The Analysis Of South Korea Air Passenger Traffic: *Jeju Island*

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1.0 Problem Definition

Forecasting is defined as a decision-making tool used to make proper budgeting, planning, and estimation of future growth. Inclusively, it improves a business' efficiency and provides adequate utilisation of capital (Chand,S. n.d). Forecasting develops assumptions about the future uncertainty given the present and past data available.

Air transportation is one of the fastest-growing sectors as it enables a country to achieve economic growth and development. People travel constantly for various reasons such as business trips or even tourisms. Consequently, it helps to generate trade, promote tourism, and also create employment opportunities which contributes to a country's economy.

In South Korea, air transport sector is a major part which contributes to the country's economy. According to the World Tourism Organisation (WTO), international tourist arrivals grew by 7.4% in 2000. Over the years, South Korea was able to increase the growth of its transportation sector with the rapid increase in freight and passenger traffic. Hence, it becomes a critical factor in sustaining the well-being of the people in Korea.

In this study, the focus would be on predicting the number of arrivals in Jeju Island, which is one of the most overwhelming island around the world with many volcanic landscapes, various entertainments and picturesque waterfalls.

1.1 Issues: Population and Demographics issues

Jeju international airport remains the top 5 busiest airports around South Korea. Statistically, over 15 millions of tourists visit Jeju Island every year. Since there are only around 660,000 people are living in Jeju Island, tourism is the major revenue source for Jeju Island. The development of many luxury hotels and resort has designed to cater the demand of tourists. It is also famous for its nature such as the World Heritage Site Jeju Volcanic Island and Lava Tubes. Therefore, Jeju Island has claimed to be the New Seven Wonders of Nature in 2011. Hence, the island creates a unique hub by both domestic and international tourists (Kim, 2017).

However in 2017, with the amount of people entering the island, which is only an area under 2,000 sq km, is an issue as it is overpopulated with tourists - approximately 65,000 flights and about 15 million tourists visited the island (Baker, 2018). Also, the local residents has also made complaints as they deal with the pressure from the increase in number of people and noise in the island.

1.2 Issues: The Need to Build another Airport in the Island

In relation to its huge popularity, the government decided to build a new airport in Southern Jeju two years ago. This was because Jeju International Airport is too crowded to support the demand as it continues to increase gradually. Thus, increases the risk of people's safety in the airport (Jung, 2018). Many are concern for the capacity of the island's environment but others sees these as an opportunity for the economy growth (Southcott, 2015). It was estimated that the number of current users are approximately 30 million, which is stated as 4 million more than it was designed to handle. Many of the residents opposed the idea as it causes more damage to the environment due to over populations. However, the problem arising with the agreement to build a new airport is still in debate and would be taken into court later.

One of the major projects - Ora, a mega-resort that covers an area of 3.5 million square meters, designed to take approximately 60,000 people. This project would add up to almost 10% addition to the island's population at peak times. By this, more planes and airports is needed for the absorbed population in the near future.

1.3 Issues: Overpopulated with Foreigners' business and Developments

Jeju Island was seen as a popular tourist destination mainly for the Chinese and Japanese. Almost 80% of all foreign visitors to Jeju are Chinese tourists. One of the reason was that it is visa-free for up to 30 days for Chinese. Moreover, many of the commercial facilities are also owned by foreigners or major companies. More than 5.92 million square meter of the land is owned by Chinese - resulting to an increased since 2009. Mainly, the Chinese investors were attracted to the island as the Chinese are able to obtain permanent resident status. In 2014, the result to this policy made approximately 860 billion won of investment.

The advantages however is outweighed by the drawbacks as local small businesses did not account for half of the profits. Another drawback is that foreign capital did not benefit the employment rates in the island but increased the housing prices, making it problematic for locals to buy properties (Kim, 2014).

Moreover, the increase of development in the Island caused a shortage in water and sewage systems to breakdown (Jackson, 2017).

Throughout the paper, forecasting the number of arrivals in Jeju Island will be done to ensure proper planning and decision-making for constructing another airport in Jeju Island which is also used to improve the safety of people visiting Jeju Island. Understanding the number of passengers entering the Island also gives government an idea of different types of visitors that may affect the business in the Island. As more tourists enter the Island year by year, government must make wise planning on how to improve the businesses - local and foreigners.

2.0 Data Description and Visualization

2.1 Description of Data Set

The data was extracted from CEIC, reported by Korea Airports Corporation. It reports the number of arrivals to Jeju Island's Airport. Representing in terms of millions in passenger arrivals, there are a total of 259 data points that consist of the timeline starting from January 1997 till December 2017, thus it is a monthly time series data set. (See Figure 2.1)

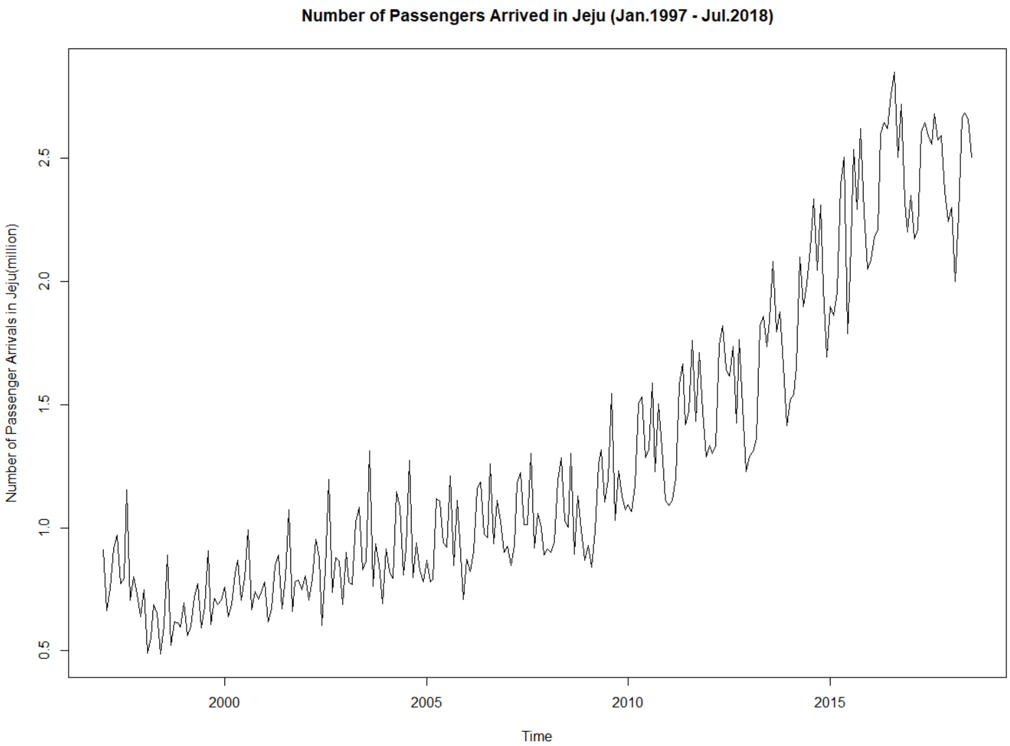

Figure 2.1*: Time series graph*

2.2 Description and Interpretation of the time series graph

The graph above in **Figure 2.1** displayed a non-linear exponential upward trend which shows strong seasonality due to its fluctuations, while there is not much cyclicality being observed. It is seen that there is an enormous decline before 2000, as well as right after 2015. The degree of upward trend after 2010 is much steeper compared to the degree of upward trend between 2000 to 2010. This is in line with the policy by the Korean Government to impose Jeju as a visa-free state in order to encourage Jeju as a tourist hub of the country (Quartz, 2014).

The decline before 2000 has showed that Korea’s air traffic passengers was being affected by Korea mostly due to the Asian Financial Crisis, during 1997, as Korea had an unstable economy. This is because of internal issues such as mistakes of economic policy, a string of conglomerate bankruptcies made the Korean economy to be much more vulnerable to shocks of the Asian Financial Crisis (Lee & McNutty, 2003).

