

# **V.Ger Travel Company - An Analysis**

**ITNBD4 Assignment**

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# 1 Summary

Summary of the report

## 2 Introduction

### 2.1 Background & Approach

The travel conglomerate V.Ger Travel (VGT) has a broad range of operations, including hotels, resorts, car rentals and also air travel through charter flights. Travel bookings originate primarily from VG's own travel web site which is supported by several operational information systems that cover all aspects of it's business from customer relations through to logistics and maintenance. There is a wealth of data available with over 10 years history of travel bookings, however, the use of modern Data Science methods to harness this data is in its infancy at VGT.

This report describes the recommendations of the new Chief Data Officer (CDO) as to how to implement modern Data Science techniques to utilise VGT's data to improve its efficiency and profit. Having completed an initial high level review, two opportunity areas were identified that appeared to offer the biggest opportunities for increasing efficiency and also that are achievable as a first step in implementing new techniques. The two use cases are:

- Hotel Demand Forecasting
- Customer Satisfaction & Loyalty

Each of these use cases are explored in the following sections, each of which describes:

- Business Scope & Benefits - What is proposed and why is this helpful
- Data Analysis Approach - The suggested analysis techniques and the data required
- Simulated Data Analysis - An example of the analysis using simulated data
- Conclusions & Next Steps - Findings and how to move forward

*????? - Assumptions made about data prep/data wrangling .. eg normalisation of data etc - Any assumptions about company size, number of hotels etc ?????*

### 2.2 Results & Further Details

A summary of the approach taken and key results of the analysis are described for each use case in the individual sections of this report. Full details of the approach are also detailed in:

- Appendices - Step by step approach, with data tables and plots
- Jupyter Notebooks - Full listings of Python code and results in [GitHub Repository](#)
- Data Files - Generated CSV files in [GitHub Repository](#)

### 2.3 Conclusions

*????? ConclusionshHere as well as last part of each use case ?????*

## 3 Hotel Demand Forecasting

### 3.1 Business Scope & Benefits

The hotel operations of VGT are a significant part of its business and any efficiencies in this area have the potential to make large contributions to the overall profitability of the business. The profit contribution from individual hotels can be maximised by ensuring revenue is as high as possible and at the same time minimising the hotel's operating costs. One way to do this is to provide a hotel's management team with the tools to carry out reliable demand forecasting.

Hotel demand forecasting is the prediction of the demand for rooms and related hotel services to help a hotel's management team determine pricing, staffing and marketing strategies (Johansson, 2022). If the demand for hotel rooms can be reliably forecast then this enables:

- **Dynamic Pricing** - Adjust future prices in response to forecast demand. When high demand is expected then future room rates can be increased; when low demand is expected then discounts can be offered or packages can be advertised. And marketing strategies can be determined to respond to the demand forecasts. xx increase occupancy and revenue
- **Staffing Levels** - Hotel staffing can be adjusted to maintain customer service levels but not over staff when demand is expected to be lower. xx control costs
- **Inventory Management** - Similarly inventory can be adjusted, for example catering supplies maintained just sufficient to meet the forecast number of customers using catering facilities. xx control costs

There are many factors that will influence the demand for hotel rooms, some may remain stable whilst others are less so and will vary over time or in response to external factor, these include:

- **Location & Market** - Is the hotel a budget or a boutique hotel? Is it in a business district, near a beach or a ski resort etc. Are customers mainly business travelers or tourists?
- **Economic** - Macro level impact from the state of the economy.
- **Local Competition** - Competition with local hotels.
- **Seasonality** - When are the high and low seasons? Is it a summer or a winter resort? What are the local weather patterns and seasons. Are there weather related attractions?
- **Local Events** - When are any local festivities, sports events, school holidays, religious events, music conferences, business conferences?

#### 3.1.1 Occupancy & Revenue Indicators

An important indicator of demand is the occupancy rate (Jeffrey and Hubbard, 1994) and (FHA, 2023) which is simply the percentage of the total rooms occupied for a given time period. The occupancy rate varies across the industry but a target of 60% to 80% is typical.

Occupancy is used alongside revenue related indicators to provide a measure of revenue health, the three main indicators (for a given time period, eg daily) are:

- Occupancy Rate (OCC%) - Percentage of available rooms that are occupied, or expected to be occupied.
- Average Daily Rate (ADR) - Average revenue per room occupied, across all room price bands.
- Revenue Per Available Room (RevPAR) - Revenue reflecting all available rooms. Calculated by:  $OCC\% * ADR$ . A good overall indicator of revenue.

### 3.1.2 Forecasting Occupancy & Business Benefits

The time period used for forecasting will vary depending on the objectives desired (Lighthouse, 2024) and (Lighthouse, 2023) for example:

- Short Term - Forecast occupancy for next month so room pricing can be adjusted appropriately.
- Long-term - Forecast occupancy for next year so price bands and packages can be set, marketing strategies defined and required staffing levels determined.

