

Appendix D. Python code

The study considers Python as an application to establish the forecasting model and implement the external parameters such as vaccination rate, covid-variant, and control measures into the final model. The following figures describe the detailed code, explanation of the code is directly provided next to the coding sentences:

1. Import libraries into Python file:

```
1
2 import pandas as pd
3 import numpy as np
4 import matplotlib.pyplot as plt
5 from statsmodels.tsa.stattools import adfuller
6 from statsmodels.tsa.arima.model import ARIMA
7 from pandas import DataFrame
8 from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
9 import warnings; warnings.filterwarnings(action='once')
10 import math
```

2. Import excel file, this excel file contains the COVID-19 confirmed cases have been recorded daily from 27th April to 24th November 2021. After which, the data was plotted in order to visualize the distribution of the collected data

```
11
12 WB = pd.read_excel("Data import for ADF.xlsx")
13 # Plot data into a graph:
14 y = list(WB['Data value'])
15 x = list(WB['Date'])
16 plt.title('Recorded confirmed cases time series plot')
17 plt.plot(x, y)
18 plt.show()
19
```

3. The first step in model ARIMA development is considering whether the data is stationary. Hence, an ADF test is provided in the code. From which, d parameters will then be determined based on the stationarity of data in which differencing stage. The COVID-19 confirmed cases in this study is considered to be stationary on the first differencing, which means $d = 1$ in ARIMA model:

```
20 # ADF test
21 # Considering the stationarity of the original data
22 X = WB['Data value'].values
23 result = adfuller(X)
24 print('The result of ADF test of the original value is:')
25 print('ADF Statistic: %f' % result[0])
26 print('p-value: %f' % result[1])
27 print('Critical Values:')
28 for key, value in result[4].items():
29     print(key, value)
30
31 if result[0] < result[4]["5%"]:
32     print("Reject Ho - Time Series is Stationary")
33 else:
34     print("Failed to Reject Ho - Time Series is Non-Stationary")
35
36 # Considering the 1st differencing
37 WB['1st_Differencing'] = WB['Data value'] - WB['Data value'].shift(1)
38 plt.plot(x, WB['1st_Differencing'])
39 plt.title('First differencing of recorded confirmed cases')
40 plt.show()
41 result2 = adfuller(WB['1st_Differencing'].dropna())
42 # Note we are dropping na values because the first value of the first difference is NA
43 print('-----')
44 print('The result of ADF test of 1st Differencing is:')
45 print('Critical Values:')
46 for key, value in result2[4].items():
47     print(key, value)
48 print('ADF Statistic: %f' % result2[0])
49 print('p-value: %f' % result2[1])
50 if result2[0] < result2[4]["5%"]:
51     print("Reject Ho - Time Series is Stationary")
52 else:
53     print("Failed to Reject Ho - Time Series is Non-Stationary")
```

4. AR(p) and MA(q) were determined using ACF and PACF method, the code is as following:

```

54 # ACF and PACF method
55 WB['1st_Differencing'] = np.asarray(WB['1st_Differencing'])
56 fig, (ax1, ax2) = plt.subplots(1,2,figsize=(16,6), dpi= 80)
57 ACF_plot = plot_acf(WB['1st_Differencing'].dropna(),ax=ax1, lags=60)
58 PACF_plot = plot_pacf(WB['1st_Differencing'].dropna(),ax=ax2, lags=60, method='ywm')
59 # Decoration:
60 # 1.lighten the borders
61 ax1.spines["top"].set_alpha(.3); ax2.spines["top"].set_alpha(.3)
62 ax1.spines["bottom"].set_alpha(.3); ax2.spines["bottom"].set_alpha(.3)
63 ax1.spines["right"].set_alpha(.3); ax2.spines["right"].set_alpha(.3)
64 ax1.spines["left"].set_alpha(.3); ax2.spines["left"].set_alpha(.3)
65 # 2.Font size of tick labels
66 ax1.tick_params(axis='both', labelsz=12)
67 ax2.tick_params(axis='both', labelsz=12)
68 plt.show()
69

```

5. To implement the external parameters into the model, the study uses Pearson's correlation to determine the relationships between Confirmed cases and external data defined. However, since the correlation can easily be calculated through excel, the following code only considers when the Beta parameters of external data have been defined and implement these parameters into the ARIMA model for simplicity:

```

70 # Implementing external parameters, the coefficients were performed in excel file
71 WB2 = pd.read_excel("External Parameters.xlsx")
72 Vaccination = WB2['Vaccination coverage (PPM)'].values
73 Social_distance = WB2['Social distancing'].values
74 Incubation = WB2['Incubation period'].values
75 Generation_time = WB2['Generation time'].values
76 beta_vaccination = 0.361
77 beta_distancing = 0.577
78 beta_incubation = -0.03
79 beta_generation = 0.092
80 X1 = beta_vaccination*Vaccination
81 X2 = beta_distancing*Social_distance
82 X3 = beta_incubation*Incubation
83 X4 = beta_generation*Generation_time
84 WB['External'] = X1 + X2 + X3 + X4
85