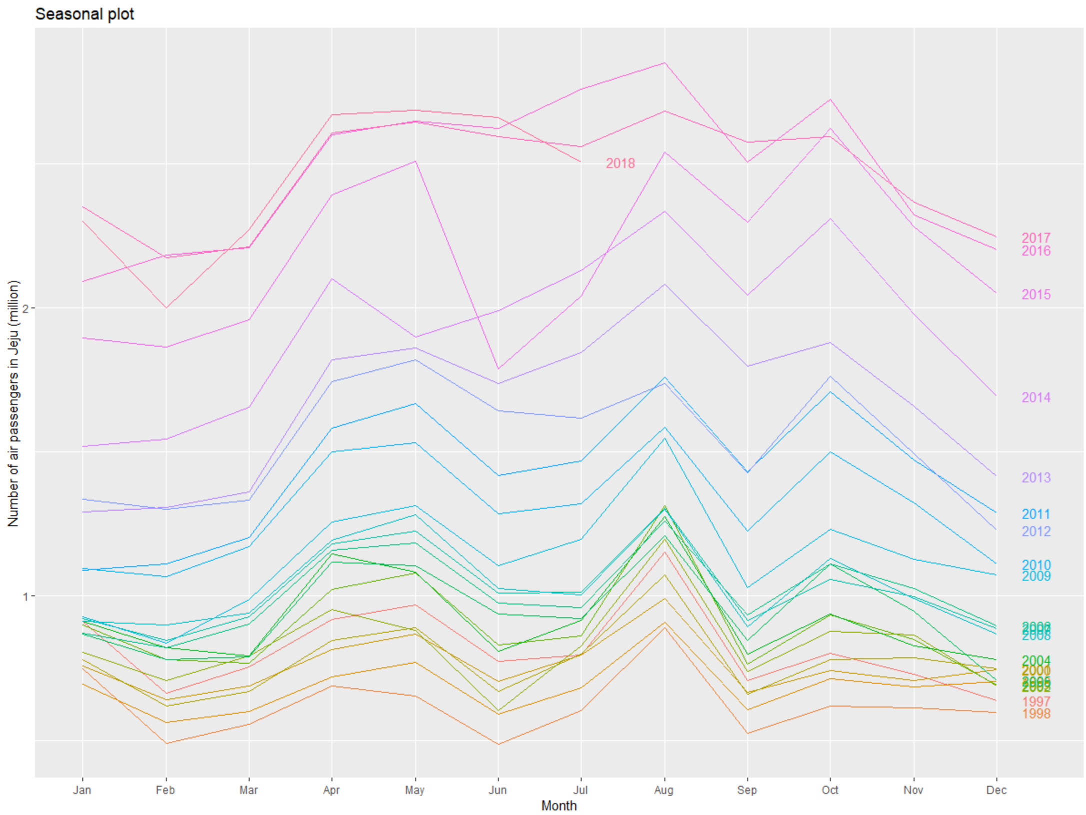

Figure 2.2: *Seasonal plot of air passengers in Jeju island*

Figure 2.2 above has displayed the monthly components in the time series for each years, starting from 2000 and ending with 2018. However, the team wants to highlights the seasonal component of the graph, where at the beginning of the graph, there is only a huge decline before it continuously goes upwards.

In the graph, there seems to be an unusual drop and then noticing a sudden shift in number of air passenger in June 2015. Hence, a seasonal pattern is harder to identify in 2015.

In the earlier years, between 2000 to 2008, the monthly time series seems to be almost identical. Every August of the years between 2000 to 2008, it shows the highest number of air passengers arriving to Jeju Island. In the later years (between 2012 to 2018), there was a sudden increase in the month of March to May. This is because, statistics shows that the busiest time for Jeju Island is during those months. By this, most of the hotels and flights are likely to be more expensive. However, the graph shows that December has the least number of air passengers as tourists are least likely to visit Jeju Island.

Overall, the number of air passengers has increased during the years. Hence, a strong seasonal pattern can be seen except in the year 2015.

At the same time, based on the results seen in Figure 2.2, it is evident that there is seasonality within the data. However the data should be proceeded to the ACF test for the presence of seasonality.

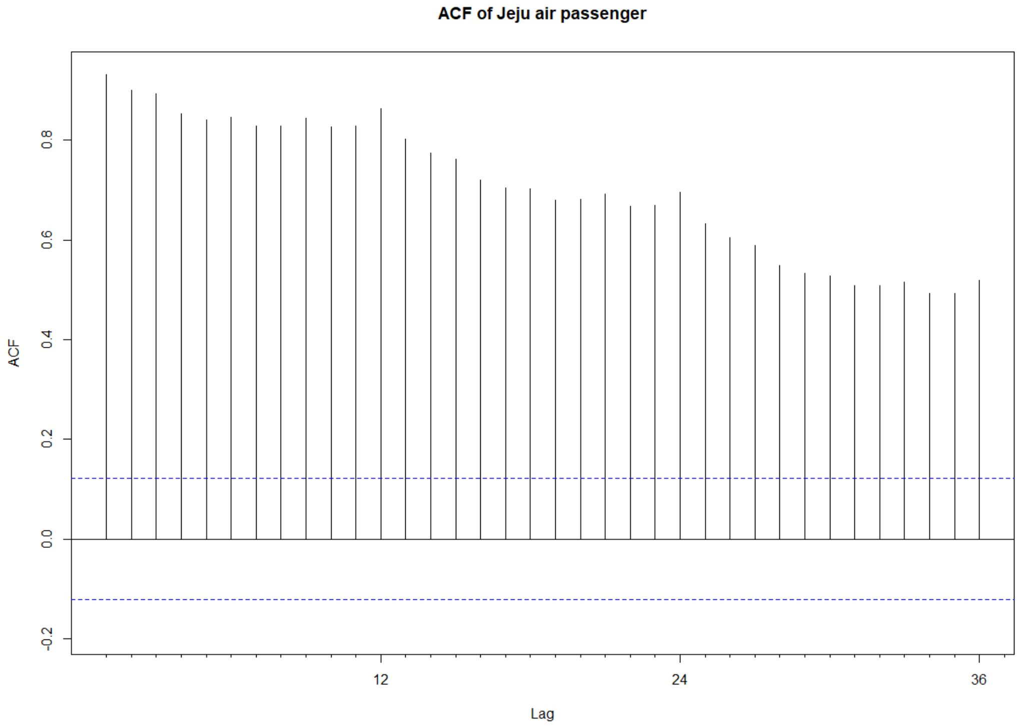

Figure 2.3: *Autocorrelation plot of air passengers in Jeju*

ACF plot (Figure 2.3) has suggested that its pattern displayed a slow decay throughout all the lags. At the same time, it shows strong positive significance, hence it is concluded that there is strong seasonality.

3.0 Data Preprocessing / cleaning

Data preprocessing is an essential process as it impacts the success rate of the results. It is beneficial as it helps reduce the complexity of the data for better analytical observation (Swaminathan, n.d).

Firstly, data preprocessing is done by filling in missing values or readjusting the noisy data. However, the data retrieved did not show any missing or inconsistency of data in the data set.

Moving on, data preprocessing helps to generalized and normalized the data set. Data reduction is also one of the steps to preprocessing. However, the data retrieved in this study is an univariate data. Only variable of the number of passengers were present. The data extracted on the variable was shown as, example, “6040708” which was difficult to read. To reduce any risk of misinterpretation, the team has changed it into millions per month. This shows a clearer illustration.

Furthermore, the data retrieved was based on a monthly time series. Hence, the team did not need to preprocess the data separately. It is decided that a monthly time series is more appropriate as it indicates a strong seasonal pattern based on Figure 2.2. The data given had a time series ranging from January 1997 till December 2017. The team has agreed to reduce the data set, starting from January 2000. This is mainly because before 2000, there is a huge decline in passengers arrival that is due to the Asian Financial crisis, which is not exactly needed to forecast the patterns from 2015 onwards. This is because at the point after 2000 onwards, the country’s economy has been in the progress of moving towards a developed country. Taken this into consideration, the financial crisis that happened in 1997 was unexpected to Korea’s economy as the country’s growth was unable to sustain the pressure of the crisis. Furthermore, the level of the value has got back to a similar level at the year of 2000 which was the origin level. By this, the forecast accuracy will be affected due to the effect of the crisis, which is the starting point of the graph. Hence, removing the data before 2000 will show us a more accurate and reliable forecast.