To recap, if occupancy (and the associated revenue indicators) can be reliably forecast then plans can be put in place to maximise revenue by adjusting pricing and marketing strategies and controlling costs by flexing staffing and inventory levels.

## 3.2 Data Analysis Approach

At VGT, no rigorous forecasting is currently in place so to begin with a relatively simple approach will be implemented in a small number of hotels. If the benefits of this are confirmed, then it can then be extended in sophistication using more complex forecasting models and for longer time periods. It can then be implemented across all hotels in VGT.

The objective of this first step is to establish a model that can be used to forecast the daily occupancy (OCC%) at an individual hotel for the coming month, ie the forecast is for 30 to 40 days in the future. The forecast will then be used by hotel's management team to: i) adopt dynamic pricing; ii) execute supporting short-term marketing; iii) fine-tune staffing rotas and holiday leave for the coming weeks. This should improve the efficiency of the hotel's operations by increasing room bookings whilst ensuring staffing costs are controlled at an appropriate level.

### 3.2.1 Forecasting Model & Data Required

The scope of the envisaged forecasting model is to calculate a month of daily OCC% for each room category in an hotel. The output of the forecast model will be provided in spreadsheet form so that the hotel management team can manually make adjustments to try to improve revenue and staffing levels. The actual occupancy and revenue can then be tracked against the forecast throughout the month in order to assess how accurate the forecasting model is and to help refine it.

*Forecasting Model Data*

The data required for the forecasting model is the last 4 years of daily room occupancy. In this analysis a single hotel with two classes of room (standard and premium) will be used. A 4 year history of daily room bookings was selected with 3 years used to be used for training and 1 year for validation. This length of history was chosen as a starting point because a previous occupancy study (Phumchusri and Suwatanapongched, 2023) found that the choice could be quite dependent on the scenario; however, there needs to be a balance of too short and missing seasonality vs too long and not being sufficiently responsive. Phumchusri and Suwatanapongched (2023) also found that using 4 years history of daily occupancy to forecast 2 to 8 weeks was a good approach.

The specific data required is:

- For an individual hotel and each room category (standard and premium)
- Daily
- Room capacity
- Room rate
- Rooms occupied

#### *Tracking Spreadsheets*

The data comprising the revenue forecasting and tracking spreadsheet is:

- Forecast OCC% (derived from the forecasting model)
- Daily room rates by room category that can be manually adjusted
- Daily Revenue, ADR, RevPAR (derived from the OCC% and room rates)
- Special events, a facility to mark local events that may impact demand. For example, sports events, concerts, conference, unusual weather forecasts
- Actual OCC%, Revenue, ADR, RevPAR

The data provided for the staffing forecasting spreadsheet is:

- Forecast OCC% (from the forecasting model)
- Averaged staff requirements per room
- Staffing levels (derived from the OCC%)
- Actual staffing levels

### **3.2.2 Techniques Considered**

There are several potential tools that can be used with historical time series data to forecast future occupancy rates, ranging from established ‘simpler’ techniques such as linear regression through to more sophisticated machine learning and neural network models (Huang and Zheng, 2022). However, given the relative infancy of Data Science at VGT, the use of more sophisticated tools will be prioritised for future work. In this investigation, the following techniques will be examined:

1. Ordinary Least Squares (OLS) linear regression
2. ARIMA, SARIMA - Use to fully incorporate seasonality
3. SAIMAX - If exogenous factors need to be accounted for
4. ?? *LightGBM .... if time allows!*

## OLS Linear Regression

Investigating techniques for reliably identifying the factors influencing hotel occupancy has been ongoing for several years. See Andrew, Cranage and Lee (1990) and Jeffrey and Hubbard (1994) for earlier work focusing on the use of regression analysis of time series data. Although it is likely that the nature of hotel business means that occupancy will be seasonal, linear regression will still be investigated first.

## ARIMA, SARIMA

Occupancy forecasting using ARIMA using factors such as room capacity and marketing expenditure has successfully been used (Chow, Shyu and Wang, 1998). A comparison of forecasting methods (Weatherford and Kimes, 2003) included historical time series analysis of occupancy using ARIMA. The best time period used was not clear and it is a balance of too short and missing seasonality vs too long and not being sufficiently responsive. Also the best analysis method appears to depend on the characteristics of individual hotels and hotel chains. Using a SARIMA approach using 4 years history of daily occupancy to forecast 2 to 8 weeks was found to be a strong approach (Phumchusri and Suwatanapongched, 2023).

## SARIMAX

?? LightGBM .... if time allows!

