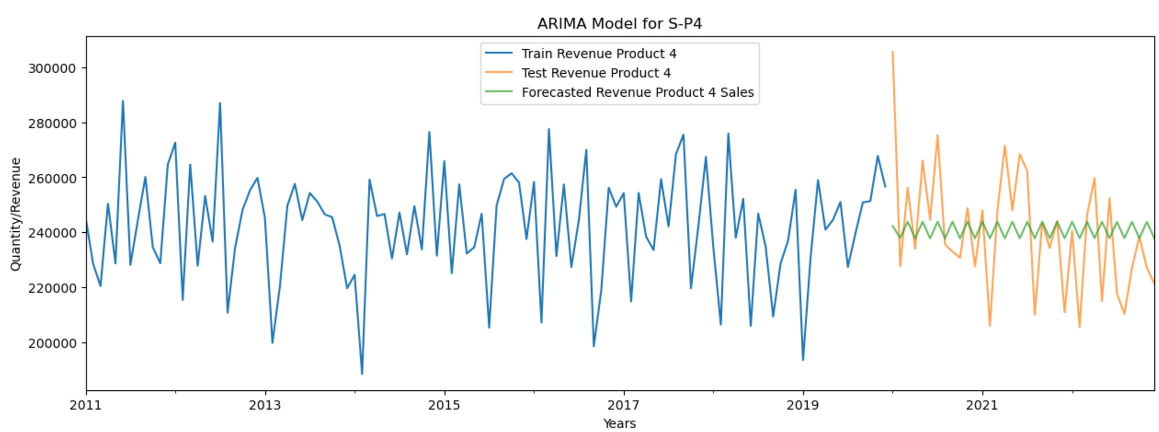




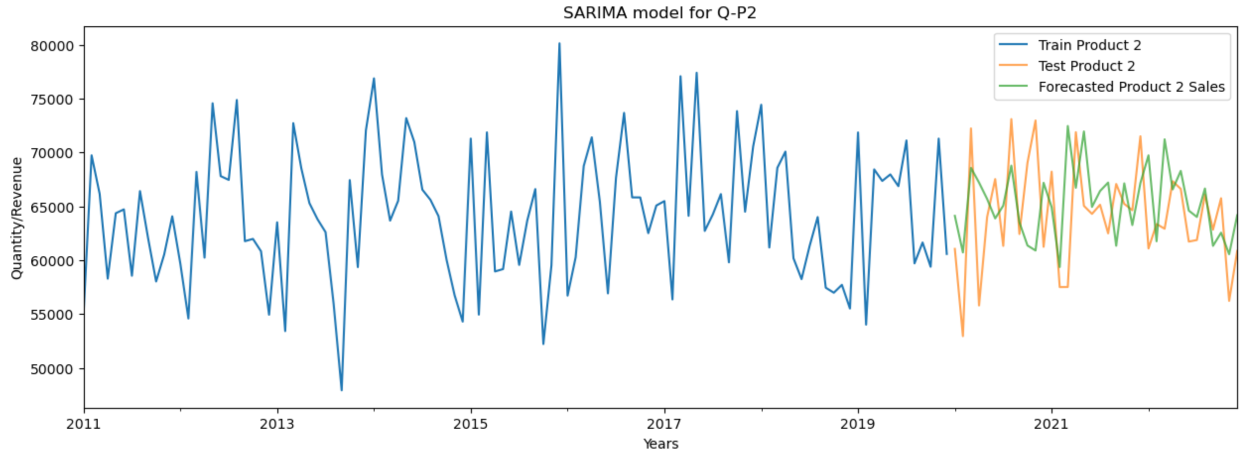

ARIMA Model for S-P1
Train Revenue Product 1
Test Revenue Product 1
Forecasted Revenue Product 1 Sales
Quantity/Revenue
Years