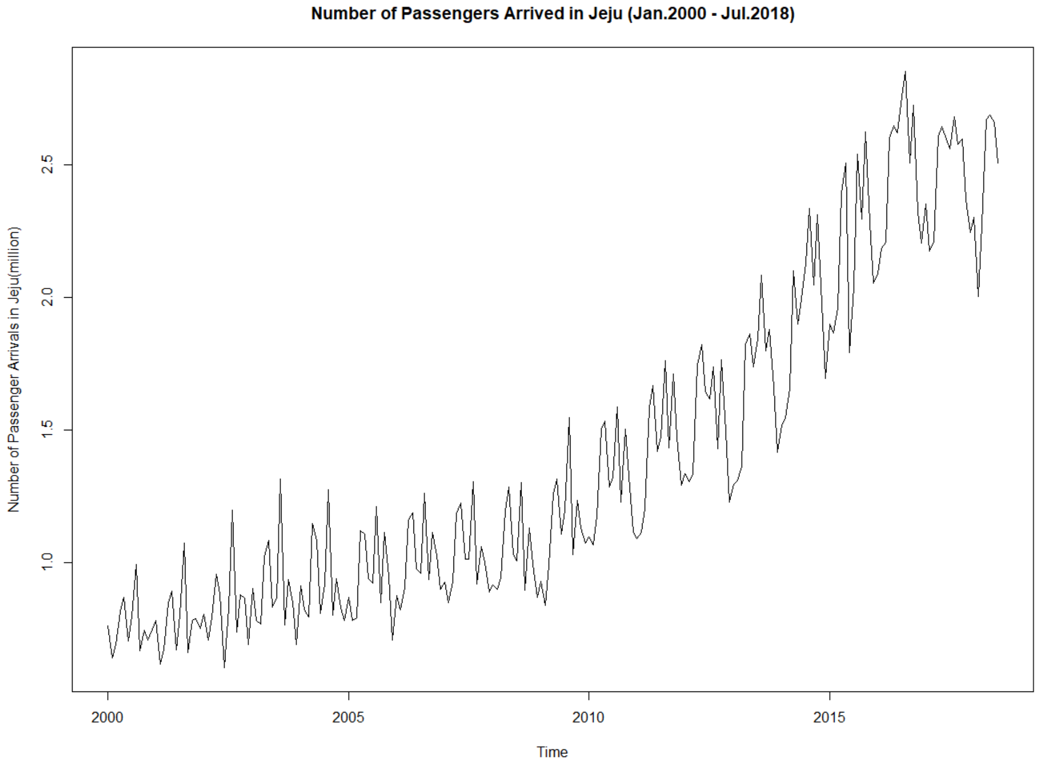

***Figure 3.0**:Time series of number of passengers arrived in Jeju (Jan.2000 onwards)*

Hence, the Figure 3.0 shows the data set between 2000 to 2018, after preprocessing. This indicate the importance of removing the data before 2000, where Korean Economy was not as stable, and its economy starts to only recover or stabilize after 2000. This is vital for the data to be started under a neutral point, so to avoid the future data to be affected when it is obvious that the economy has already been stabilized.

4.0 Method Formulation

4.1 Partition of Datasets

There is a total of 223 observations in the dataset, after the exclusion of data before the year 2000.

4.1.1 Concept of Training set and test set

The first step taken was to partition the data set into two parts - Training set and Test set. Ideally, training data set is referred to an "in-sample data" while test data is referred to "out-of-sample data".

Training set is the data set used to train and fit to the model. It is used for forecasting the methods/models respectively. The data from January 2000 to December 2014 was taken as the data set for training. This accounts for 75% of the data, which is a total number of 180 observations. The test set however is used to compare the results from the forecast produced from the training set. The rest of the 25% is used for the test set, which is a total number of 48 observations from January 2015 to July 2018. This is because splitting the data at 70% indicates that it is under forecast while accounting for 80% of data to the training set shows a result of over forecasting from the graphs. Hence, a training data set should be large enough to yield statistically meaningful estimations.

Evaluating the estimated parameters using the training set helps to determine the accuracy of forecasting method/models. After, the forecast is used as a comparison to the test data set (Hyndman, 2014).

4.1.2 Introduction to Methods

Forecasting has become an integral part of business decisions. Each data being forecast has a unique history, and hence an optimal method. A method that accurately forecasts a data set consequently prove inaccuracy in another method. A time series data has a set of historical data points that is set at a chronologically ordered manner. Below shows the different methods used to obtained parameter estimates and errors.

4.2 Parameters Estimate and Within Sample Errors of the Methods & Models

Model	alpha	beta	gamma	phi
SES	0.3299	-	-	-
Holt’s Linear	0.0345	0.0043	-	-
Exponential	0.0513	0.0031		
Additive-damped	0.0907	0.005		0.98
Multiplicative-damped	0.0467	0.0054		0.98
Holt-winter	0.1919	0.0114	1e-04	-
Holt-winter Multiplicative damped	0.1327	0.0271	4e-04	0.9736
ETS(M,A,M)	0.2161	0.0066	0.447	-
ETS(M,Ad,A)	0.2423	0.01	0.4946	0.98

***Table 4.1**: Tables of Estimate in Parameters.*

Method	RMSE	MAE	MAPE	MASE
SES	0.1846343	0.1454731	12.68694	1.524431
Holt’s Linear	0.1802734	0.1447296	12.60751	1.516640
Exponential	0.1794865	0.1448254	12.64669	1.517643
Additive-damped	0.1835638	0.1462713	12.60414	1.532795
Multiplicative-damped	0.1821467	0.1449614	12.433989	1.519069
Holt-winter	0.07843379	0.05878474	5.467530	0.6160127
Holt-winter Multiplicative damped	0.07985019	0.05857839	5.391652	0.6138503
ETS(M,A,M)	0.07203095	0.0535506	4.725122	0.5611634
ETS(M,Ad,A)	0.07188191	0.0538648	4.742243	0.564456

***Table 4.2:** Within-sample errors accuracy test result*

Table 4.2 represents that within-sample errors in training set from the 7 forecasting method/model. RMSE, which was mentioned above is widely taken into consideration for choosing the best quality method/model. (Appendix 1 to Appendix 7)

4.3 Best Goodness of Fit and Expectations

ETS(M,A,M) seasonality method has shown the best goodness of fit, where looking at the overall errors in **Table 4.2**, the errors from ETS(M,A,M) showed the lowest for MAE, MAPE and MASE at 0.05355, 4.725 and 0.5612 respectively. However for RMSE, it is observed that there is only a slight difference in between ETS(M,A,M) and the lowest RMSE of ETS(M,Ad,A). Hence, ETS(M,A,M) has shown the best goodness of fit, taking account for the overall error values.

4.4 Expectations of Model

This result has not been expected because the original data in **Figure 3.0** has probably shown characters of an additive data, where it displayed an upward linear and additive damped trend with additive seasonality. However, the lowest errors in the MAE, MASE and MAPE has identified that there is only additive trend, which does not reflects the time series graph in **Figure 3.0**, where from 2015 onwards the graph has been showing a damped trend.

However, at later section it will be proceed to look at the result of the out of sample forecast to see whether it fits the test set model and it is expected that the damped trend capturing model will give better fitting figures in the out-of-sample test in the further section.