## 3.3 Simulated Data Analysis

### 3.3.1 Data Summary

A dataset was created to simulate the data as defined in the earlier section. The first few elements of the loaded data:

	Standard_OCC	Standard_Capacity	Standard_Rate	Premium_OCC	\
Date					
2020-01-01	129	254	325	65	
2020-01-02	126	254	325	53	
2020-01-03	137	254	325	63	

	Premium_Capacity	Premium_Rate
Date		
2020-01-01	100	575
2020-01-02	100	575
2020-01-03	100	575

And details of the data types:

	Count	Missing	Empty	Unique	Type	String	Int	Float	List
Standard_OCC	1461	0	0	177	int64	0	1461	0	0



	Count	Missing	Empty	Unique	Type	String	Int	Float	List
Standard_Capacity	1461	0	0	1	int64	0	1461	0	0
Standard_Rate	1461	0	0	1	int64	0	1461	0	0
Premium_OCC	1461	0	0	101	int64	0	1461	0	0
Premium_Capacity	1461	0	0	1	int64	0	1461	0	0
Premium_Rate	1461	0	0	1	int64	0	1461	0	0

And key descriptive statistics:

	Standard_OCC	Standard_Capacity	Standard_Rate	Premium_OCC	\
count	1461.000000	1461.0	1461.0	1461.000000	
mean	135.646133	254.0	325.0	56.141684	
std	50.216654	0.0	0.0	29.349613	
min	38.000000	254.0	325.0	0.000000	
25%	88.000000	254.0	325.0	31.000000	
50%	136.000000	254.0	325.0	57.000000	
75%	183.000000	254.0	325.0	83.000000	
max	254.000000	254.0	325.0	100.000000	

	Premium_Capacity	Premium_Rate
count	1461.0	1461.0
mean	100.0	575.0
std	0.0	0.0
min	100.0	575.0
25%	100.0	575.0
50%	100.0	575.0
75%	100.0	575.0
max	100.0	575.0

### 3.3.2 Time Series Characteristics

The occupancy time series for the two categories of room are shown in the figure below. This indicates that the occupancy has a strong seasonality with an annual peak and trough; there are also regular spikes to full capacity bookings. The premium room occupancy hits maximum and zero occupancy on several occasions.

The two occupancy time series were examined further (see details at the appendix) using lag plots, ACF plots and ADF tests which indicated autocorrelation, annual seasonality and a positive trend. Differencing was also completed to confirm non-stationarity. Finally a decomposition was completed and this confirmed the seasonality and trend, see the figure below.