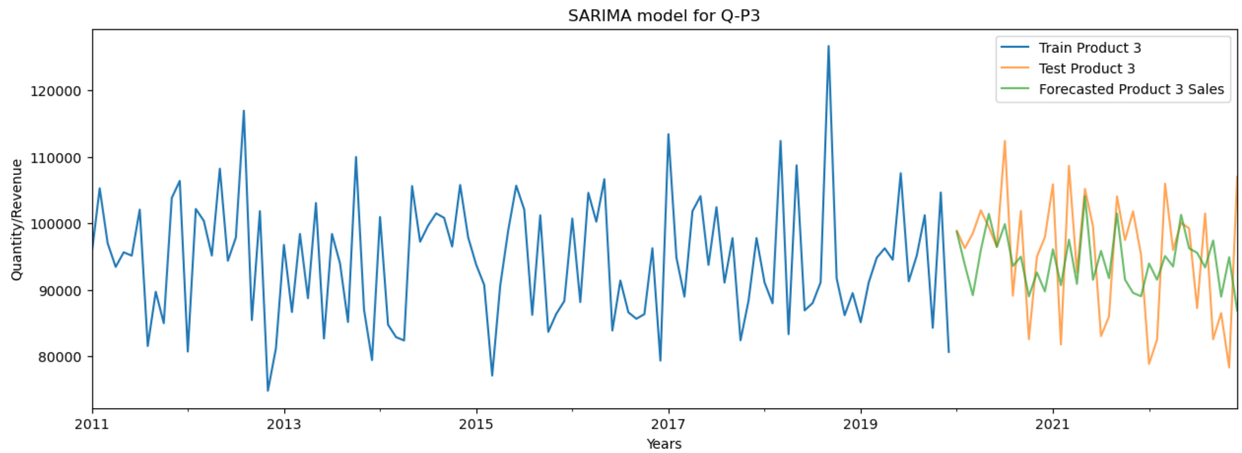

ARIMA Model for S-P2
Train Revenue Product 2
Test Revenue Product 2
Forecasted Revenue Product 2 Sales
Quantity/Revenue
Years

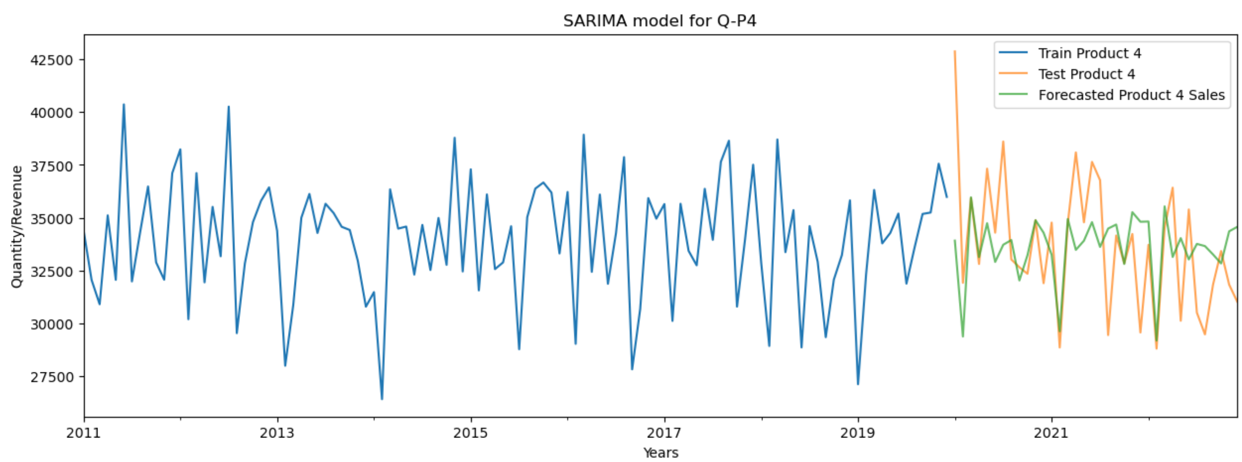

ARIMA Model for S-P3
Train Revenue Product 3
Test Revenue Product 3
Forecasted Revenue Product 3 Sales
Quantity/Revenue
Years