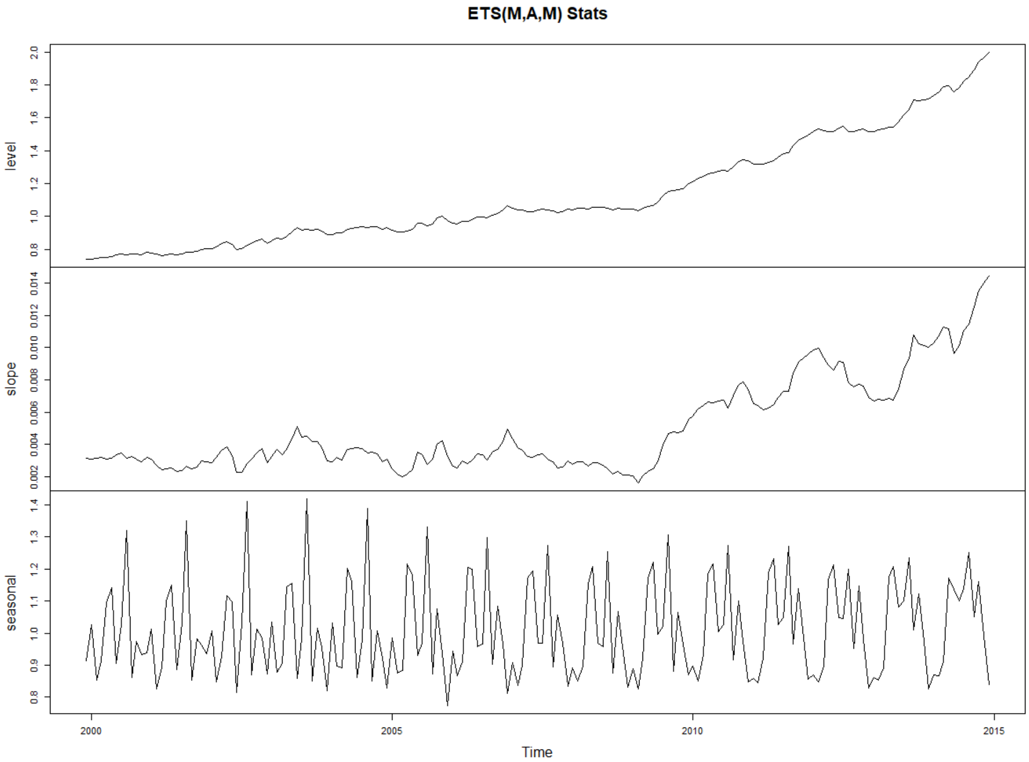

Figure 4.1:*ETS (M,A,M) model stats*

<table>
<tr><th colspan="5">Smoothing parameter of ETS(M,A,M)</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.2161</td><td>0.0066</td><td>0.447</td><td>-</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><td rowspan="6">Level</td><td rowspan="6">0.7393</td><td rowspan="12">Seasonal</td><td>1</td><td>0.9136</td></tr>
<tr><td>2</td><td>0.9482</td></tr>
<tr><td>3</td><td>0.9883</td></tr>
<tr><td>4</td><td>0.8572</td></tr>
<tr><td>5</td><td>1.3539</td></tr>
<tr><td>6</td><td>1.0195</td></tr>
<tr><td rowspan="6">Trend (Slope)</td><td rowspan="6">0.0031</td><td>7</td><td>0.8878</td></tr>
<tr><td>8</td><td>1.1371</td></tr>
<tr><td>9</td><td>1.1075</td></tr>
<tr><td>10</td><td>0.9076</td></tr>
<tr><td>11</td><td>0.8506</td></tr>
<tr><td>12</td><td>1.0287</td></tr>
</table>

***Table 4.3** ETS (M,A,M) model stats*

4.5 Interpretation of Estimated Smoothing Parameters

4.5.1 Level

The alpha value calculated by ETS(M,A,M) method shows 0.2161 in **Table 4.3** indicates that there is minor adjustment on it's error correction term for the level component, where this component is heavily influenced by the previous period of level and trend component. This also means that the level component seen in **Figure 4.1** will look more like the forecast of Air Passengers arrival rather than the seasonally adjusted data.

4.5.2 Trend (Slope)

The beta calculated in **Table 4.3** indicates that the Trend component was not being influenced as much, which is at 0.0066 almost equivalent to 0. However in the **Figure 4.1**, the graph shows that the component has shown irregular upward trend. This is due to the scale being magnified, which is shown in the graph with low gap. Therefore, the forecasted value is not highly affected much by the slope and the slope depends more on level value.

4.5.3 Seasonality

On the seasonal component, it is considered being strongly adjusted by the Gamma at 0.447, indicates that 45% of the weightage has been adjusting its seasonality, while only 55% of the weightage comes from the estimated forecast. **Referring to Figure 4.1** , its seasonality pattern has minimal constant variance from 2000 to 2010 that has only slight changes in the pattern, which are additive seasonality. However from 2010 onwards till 2016, it is observed that the seasonality pattern has evolved into a multiplicative seasonality.