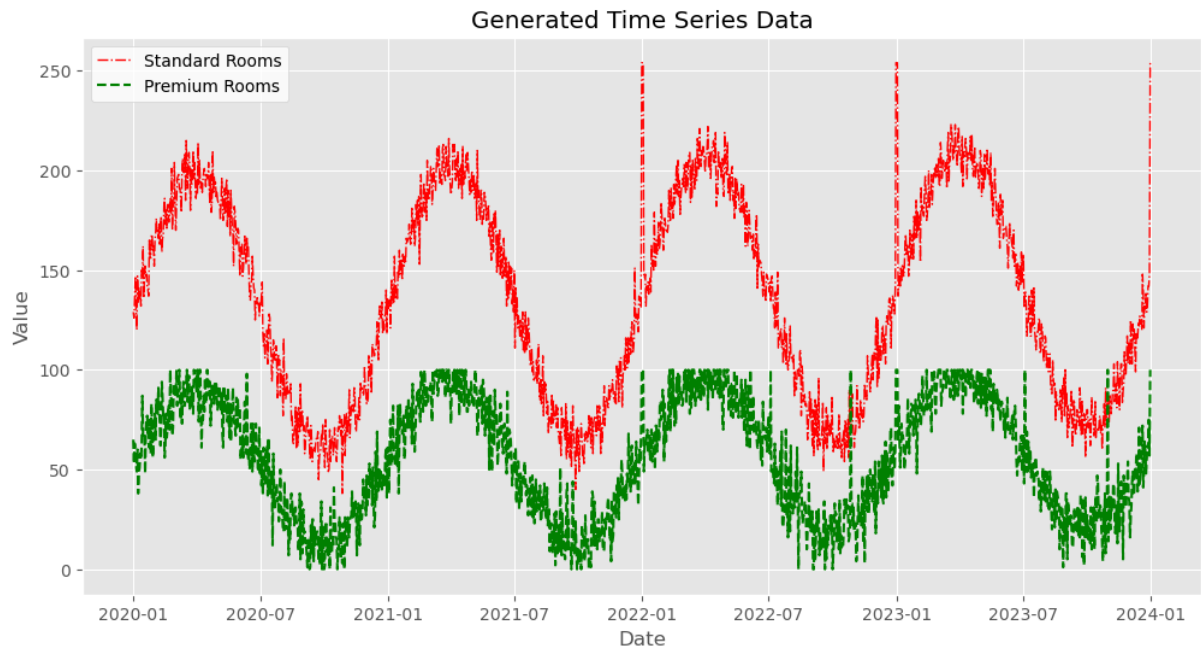


Figure 3.1: Occupancy for Each Room Category

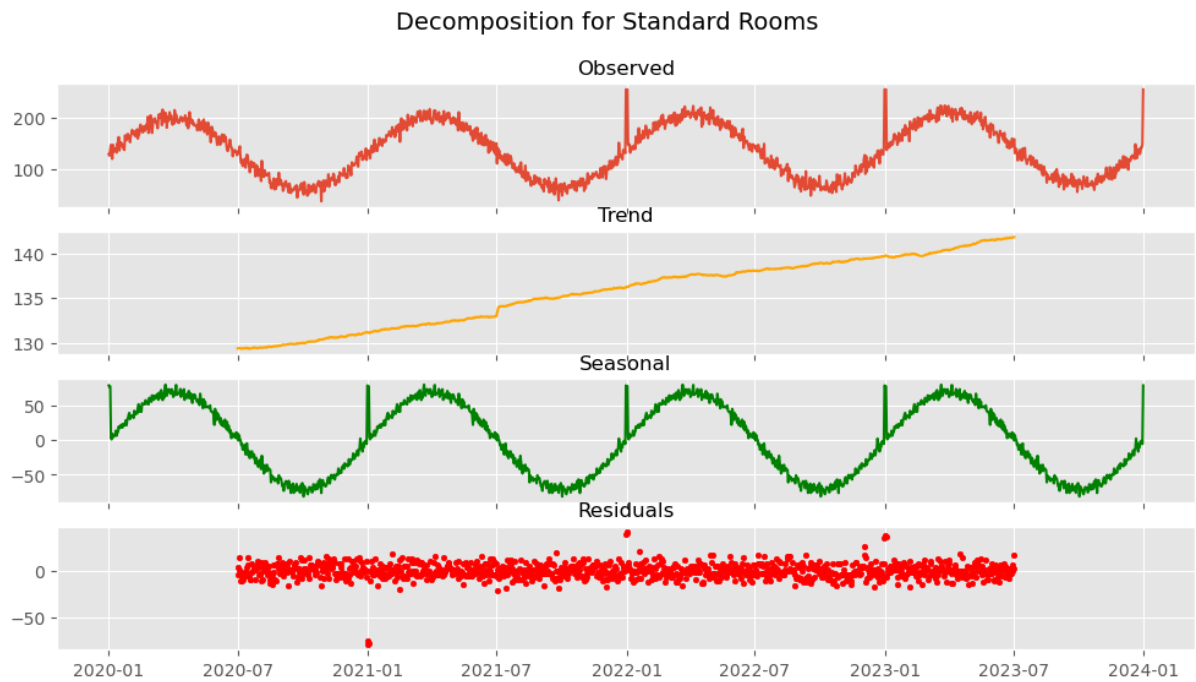
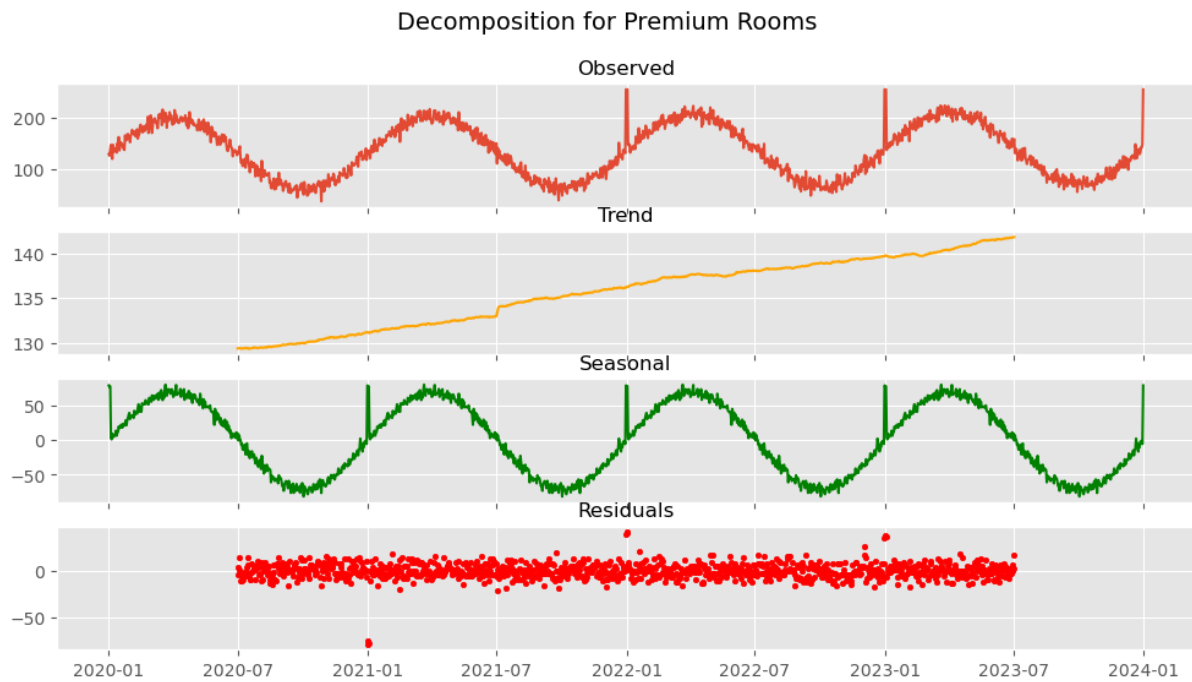