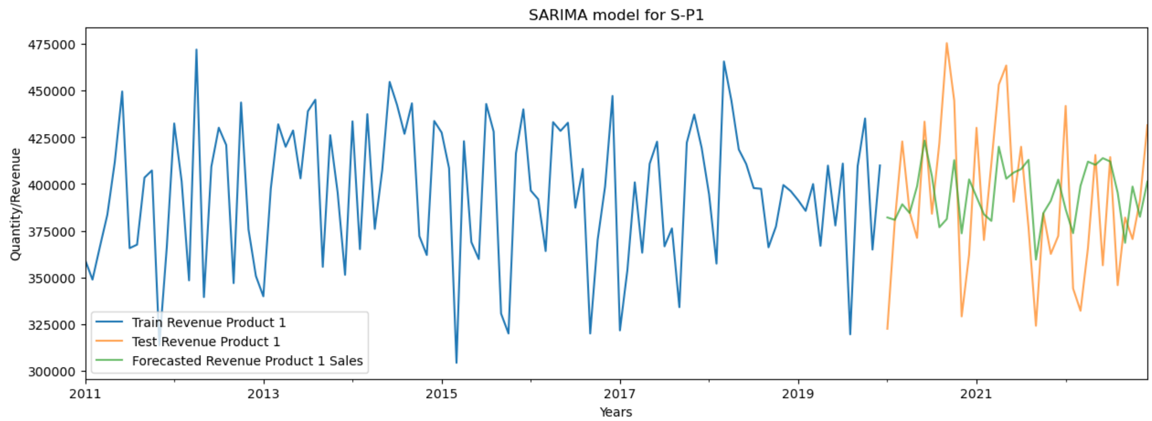

ARIMA Model for S-P4
Train Revenue Product 4
Test Revenue Product 4
Forecasted Revenue Product 4 Sales
Quantity/Revenue
Years

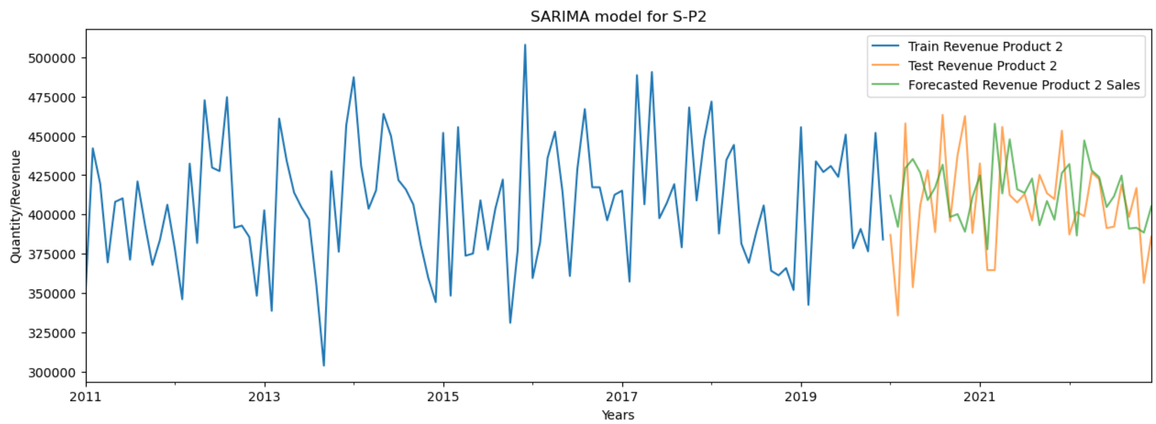
Drawing with best SARIMA model for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4