4.6 Data Plots of Methods/ Model's forecast and the full data set

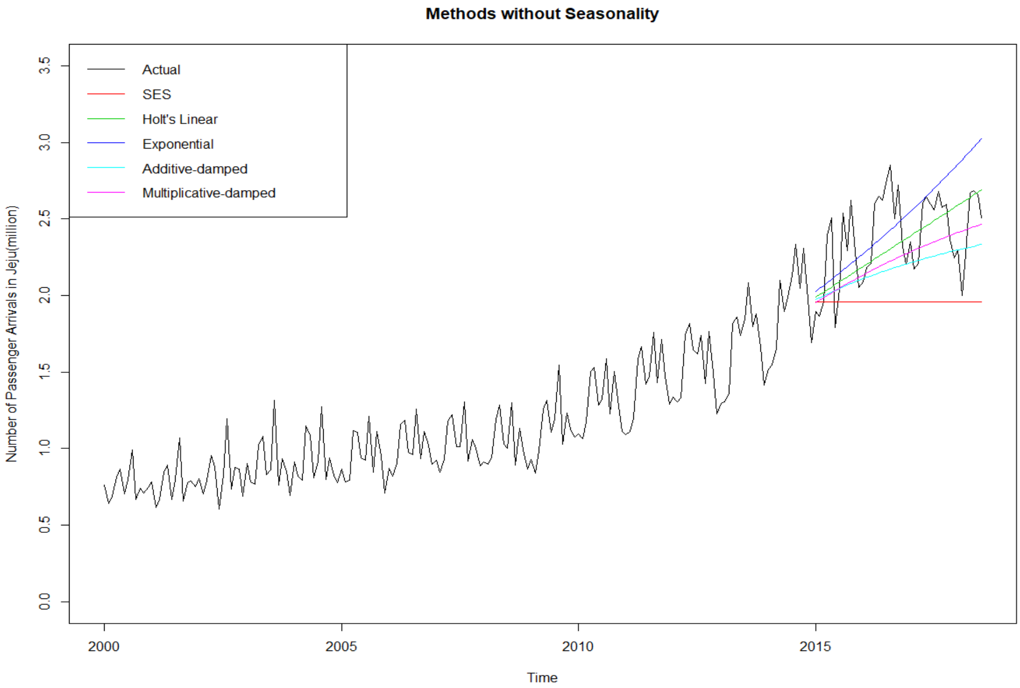

Figure 4.2 *Method without seasonality components*

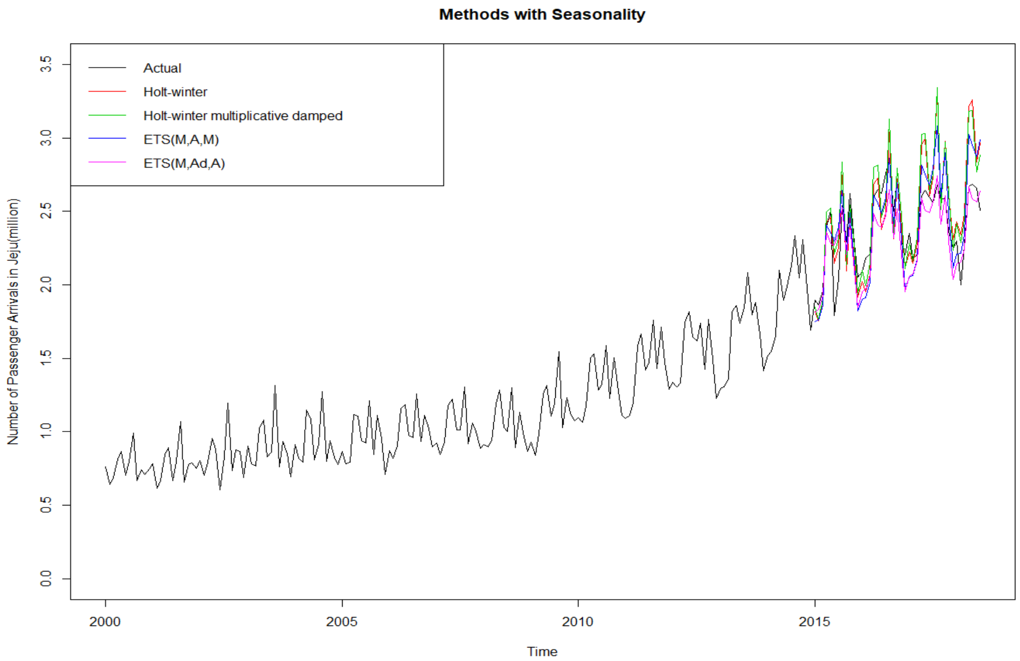

Figure 4.3 *Method with seasonality component*

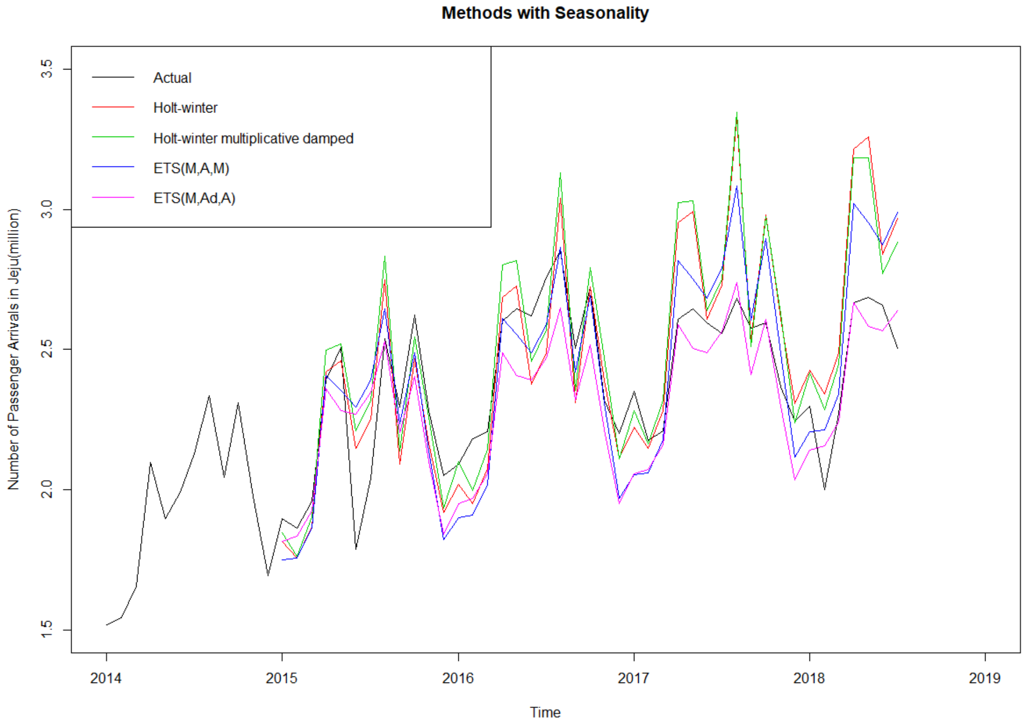

***Figure 4.4** Methods with seasonality (Magnified plot of **4.3**)*

4.7 Description of plots

Both plots which are **Figure 4.2** and **Figure 4.3** (as well as **Figure 4.4**) represent the methods and models of forecast that were produced are splitted, one without seasonality and another with the presence of seasonality for clearer visuals.

It is observed that in **Figure 4.2**, all methods without seasonality component could not project the details of the seasonality from data, therefore the graph does not seem appropriate as the data is a monthly time series data with seasonality.

On the other hand, in **Figure 4.3**, it is observed that methods and models that consist the seasonality component able to follow the patterns of seasonality within the data. It is observed that the method that follows closest to the test set data (black line) is the ETS(M,Ad,A), where it's forecast does not deviate away from the actual test set data as much as the other methods. This is probably due to its ability to capture the additive damped trend of the end of the full data set.

4.8 Explanation of Test Set forecast

In **Figure 4.4**, all methods with seasonality component has successfully project the seasonality patterns from the data. Among all, it is probably that ETS(M, Ad, A) is most fitting as there is an expectation that the method is heading towards a dampening effect. Referring to **Figure 4.4**, it is observed that ETS(M, Ad, A) moves well with the previous data pattern without any signs of disconnection. This shows there is smooth continuous flow between the training set and the forecast of the model.

5.0 Evaluate Forecasting methods/model

Method		RMSE	MAE	MAPE	MASE
SES	Train	0.1846343	0.1454731	12.68694	1.524431
	Test	0.5040650	0.4415680	17.56661	4.627246
Holt's Linear	Train	0.1802734	0.1447296	12.60751	1.516640
	Test	0.2660863	0.2121301	8.84992	2.222938
Exponential	Train	0.1794865	0.1448254	12.64669	1.517643
	Test	0.3265926	0.2699925	11.52832	2.829285
Additive-damped	Train	0.1835638	0.1462713	12.60414	1.532795
	Test	0.3191549	0.2566484	10.19661	2.689451
Multiplicative-damped	Train	0.1821467	0.1449614	12.433989	1.519069
	Test	0.2864506	0.2310780	9.303092	2.421495
Holt-winter	Train	0.07843379	0.05878474	5.467530	0.6160127
	Test	0.24721836	0.19371485	8.044849	2.0299624
Holt-winter-damped	Train	0.07985019	0.05857839	5.391652	0.6138503
	Test	0.24338226	0.18829241	7.779741	1.9731399
ETS(M,A,M)	Train	0.07203095	0.0535506	4.725122	0.5611634
	Test	0.20771242	0.1680162	7.247935	1.7606631
ETS(M,Ad,A)	Train	0.07188191	0.0538648	4.742243	0.564456
	Test	0.17380275	0.1422710	6.136439	1.490875

Table 5.1:*Out-of-sample accuracy test result*

5.1 Evaluation of Out of Sample Forecasting Accuracy

Referring to **Table 4.2**, it is noticed that the out-of-sample errors in the test set also indicates that ETS(M,Ad,A) has the best fit, and it was chosen because it detects the damped trend of the data. Therefore despite that ETS(M,A,M) had the best fit as a training set model, it was not as fit as it is in the test set, largely because it has lacked of damped trend. This proves that the most fit method in the training set does not mean that it fits the test set, as training set relies on the previous pattern of the data. Referring back to **Figure 3**, the plot also has suggested the pattern of additive seasonality instead of multiplicative seasonality. This is due to the seasonality pattern that is shown in the data. The seasonality of the data has both patterns of additive and multiplicative. There is an additive pattern in the beginning and end time of the data and multiplicative pattern between. The end additive pattern was highly captured in the recent years of the test data set, therefore ETS(M,Ad,A) captured this pattern well with damped trend.

5.2 Selection of Forecasting Method/Model

Therefore, ETS(M,Ad,A) model was chosen as the forecasting method due to its incorporation of the additive damped trend and its additive seasonality.

5.3 Goodness of Fit of Forecasting Model

The errors in the method ETS(M,Ad,A) presented in **Table 5.1** has shown the least in all errors. Hence, the model has the best goodness of fit in its forecast as compared to other methods or models.

6.0 Forecasting

6.1 ETS(M,Ad,A) model forecast

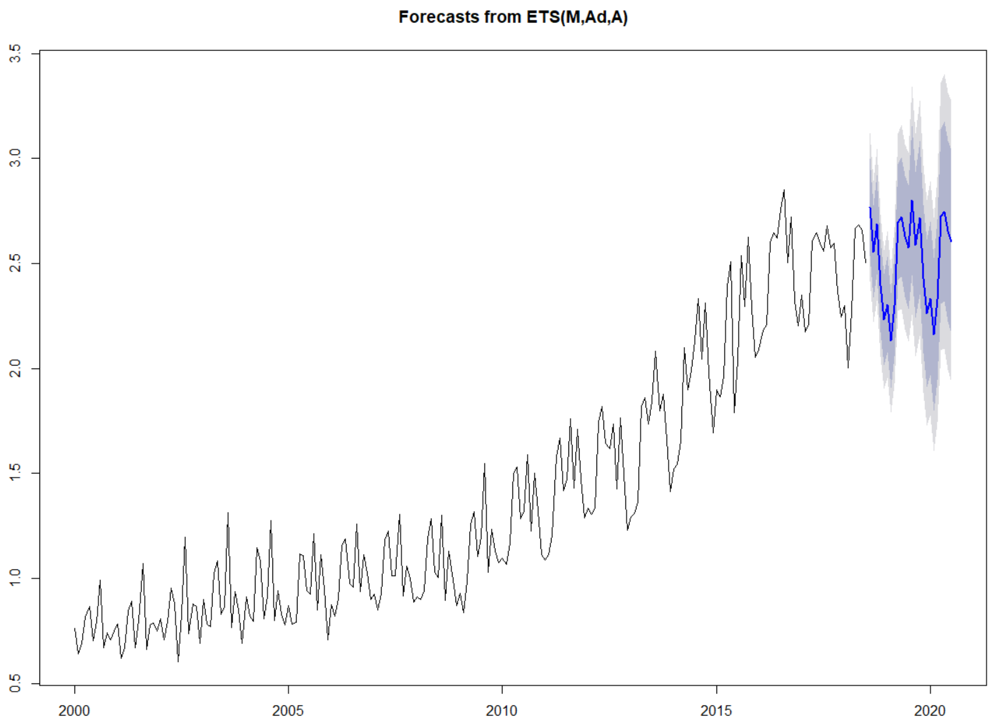

Figure 6.1 *Forecast result of ETS(M,Ad,A) with h=24*

Within-sample errors in full data set

Method	RMSE	MAE	MAPE	MASE
ETS(M,Ad,A)	0.09390823	0.06611554	4.794874	0.5672191

Table 6.1: *Within sample errors of full data set.*

Smoothing parameter and initial values of ETS(M,Ad,A) h = 24 forecast

<table>
<tr><th colspan="5">Smoothing parameter of ETS(M,Ad,A)</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.2262</td><td>0.0113</td><td>0.4298</td><td>0.98</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><th rowspan="6">Level</th><td rowspan="6">0.7358</td><th rowspan="12">Seasonal</th><td>1</td><td>-0.0469</td></tr>
<tr><td>2</td><td>-0.0489</td></tr>
<tr><td>3</td><td>-0.0118</td></tr>
<tr><td>4</td><td>-0.1071</td></tr>
<tr><td>5</td><td>0.2653</td></tr>
<tr><td>6</td><td>0.0169</td></tr>
<tr><th rowspan="6">Trend</th><td rowspan="6">0.0032</td><td>7</td><td>-0.0828</td></tr>
<tr><td>8</td><td>0.1138</td></tr>
<tr><td>9</td><td>0.0867</td></tr>
<tr><td>10</td><td>-0.0732</td></tr>
<tr><td>11</td><td>-0.1184</td></tr>
<tr><td>12</td><td>0.0063</td></tr>
</table>