Figure 3.2: Occupancy Time Series Decomposition



### 3.3.3 OLS Linear Regression

Given the strong seasonality, linear regression is unlikely to be a good model for forecasting, however a regression fit was calculated to double-check. See the figure below which shows that the fit lines could not reliably provide a forecast and even show a downward trend. And the Durban Watson statistics are less than 2 which confirms evidence of autocorrelation.

### 3.3.4 ARIMA, SARIMA

### 3.3.5 SARIMAX

### 3.3.6 Execution - Data Analysis

- Use simulated data to carry out analysis
- Show the results, forecasts ....
- ?? carry out *PACF* to determine the autoregressive order for *ARIMA* etc

## 3.4 Conclusions & Next Steps

### 3.4.1 Findings

xxx

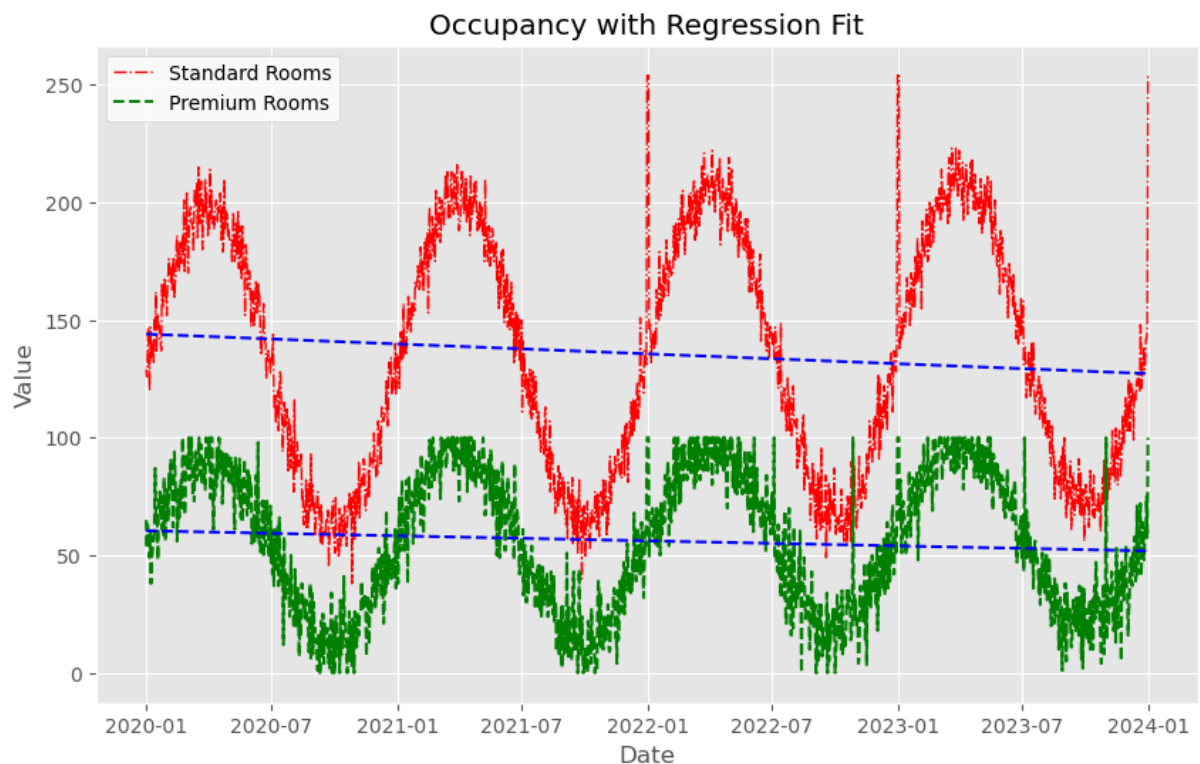


Figure 3.3: OLS Linear Regression

### 3.4.2 Next Steps

- ?? how are special events impactful on revenue predictions, can these be better used in the forecast going forward or in an improved forecasting model
- ?? recent flight searches, enquiries ... for the area

xxxx

- ?? track actual OCC% etc and compare to forecast to allow model refinement as well as intra-month fine tuning
- ?? Get competitors OCC% to compare and improve forecasting models
- ?? automate the manual pricing changes etc, ie no need for manual adjustment of the forecast spreadsheet
- xx LightGBM ..
- xx CNN, LSTM, RNN ...
- xx transformers, LLM ..

xxx improvements

- ?? isolate pricing strategies and refine the model
- ?? identify the main parameters / impacts on the forecasting ... what are the demand indicators?
- ?? categorisation of customers, families, demographics etc, business, tourist
- ?? identify correlations with holiday patterns, events .....
- ?? identify seasonal bands, high, low, shoulder etc
- ?? identify links between revenue and room price bands ...