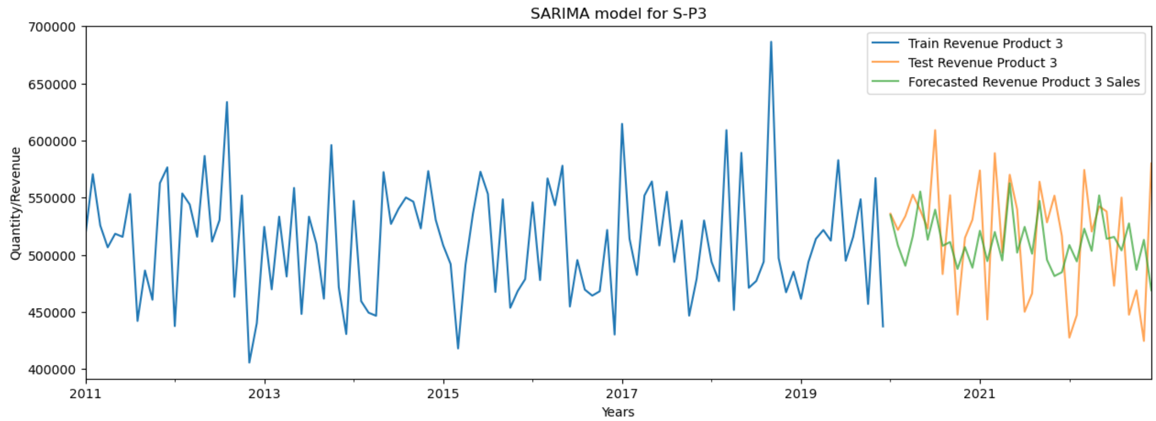


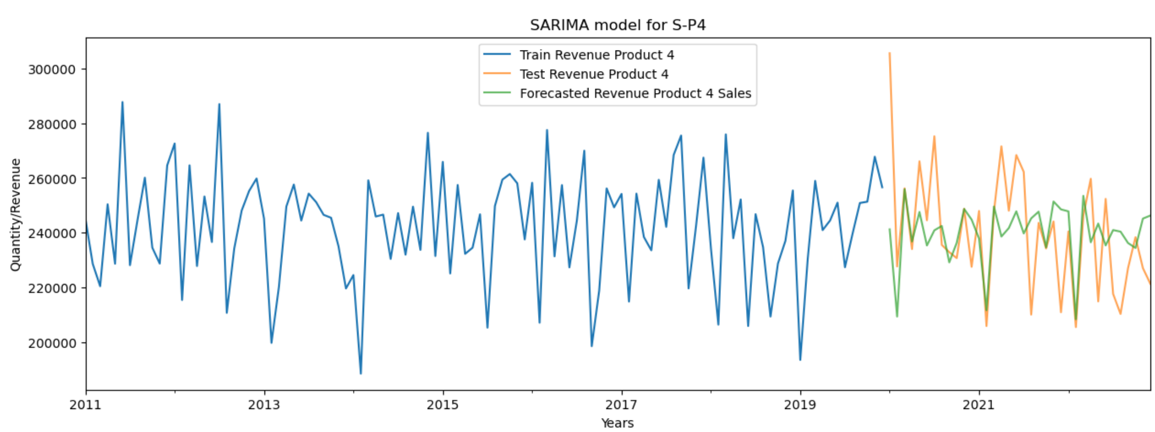





SARIMA model for S-P1
Train Revenue Product 1
Test Revenue Product 1
Forecasted Revenue Product 1 Sales
Quantity/Revenue
Years
300000
325000
350000
375000
400000
425000
450000
475000
2011
2013
2015
2017
2019
2021


SARIMA model for S-P2
Train Revenue Product 2
Test Revenue Product 2
Forecasted Revenue Product 2 Sales
Quantity/Revenue
Years
300000
325000
350000
375000
400000
425000
450000
475000
500000
2011
2013
2015
2017
2019
2021


SARIMA model for S-P3
Train Revenue Product 3
Test Revenue Product 3
Forecasted Revenue Product 3 Sales
Quantity/Revenue
Years
400000
450000
500000
550000
600000
650000
700000
2011
2013
2015
2017
2019
2021