***Table 6.2** Smoothing Parameters of full data set.*

The forecast data generally shows the damped trend for the next two years of period with following smoothing parameter and initial values. The smoothing parameter shows that similar pattern of the train set and same goes to initial values as well. With-in sample error of the full data set of number of air passengers in the Jeju island shows RMSE of 0.0939. Due to the damped trend starting from 2016 to 2018, the result of the forecasting model of the data shows that ETS(M,Ad,A) fits the best compare to other models and chosen to predict the further two years period (h = 24) which is from August 2018 to July 2020.

6.2 Linear regression model

The data set of air passengers in Jeju has seasonality with trend, hence the linear regression model needs to consist of trend and seasonal factor from January to December. The model has performed with linear regression and the following formula shows result of the linear regression.

$$y_t = 0.3159 + 0.0085t - 0.0785s_{2,t} - 0.0167s_{3,t} + 0.2941s_{4,t} + 0.3100s_{5,t} + 0.1033s_{6,t}$$

$$+0.1544s_{7,t} + 0.4164s_{8,t} + 0.0476s_{9,t} + 0.2318s_{10,t} + 0.0564s_{11,t} - 0.1016s_{12,t} + \varepsilon_t$$

***Figure 6.2** Linear forecasting formula*

Each seasonal dummy variable represents amount of increase in the given month and it is shown that January has set to base month. By using it, the prediction of two years (h = 24) has been performed and below graph shows the result.

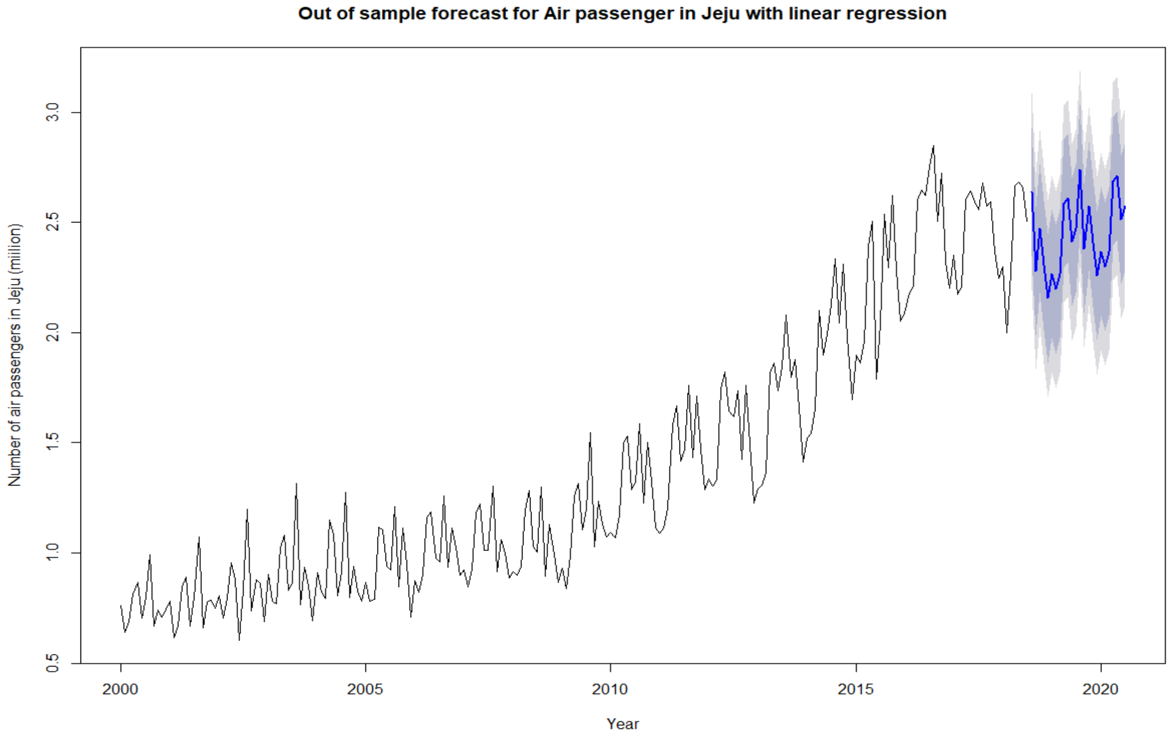

***Figure 6.3** Out of sample forecast of air passengers in Jeju with linear regression*

Linear regression methods gives the overall outcome of the data, considering predictor variables which are strongly correlated. However, compared to exponential smoothing methods, it estimates the linear trend of the data which does not capture the exponential growth and does not consider prior value to predict next level.

In Conclusion, due to the characteristics of the data, the exponential smoothing method will be the better method for the prediction and ETS(M,Ad,A) forecasting figures are selected for this study.

7.0 Conclusion

Located approximately 130 km from South Korea’s southern coast, Jeju Island is South Korea’s largest island. Furthermore, around 9 million tourists per year spend most of their time on Jeju Island (Hough, 2013).

Sustainability has been stressed as the major important topic in contemporary society such as maintaining and protecting global biodiversity, encouraging enhanced developments, and improving lifestyles of individuals in Jeju Island.

The forecasting values of air passengers in Jeju shows notable gap between the peak and the bottom. However the estimation can be fluctuated between its forecast interval, either wider or narrower between points. To prevent a huge drop from occurring and to increase the number of air passengers, there are some actions that can be taken in Jeju Island. Following sections are going to show the operations that are recommended.

7.1 Tourisms in Jeju Island

Problem:

As the economic level of Korea has been growing, the leisure of travelling overseas has increase as the spending power of the korean citizens has increased. Thus, it is causing an increased in the demand for Korean outbound tourism. This trend has continued since 1992, affecting the Korean domestic tourism demand as well as the local tourism demand of Jeju.

Because of this, the prediction for number of local tourists in Jeju will not show a huge increase (Seo, Park & Yu, 2009). Furthermore, the increase in development caused damages to the Island’s nature uniqueness. Losing its attractiveness and intention from tourisms hence affecting the future growth.

Solutions:

From tourism aspect of Jeju, improving its tourism industry in the Island will encourage a narrower gap in the forecast.

The positive perception of the tourism destination comes from experiences with entertainment and attractions which are generated by the tourists (Ramseook-Munhurrun et al., 2015). Known for its heritage sites, Jeju Island focuses on protecting its wonderful historical culture and natural sites as solutions that reconcile the conservation of diversity with sustainable use for tourism, leading to the tourists’ experience and loyalty of the place (Moon & Han, 2018). Wong and Wan (2013) also mentioned that shopping is a primary activity that tourist can do in the destination and it affect the customer satisfaction level of tourist. Therefore, it shows that the vigorous activities and options attracts the tourists to visit and increase the satisfactory of them. Then, it will bring the intention to revisit or recommendation among the tourists. At the end, it will lead to increase in the tourism demand for Jeju Island. Therefore, the investment on the dynamic activities in Jeju should be considered to stabilize and to boost the number of air passengers in Jeju which will guide to the improvement in tourism industry of Jeju.

Occasionally, Jeju government can also cooperate with institutions to provide new procedures for managing foreigner tour businesses. This is done by controlling tour guides depending on its requirements and also unregistered tour agencies into Jeju Island - delivering the best to the tourists.