## **4 Customer Satisfaction & Loyalty**

# 5 Conclusions

## 5.1 Conclusions

## 5.2 Next Steps

????? - Overall conclusions - Or possibly conclusions within each section

# References

- Andrew, W.P., Cranage, D.A. and Lee, C.K. (1990) 'Forecasting Hotel Occupancy Rates with Time Series Models: An Empirical Analysis', *Hospitality Research Journal*, 14(2), pp. 173–182. Available at: <https://doi.org/10.1177/109634809001400219>.
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- Weatherford, L.R. and Kimes, S.E. (2003) 'A comparison of forecasting methods for hotel revenue management', *International Journal of Forecasting*, 19(3), pp. 401–415. Available at: [https://doi.org/10.1016/S0169-2070\(02\)00011-0](https://doi.org/10.1016/S0169-2070(02)00011-0).

# A Hotel Demand Forecasting

## A.1 Data Load

- Load time series data and look at its characteristics
- Determine autocorrelation, seasonality, stationarity .. lag plot, ACF plot, ADF test, Differencing
- Decomposition,
- OLS Regression

## A.2 Data Characteristics

```

Standard_OCC Standard_Capacity Standard_Rate Premium_OCC \
Date
2020-01-01      129           254           325           65
2020-01-02      126           254           325           53
2020-01-03      137           254           325           63

```

```

Premium_Capacity Premium_Rate
Date
2020-01-01      100          575
2020-01-02      100          575
2020-01-03      100          575

```

	Count	Missing	Empty	Unique	Type	String	Int	Float	List
Standard_OCC	1461	0	0	177	int64	0	1461	0	0
Standard_Capacity	1461	0	0	1	int64	0	1461	0	0
Standard_Rate	1461	0	0	1	int64	0	1461	0	0
Premium_OCC	1461	0	0	101	int64	0	1461	0	0
Premium_Capacity	1461	0	0	1	int64	0	1461	0	0
Premium_Rate	1461	0	0	1	int64	0	1461	0	0

```

Standard_OCC Standard_Capacity Standard_Rate Premium_OCC \
count  1461.000000      1461.0      1461.0  1461.000000
mean    135.646133      254.0      325.0    56.141684
std     50.216654        0.0        0.0    29.349613
min     38.000000      254.0      325.0     0.000000
25%     88.000000      254.0      325.0    31.000000
50%    136.000000      254.0      325.0    57.000000

```



75%	183.000000	254.0	325.0	83.000000
max	254.000000	254.0	325.0	100.000000

	Premium_Capacity	Premium_Rate
count	1461.0	1461.0
mean	100.0	575.0
std	0.0	0.0
min	100.0	575.0
25%	100.0	575.0
50%	100.0	575.0
75%	100.0	575.0
max	100.0	575.0

### A.3 Autocorrelation, Seasonality, Stationarity

- Determine autocorrelation, seasonality, stationarity .. lag plot, ACF plot, ADF test, Differencing
- Decomposition