SARIMA model for S-P4
Train Revenue Product 4
Test Revenue Product 4
Forecasted Revenue Product 4 Sales
Quantity/Revenue
Years
200000
220000
240000
260000
280000
300000
2011
2013
2015
2017
2019
2021

Conclusion for Q-P2, Q-P3, Q-P4, S-P1, S-P2, S-P3, S-P4

	RMSE
Best AR Model Product 2 : AR(1,0,0)	4831.925740
Best ARMA Model Product 2: ARMA (2, 0, 2)	4930.656694
Best ARIMA Model Product 2: ARMA (2, 0, 2)	4930.656694
Best SARIMA Model product 2: SARIMA (3, 1, 3) x (3, 1, 3, 12)	5529.360298

The best model for product 2 is AR (1,0,0) that its RMSE is 4831.925740.

	RMSE
Best AR Model Product 3: AR (1,0,0)	9097.457688
Best ARMA Model Product 3: ARMA (3, 0, 3)	9034.622200
Best ARIMA Model Product 3: ARMA (3, 0, 3)	9034.622200
Best SARIMA Model product 3: SARIMA (3, 1, 3) x (3, 1, 3, 12)	8739.050509

The best model for product 3 is SARIMAX (3, 1, 3) x (3, 1, 3, 12) that its RMSE is 8739.050509.

	RMSE
Best AR Model Product 4: AR (1,0,0)	3080.921856
Best ARMA Model Product 4: ARMA (1, 0, 1)	3061.521141
Best ARIMA Model Product 4: ARMA (2, 0, 1)	2954.061145
Best SARIMA Model product 4: SARIMA (3, 1, 3) x (3, 1, 3, 12)	2920.618921

The best model for product 4 is SARIMAX (3, 1, 3) x (3, 1, 3, 12) that its RMSE is 2920.618921.

	RMSE
Best AR Model Revenue Product 1: AR (2,0,0)	40176.861072
Best ARMA Model Revenue Product 1: ARMA (1, 0, 1)	40052.637944
Best ARIMA Model Revenue Product 1: ARMA (1, 0, 1)	40052.637944
Best SARIMA Model Revenue product 1: SARIMA (3, 1, 3) x (3, 1, 3, 12)	37954.147761

The best model for Revenue product 1 is SARIMAX (3, 1, 3) x (3, 1, 3, 12) that its RMSE is 37954.147761.

	RMSE
Best AR Model Revenue Product 2: AR (1,0,0)	30634.409195
Best ARMA Model Revenue Product 2: ARMA (2, 0, 2)	31293.444292
Best ARIMA Model Revenue Product 2: ARMA (2, 0, 2)	31293.444292
Best SARIMA Model Revenue product 2: SARIMA (3, 1, 3) x (3, 1, 3, 12)	34607.294546

The best model for Revenue product 2 is AR (1,0,0) that its RMSE is 30634.409195.

	RMSE
Best AR Model Revenue Product 3: AR (1,0,0)	49308.220668
Best ARMA Model Revenue Product 3: ARMA (3, 0, 3)	48968.143077
Best ARIMA Model Revenue Product 3: ARMA (3, 0, 3)	48968.143077
Best SARIMA Model Revenue product 3: SARIMA (3, 1, 3) x (3, 1, 3, 12)	48102.761913

The best model for Revenue product 3 is SARIMAX (3, 1, 3) x (3, 1, 3, 12) that its RMSE is 48102.761913.

	RMSE
Best AR Model Revenue Product 4: AR (1,0,0)	21966.972834
Best ARMA Model Revenue Product 4: ARMA (2, 0, 1)	21090.605765
Best ARIMA Model Revenue Product 4: ARMA (2, 0, 1)	21090.605765
Best SARIMA Model Revenue product 4: SARIMA (3, 1, 3) x (3, 1, 3, 12)	20879.880150

The best model for Revenue product 4 is SARIMAX (3, 1, 3) x (3, 1, 3, 12) that its RMSE is 20879.880150.