7.2 Maintaining Relationship between countries

Problem:

About 90% of its foreign visitors comes from China, having approximately 400 over guides for Chinese tourist in the Island. The banned of selling package tours was due to the controversial between countries. Taking that into consideration, more than 50% dropped of business was received. Furthermore, because of 'Korean Performing Arts Activities Ban', there was a dropping trend from 2016 since it was implemented. According to Chai (2018), the duration of this ban effect is expected to be extended even though the relationship between countries is getting better. However, the number of tourist from China started to recover as time passes. In relation, the trust of the public's favor towards the Korean culture gradually move towards the past behaviour and the actions of Korean Govt. It is needed to bring Chinese favor towards the tourism and cosmetic industries who are major player in the industry. Jeju was able to remain its nature reputation resulting to 10% increased in domestic travellers, statistically observed (Zhen, 2017). By this, domestic travellers can overcome the drastic decrease in number of Chinese tourists, indicating that the forecast would not show a huge difference. Therefore, it will take a time to back to the growing period like before 2016.

Solution:

Tourism indisputably remains as a key element of Jeju's local economy, employment opportunities, and source of income for many locals. Ideally, 95% of the international visitors travelled with the use of airplane hence the need for an increase in air routes and seat supply is deemed a necessity as it promotes growth. By this, building another airport would be a necessity for the future economy of the Island, as well as the safety of people. However, the government can collect a "tourism tax" (essentially entrance fees to enter) to sustain the population. Also, gaining support from locals can be done by agreeing to build the airport at a given site that is suitable for development - preventing the nature of the island at all cost. In relation, to the addressed problem above. The government can also expand international direct flight routes from China. As well as promoting into markets in Japan and Southeast Asia.

7.3 Further recommendation and Limitations

The income level of the Island is an important determinant of Jeju's inbound tourism. As locals stresses the unfair treatment received due to the reduction of profits from own businesses as major projects over shadow them, government can look into introducing projects such as Tourism Doo-rae, which had previously been conducted before in 2013-2014, as the benefits were seen by over 100 local communities. This can be beneficial as it helps establish the tourism businesses by supporting local accommodation and restaurants.

Moving on, there are some limitations in this study. Firstly, the data represents the number of air passengers in Jeju without categorizing which country they are origin. Therefore, the collection of the data is mixed with domestic passengers and foreign passengers as well which may not indicate actual demand of visiting Jeju island. Secondly, there are other outside factors that it might affect the actual trend of air passengers in Jeju island which are not discussed above. Future unforeseen events could have an effect on the performance of the models since they were not considered in the forecasting process. Lastly, improving the quality of forecast accuracy can be done by using a more advanced forecast method/model that is more reliable for long term forecasting periods for better accuracy results. For the future study, by looking at the other factors of Jeju island or air passengers, it would lead to valuable findings.

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9.0 Appendix

Appendix A: Forecast Method of All Models

Appendix A.1

Forecast method: Simple exponential smoothing

Model Information: Simple exponential smoothing

Call: ses(y = jeju_train, h = 43, initial = "optimal")

<table>
<tr><th colspan="5">Smoothing parameter</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.3299</td><td>-</td><td>-</td><td>-</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><th rowspan="6">Level</th><td rowspan="6">0.7366</td><th rowspan="12">Seasonal</th><td>1</td><td>-</td></tr>
<tr><td>2</td><td>-</td></tr>
<tr><td>3</td><td>-</td></tr>
<tr><td>4</td><td>-</td></tr>
<tr><td>5</td><td>-</td></tr>
<tr><td>6</td><td>-</td></tr>
<tr><th rowspan="6">Trend (Slope)</th><td rowspan="6">-</td><td>7</td><td>-</td></tr>
<tr><td>8</td><td>-</td></tr>
<tr><td>9</td><td>-</td></tr>
<tr><td>10</td><td>-</td></tr>
<tr><td>11</td><td>-</td></tr>
<tr><td>12</td><td>-</td></tr>
</table>

sigma	AIC	AICc	BIC
0.1857	332.5561	332.6925	342.1350

Error measures

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Train	0.0206205	0.1846343	0.1454731	-0.4484241	12.68694	1.524431	0.1007158

<u>Code for the method</u>

```
jeju_ses <- ses(jeju_train, h = 43, initial = "optimal") #SES
jeju_ses
summary(jeju_ses)
```

Appendix A.2

Forecast method: Holt's method

Model Information: Holt's method

Call: holt(y = jeju_train, h = 43, initial = "optimal")

<table>
<tr><th colspan="5">Smoothing parameter</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.0345</td><td>0.0043</td><td>-</td><td>-</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><th rowspan="6">Level</th><td rowspan="6">0.7114</td><th rowspan="12">Seasonal</th><td>1</td><td>-</td></tr>
<tr><td>2</td><td>-</td></tr>
<tr><td>3</td><td>-</td></tr>
<tr><td>4</td><td>-</td></tr>
<tr><td>5</td><td>-</td></tr>
<tr><td>6</td><td>-</td></tr>
<tr><th rowspan="6">Trend (Slope)</th><td rowspan="6">0.0052</td><td>7</td><td>-</td></tr>
<tr><td>8</td><td>-</td></tr>
<tr><td>9</td><td>-</td></tr>
<tr><td>10</td><td>-</td></tr>
<tr><td>11</td><td>-</td></tr>
<tr><td>12</td><td>-</td></tr>
</table>

sigma	AIC	AICc	BIC
0.1823	327.9512	328.2960	343.9159

Error measures

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Train	0.01481255	0.1802734	0.1447296	-1.22894	12.60751	1.51664	0.2858142

Code for the method

```
jeju_holt <- holt(jeju_train, h = 43, initial = "optimal") #Holt linear
jeju_holt
summary(jeju_holt)
```

Appendix A.3

Forecast method: Holt's method with exponential trend

Model Information: Holt's method with exponential trend

Call: holt(y = jeju_train, h = 43, initial = "optimal", exponential = TRUE)

<table>
<tr><th colspan="5">Smoothing parameter</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.0513</td><td>0.0031</td><td>-</td><td>-</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><th rowspan="6">Level</th><td rowspan="6">0.744</td><th rowspan="12">Seasonal</th><td>1</td><td>-</td></tr>
<tr><td>2</td><td>-</td></tr>
<tr><td>3</td><td>-</td></tr>
<tr><td>4</td><td>-</td></tr>
<tr><td>5</td><td>-</td></tr>
<tr><td>6</td><td>-</td></tr>
<tr><th rowspan="6">Trend (Slope)</th><td rowspan="6">1.005</td><td>7</td><td>-</td></tr>
<tr><td>8</td><td>-</td></tr>
<tr><td>9</td><td>-</td></tr>
<tr><td>10</td><td>-</td></tr>
<tr><td>11</td><td>-</td></tr>
<tr><td>12</td><td>-</td></tr>
</table>

<table>
<tr><th colspan="2">sigma</th><th colspan="2">AIC</th><th colspan="2">AICc</th><th colspan="2">BIC</th></tr>
<tr><td colspan="2">0.1584</td><td colspan="2">310.2259</td><td colspan="2">310.5707</td><td colspan="2">326.1907</td></tr>
<tr><th colspan="8">Error measures</th></tr>
<tr><th></th><th>ME</th><th>RMSE</th><th>MAE</th><th>MPE</th><th>MAPE</th><th>MASE</th><th>ACF1</th></tr>
<tr><th>Train</th><td>0.01139981</td><td>0.1448254</td><td>0.1794865</td><td>-1.496328</td><td>12.64669</td><td>1.517643</td><td>0.2685655</td></tr>
</table>

Code for the method

```
jeju_exp <- holt(jeju_train, h = 43, exponential = TRUE, initial = "optimal") #exponential
jeju_exp
summary(jeju_exp)
```

Appendix A.4

Forecast method: Damped Holt's method

Model Information: Damped Holt's method

Call: holt(y = jeju_train, h = 43, damped = TRUE, initial = "optimal")

<table>
<tr><th colspan="5">Smoothing parameter</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.0907</td><td>0.005</td><td>-</td><td>0.98</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><th rowspan="6">Level</th><td rowspan="6">0.7563</td><th rowspan="12">Seasonal</th><td>1</td><td>-</td></tr>
<tr><td>2</td><td>-</td></tr>
<tr><td>3</td><td>-</td></tr>
<tr><td>4</td><td>-</td></tr>
<tr><td>5</td><td>-</td></tr>
<tr><td>6</td><td>-</td></tr>
<tr><th rowspan="6">Trend (Slope)</th><td rowspan="6">0.0079</td><td>7</td><td>-</td></tr>
<tr><td>8</td><td>-</td></tr>
<tr><td>9</td><td>-</td></tr>
<tr><td>10</td><td>-</td></tr>
<tr><td>11</td><td>-</td></tr>
<tr><td>12</td><td>-</td></tr>
</table>