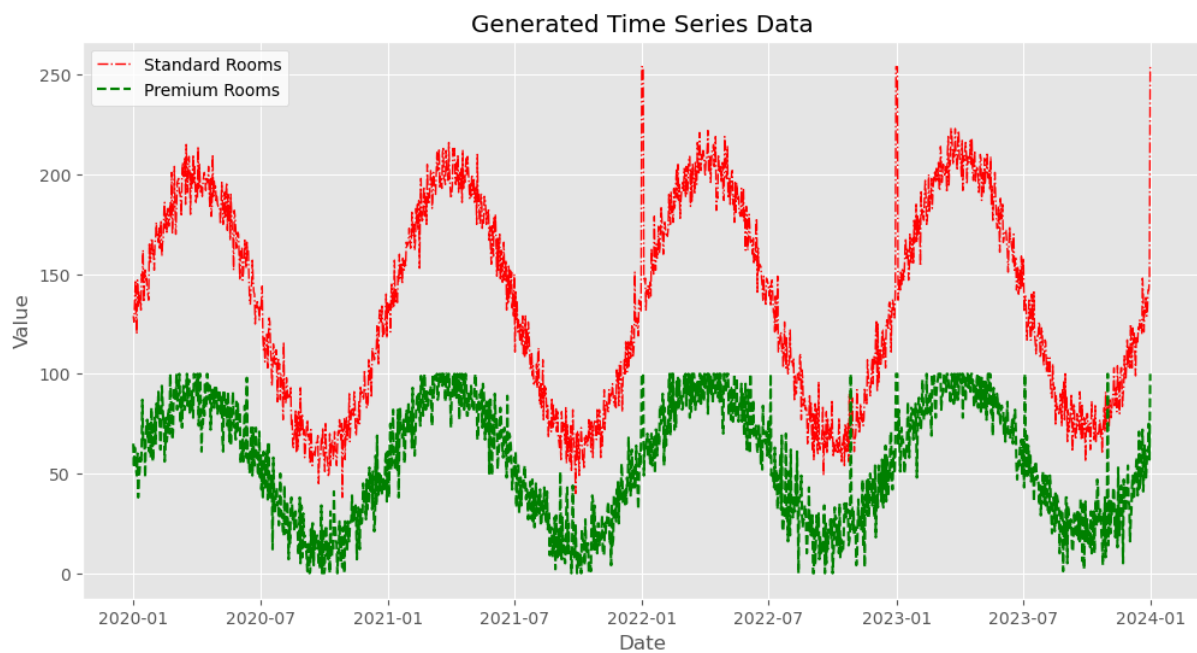


Figure A.1: Occupancy for Each Room Category

- Shows definite annual seasonality with peak high and low seasons
- Also some infrequent spikes in bookings
- Possibly a small upward trend over time
- Premium rooms hit max and zero bookings several times ...
- Both categories of room show definite autocorrelation
- Premium rooms bunched up at max value and autocorrelation may be slight less strong
- Some outliers when rooms are fully booked

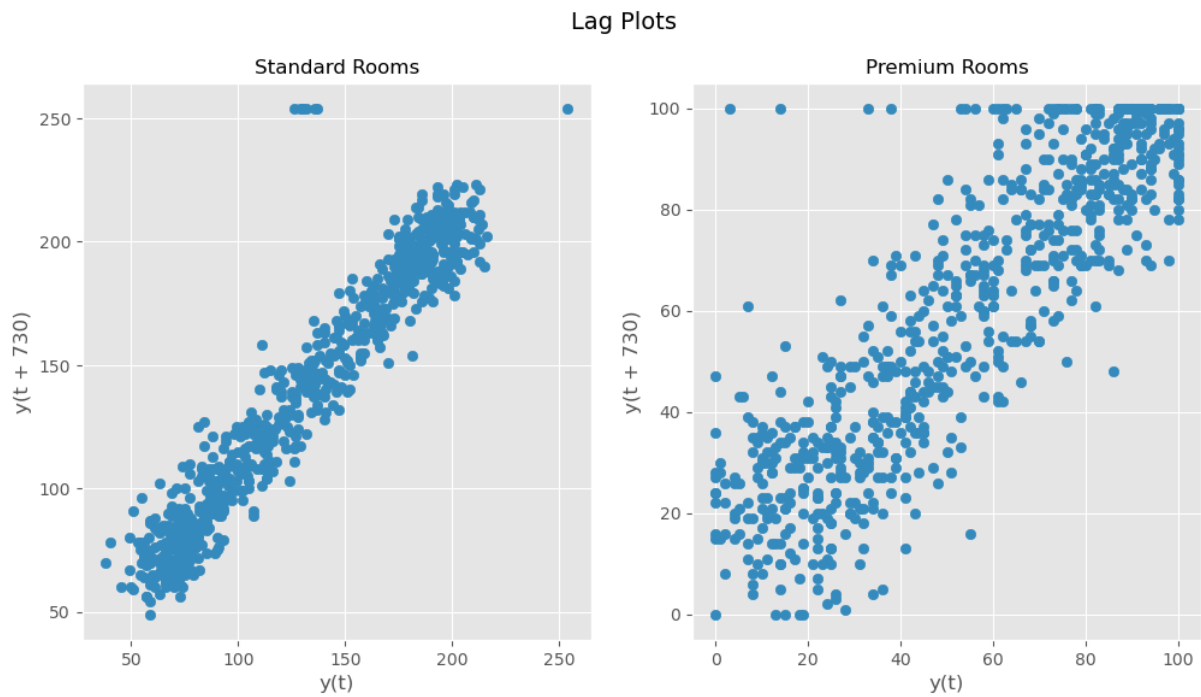
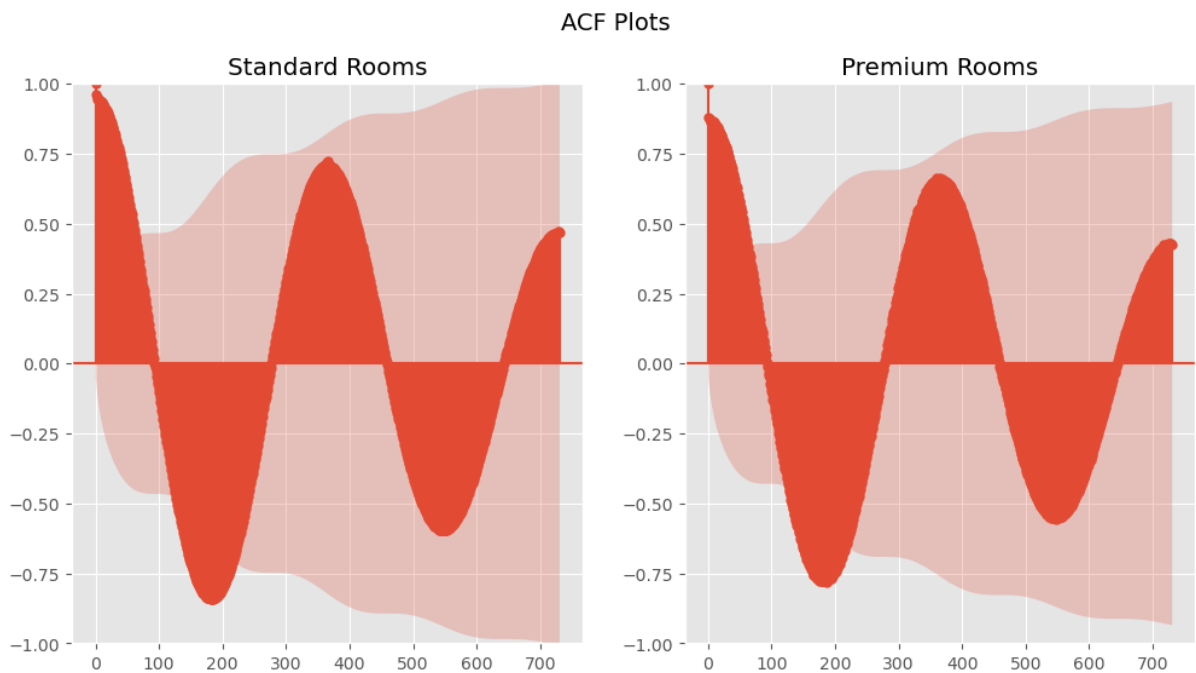