Appendix 14) Forecast table of the best model with the lowest RMSE 95% confidence interval

	forecast	lower_ci_95	upper_ci_95	lower_ci_99	upper_ci_99
2020-01-01	115953.424199	95057.551431	141442.698460	95057.551431	141442.698460
2020-02-01	116854.802732	95744.508305	142619.615093	95744.508305	142619.615093
2020-03-01	118097.324744	96741.991966	144166.745260	96741.991966	144166.745260
2020-04-01	120802.468866	98913.279432	147535.665261	98913.279432	147535.665261
2020-05-01	120216.044846	98364.897144	146921.288570	98364.897144	146921.288570

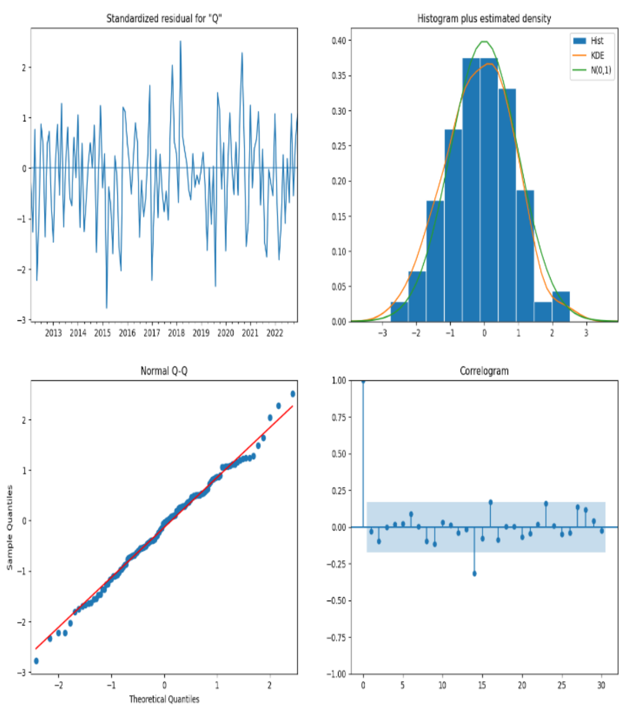
Appendix 15) Plot ACF and PACF for residuals of the best model to ensure no more information is left for extraction.

Inference Note: 4 plots in the residuals diagnostic plots tell us:

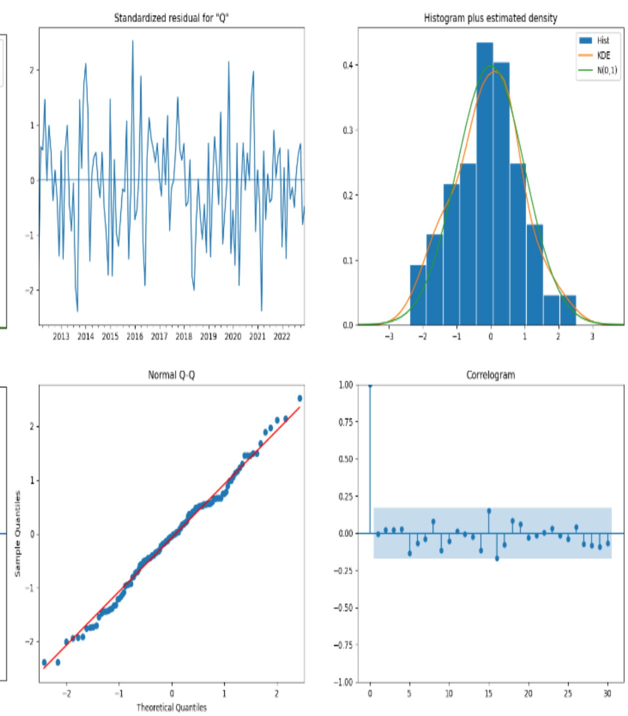
- Standardized residuals plot the top left plot shows 1-step-ahead standardized residuals. If model is working correctly, then no pattern should be obvious in the residuals which is clearly not visible from the plot as well.