```

6. The ARIMA parameters and external parameters were used to forecast the COVID-19 confirmed cases in this stage, the following code provides a way to plot these data and include the real data for fitting. Noted that in this stage, a 95% confidence level is applied for COVID-19 confirmed cases collected

```
86 # ARIMA model: provide a forecasting model of ARIMA => ARIMA (1,1,0)
87 model = ARIMA(WB['Data value'], order=(1,1,0))
88 RESULT = model.fit()
89 print(RERESULT.summary())
90
91 fig2, ax = plt.subplots(1,2,figsize=(16,6), dpi= 80)
92 residuals = DataFrame(RERESULT.resid) # Line plot of residuals
93 residuals.plot(title="Residuals", ax=ax[0])
94 residuals.plot(title="Density", ax=ax[1], kind='kde') # Density plot of residuals
95 plt.show()
96
97 # Summary stats of residuals
98 print(residuals.describe())
99 # Forecast ARIMA (1,1,0)
100 WB['ARIMA(1,1,0)'] = RESULT.predict(start=0, end=207, dynamic=False)
101 WB['Final Forecast result'] = WB['ARIMA(1,1,0)'] + WB['External']
102
103
102
103 # 95% Confidence interval:
104 CI = 1.96*np.std(WB['Data value'])/np.sqrt(len(x)) # since Confidence level = 95%, z-value = 1.96
105 # Plot
106 fig3, ax3 = plt.subplots(1,1)
107 plt.title('Forecast of COVID-19 Confirmed Cases in HCMC', alpha = 0.5)
108 plt.plot(x, WB['Data value'])
109 plt.plot(x, WB['Final Forecast result'])
110 ax3.fill_between(x, (WB['Data value'] - CI), (WB['Data value'] + CI), color = "b", alpha = 0.2)
111 plt.legend(["COVID-19 Confirmed Cases", "ARIMA(1,1,0) Forecast"])
112 plt.show()
```

7. After providing forecast results, the study continued with calculating and plotting a 7-day moving average between forecasting results and real data. MSE and RMSE calculation was also included in this part for error comparison in this study:

```

114 # Calculate the 7-day moving average of both confirmed cases and forecasting results:
115 # For confirmed cases:
116 window_size1 = 7
117 i = 0
118 moving_avg1 = [] # Provide an empty list to store moving averages
119 # Loop through the array to consider every window of size 7:
120 while i < len(WB['Data value']) - window_size1 + 1:
121     list1 = list(WB['Data value'])
122     window1 = list1[i:i+window_size1] # Store elements from i to i+window_size in list to get the current window
123     window_average1 = round(sum(window1) / window_size1, 2) # Calculate the average of current window
124     moving_avg1.append(window_average1) # Store the average of current window in moving average list
125     i = i+1

127 # for forecasting results:
128 window_size2 = 7
129 j = 0
130 moving_avg2 = [] # Provide an empty list to store moving averages
131 # Loop through the array to consider every window of size 7:
132 while j < len(WB['Final Forecast result']) - window_size2 + 1:
133     list2 = list(WB['Final Forecast result'])
134     window2 = list2[j:j+window_size2] # Store elements from i to i+window_size in list to get the current window
135     window_average2 = round(sum(window2) / window_size2, 2) # Calculate the average of current window
136     moving_avg2.append(window_average2) # Store the average of current window in moving average list
137     j = j+1

139 x1 = np.linspace(0,201,201) # Specify the number of observation in 7-day moving average => 201 observations
140 plt.plot(x1, moving_avg1)
141 plt.plot(x1, moving_avg2)
142 plt.legend(["COVID-19 Confirmed Cases", "ARIMA(1,1,0) Forecast"])
143 plt.title('7-day moving average of Covid-19 confirmed cases & forecasting result', alpha=0.5)
144 plt.show()

146 # RMSE Calculation:
147 MSE = np.square(np.subtract(WB['Data value'], WB['Final Forecast result'])).mean()
148 RMSE = math.sqrt(MSE)
149 print("Mean Square Error: ", MSE)
150 print("Root Mean Square Error: ", RMSE)

```