<table>
<tr><th colspan="2">sigma</th><th colspan="2">AIC</th><th colspan="2">AICc</th><th colspan="2">BIC</th></tr>
<tr><td colspan="2">0.1862</td><td colspan="2">336.4627</td><td colspan="2">336.9483</td><td colspan="2">355.6205</td></tr>
<tr><th colspan="8">Error measures</th></tr>
<tr><th></th><th>ME</th><th>RMSE</th><th>MAE</th><th>MPE</th><th>MAPE</th><th>MASE</th><th>ACF1</th></tr>
<tr><th>Train</th><td>0.02429795</td><td>0.1835638</td><td>0.1462713</td><td>-0.6089116</td><td>12.60414</td><td>1.532795</td><td>0.264156</td></tr>
</table>

<u>Code for the method</u>

jeju_damped_add <- holt(jeju_train, h = 43, damped = TRUE, initial = "optimal") #Additive Damped trend

jeju_damped_add

summary(jeju_damped_add)

Appendix A.5

Forecast method: Damped Holt's method with exponential trend

Model Information: Damped Holt's method with exponential trend

Call: holt(y = jeju_train, h = 43, damped = TRUE, initial = "optimal", exponential = TRUE)

Smoothing parameter				
Components	**alpha**	**beta**	**gamma**	**phi**
Parameter	0.0467	0.0054	-	0.98
Initial States				
Level	0.7129	**Seasonal**	1	-
			2	-
			3	-
			4	-
			5	-
			6	-
Trend (Slope)	1.0058		7	-
			8	-
			9	-
			10	-
			11	-
			12	-

sigma	**AIC**	**AICc**	**BIC**
0.1619	314.6913	315.1768	333.8490

Error measures							
	ME	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**	**ACF1**
Train	0.02481882	0.1821467	0.1449614	-0.3031106	12.43399	1.519069	0.2834265

<u>Code for the method</u>

```
jeju_damped_multi <- holt(jeju_train, h = 43, damped = TRUE, initial = "optimal",
exponential = TRUE) #Multiplicative
jeju_damped_multi
summary(jeju_damped_multi)
```

Appendix A.6

Forecast method: Holt-Winters' multiplicative method

Model Information: Holt-Winters' multiplicative method

Call: hw(y = jeju_train, h = 43, seasonal = "multiplicative", initial = "optimal")

<table>
<tr><th colspan="5">Smoothing parameter</th></tr>
<tr><th>Components</th><th>alpha</th><th>beta</th><th>gamma</th><th>phi</th></tr>
<tr><td>Parameter</td><td>0.1919</td><td>0.0114</td><td>1e-04</td><td>-</td></tr>
<tr><th colspan="5">Initial States</th></tr>
<tr><th rowspan="6">Level</th><td rowspan="6">0.7807</td><th rowspan="12">Seasonal</th><td>1</td><td>0.8407</td></tr>
<tr><td>2</td><td>0.958</td></tr>
<tr><td>3</td><td>1.1001</td></tr>
<tr><td>4</td><td>0.9414</td></tr>
<tr><td>5</td><td>1.2475</td></tr>
<tr><td>6</td><td>1.0298</td></tr>
<tr><th rowspan="6">Trend (Slope)</th><td rowspan="6">0.004</td><td>7</td><td>0.9917</td></tr>
<tr><td>8</td><td>1.1463</td></tr>
<tr><td>9</td><td>1.1386</td></tr>
<tr><td>10</td><td>0.8872</td></tr>
<tr><td>11</td><td>0.8412</td></tr>
<tr><td>12</td><td>0.8775</td></tr>
</table>

sigma	AIC	AICc	BIC
0.0761	55.27424	59.05202	109.55451

<table>
<tr><th colspan="8">Error measures</th></tr>
<tr><th></th><th>ME</th><th>RMSE</th><th>MAE</th><th>MPE</th><th>MAPE</th><th>MASE</th><th>ACF1</th></tr>
<tr><th>Train</th><td>0.00770876
2</td><td>0.07843379</td><td>0.05878474</td><td>0.01345805</td><td>5.46753</td><td>0.6160127</td><td>0.1402246</td></tr>
</table>

Code for the method

jeju_hw <- hw(jeju_train, h = 43, seasonal = "multiplicative", initial = "optimal") #holt-Winters

jeju_hw

summary(jeju_hw)

Appendix A.7

Forecast method: Damped Holt-Winters' multiplicative method

Model Information: Damped Holt-Winters' multiplicative method

Call: hw(y = jeju_train, h = 43, seasonal = "multiplicative", damped = TRUE, initial = "optimal")

Smoothing parameter				
Components	**alpha**	**beta**	**gamma**	**phi**
Parameter	0.1327	0.0271	4e-04	0.9736
Initial States				
Level	0.7618	**Seasonal**	1	0.821
			2	0.9675
			3	1.1005
			4	0.9332
			5	1.2487
			6	1.0324
Trend (Slope)	-0.0045		7	0.9949
			8	1.1475
			9	1.1507
			10	0.8878
			11	0.8326
			12	0.8832

sigma	**AIC**	**AICc**	**BIC**				
0.0775	61.14425	65.39269	118.61747				
Error measures							
	ME	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**	**ACF1**
Train	0.01182885	0.07985019	0.05857839	0.5102499	5.391652	0.6138503	0.2003561

Code for the method

```
jeju_hw_damped <- hw(jeju_train, h = 43, seasonal = "multiplicative", initial = "optimal", damped = TRUE) #holt-Winters
jeju_hw_damped
summary(jeju_hw_damped)
```

Appendix A.8

Forecast method: ETS(M,A,M)

Model Information: ETS(M,A,M)

Call: ets(y = jeju_train)

Smoothing parameter					
Components	**alpha**	**beta**	**gamma**	**phi**	
Parameter	0.2161	0.0066	0.447	-	
Initial States					
Level	0.7393	**Seasonal**	1	0.9136	
			2	0.9482	
			3	0.9883	
			4	0.8572	
			5	1.3539	
			6	1.0195	
Trend (Slope)	0.0031		7	0.8878	
			8	1.1371	
			9	1.1075	
			10	0.9076	
			11	0.8506	
			12	1.0287	

sigma	**AIC**	**AICc**	**BIC**
0.064	-7.865321	-4.087543	46.414945

Error measures							
	ME	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**	**ACF1**
Train	0.008643337	0.07203095	0.0535506	0.3145872	4.725122	0.5611634	0.2732252

<u>Code for the method</u>

```
jeju_ets <- ets(jeju_train) #ets without damped

summary(jeju_ets)

plot(jeju_ets)

jeju_ets


jeju_ets_forecast <- forecast(jeju_ets, h = 43) #ets forecast

jeju_ets_forecast

summary(jeju_ets_forecast)

plot(jeju_ets_forecast)
```

Appendix A.9

Forecast method: ETS(M,Ad,A)

Model Information: ETS(M,Ad,A)

Call: ets(y = jeju_train, damped = TRUE)

Smoothing parameter				
Components	**alpha**	**beta**	**gamma**	**phi**
Parameter	0.2423	0.01	0.4946	0.98
Initial States				
Level	0.7321	**Seasonal**	1	-0.0442
			2	-0.0577
			3	-0.0205
			4	-0.1164
			5	0.2555
			6	0.0126
Trend (Slope)	0.0052		7	-0.0793
			8	0.0989
			9	0.0766
			10	-0.052
			11	-0.1113
			12	0.0379

sigma	**AIC**	**AICc**	**BIC**
0.0647	-3.6937768	0.5546705	53.7794466

Error measures							
	ME	**RMSE**	**MAE**	**MPE**	**MAPE**	**MASE**	**ACF1**
Train	0.01248851	0.07188191	0.0538648	0.452206	4.742243	0.564456	0.3454022

Code for the method

```
jeju_ets_damped <- ets(jeju_train, damped = TRUE) #ets with damped
summary(jeju_ets_damped)
plot(jeju_ets_damped)
jeju_ets_damped

jeju_ets_forecast_damped <- forecast(jeju_ets_damped, h = 43) #ets with damped forecast
jeju_ets_forecast_damped
summary(jeju_ets_forecast_damped)
plot(jeju_ets_forecast_damped)
```

Appendix B: Linear Regression R Codes

Q8 Linear regression code

Code for the method

```
#linear regression for Q8

reg <- tslm(jejuair_ts_new ~ trend + season)
summary (reg)
reg_forecast <- forecast(reg, h = 24)
reg_forecast

plot(reg_forecast, main = "Out of sample forecast for Air passenger in Jeju with linear
regression", xlab = "Year", ylab = "Number of air passengers in Jeju (miilion)")

accuracy(reg_forecast)
```