- Histogram plus estimated density plot This plot shows the distribution of the residuals. The orange line shows a smoothed version of this histogram, and the green line shows a normal distribution. If the model is good these two lines should be the same. Here there are small differences between them, which indicate that our model is doing just well enough.
- Normal Q-Q plot the Q-Q plot compare the distribution of residuals to normal distribution. If the distribution of the residuals is normal, then all the points should lie along the red line, except for some values at the end, which is exactly happening in this case.
- Correlogram plot the correlogram plot is the ACF plot of the residuals rather than the data. 95% of the correlations for lag >0 should not be significant (within the blue shades). If there is a significant correlation in the residuals, it means that there is information in the data that was not captured by the model, which is clearly not in this case.

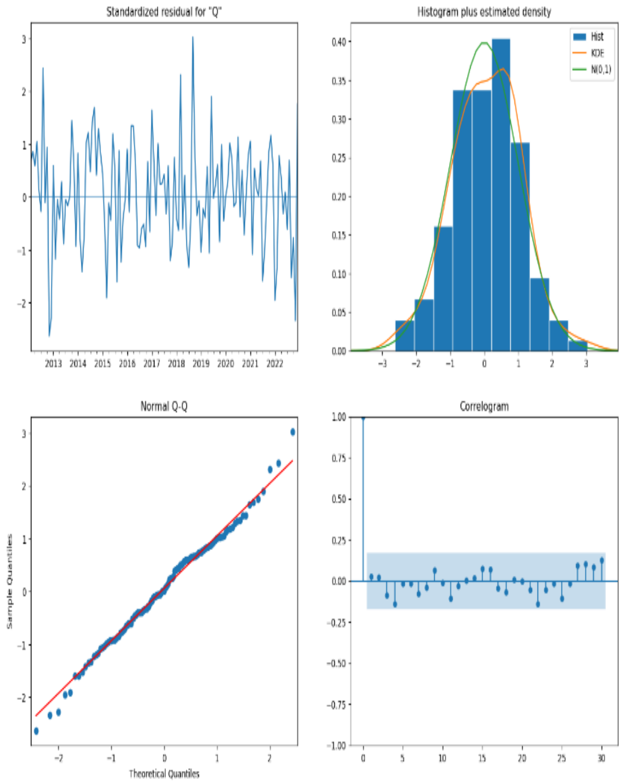
Other Conclusions for Q-P1 (The quantity of product 1)



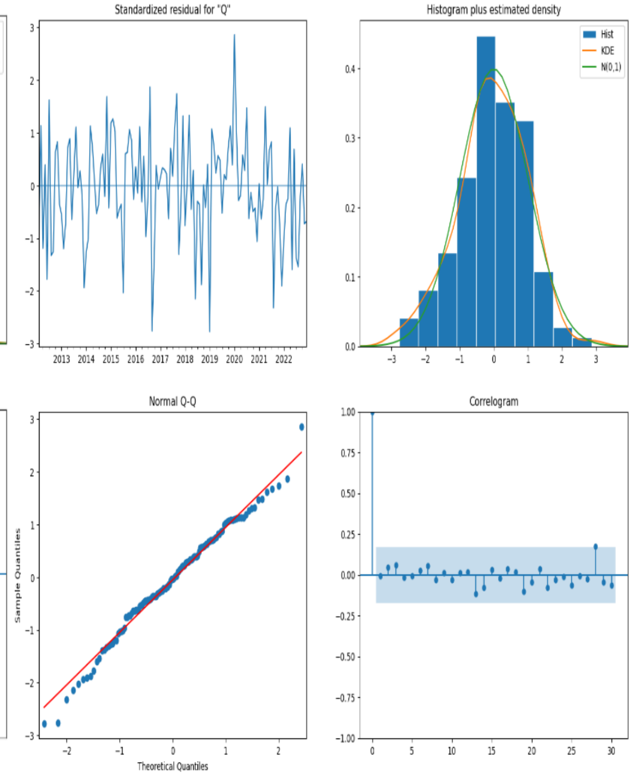
Other Conclusions for Q-P2 (The quantity of product 2)



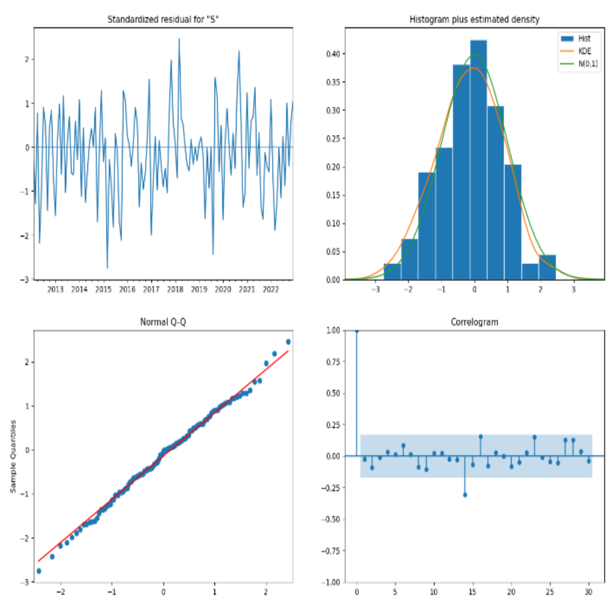
Other Conclusions for Q-P3 (The quantity of product 3)



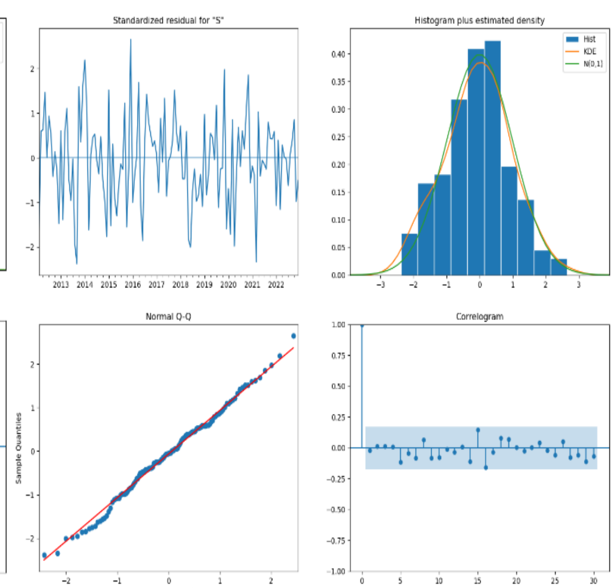
Other Conclusions for Q-P4 (The quantity of product 4)



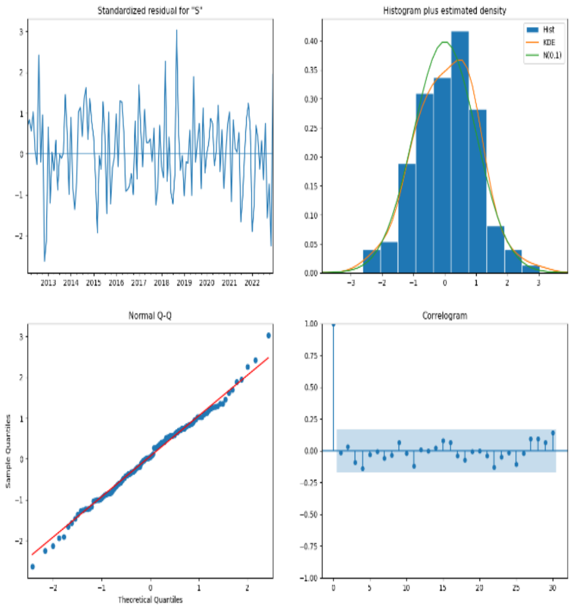
Other Conclusions for S-P1 (The revenue of product 1)



Other Conclusions for S-P2 (The revenue of product 2)



Other Conclusions for S-P3 (The revenue of product 3)



Other Conclusions for S-P4 (The revenue of product 4)