Figure A.2: Lag Plots - Test



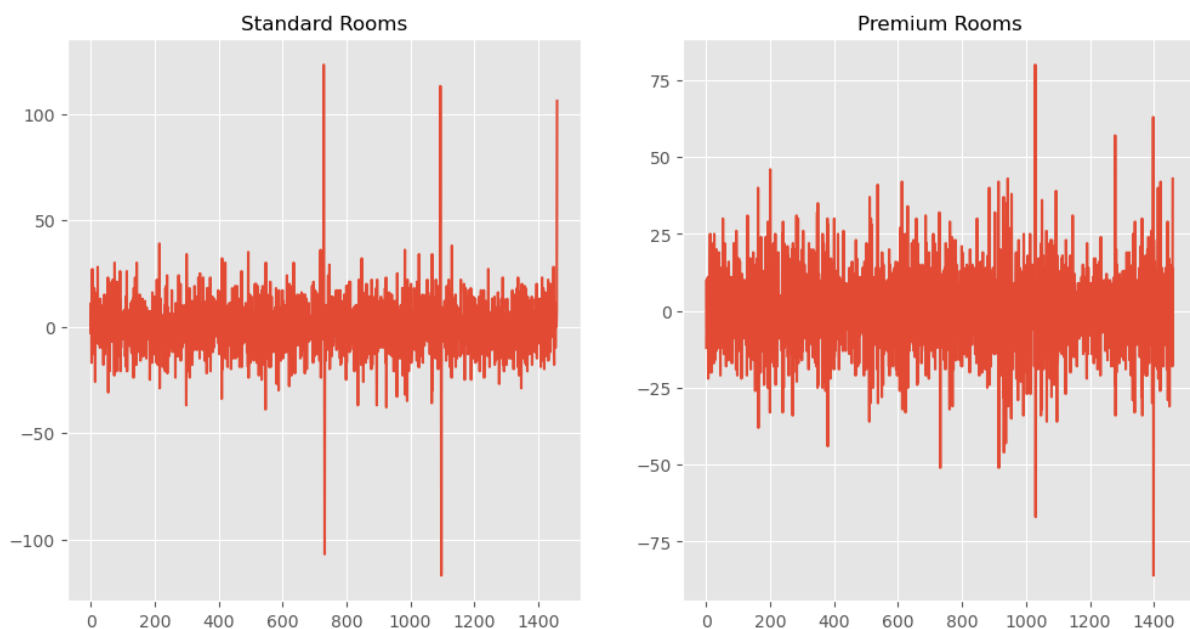
- Both exhibit strong autocorrelation that diminishes slowly after approximately 250 days
- A positive trend is suggested by the slowly diminishing autocorrelation
- Multiple peaks at 350 days indicates annual seasonality
- ?? carry out PACF to determine the autoregressive order .... does indicate that it is autoregressive

ADF Test for Standard Rooms

ADF Statistic: -2.362457191578427  
p-value: 0.15261408046089647  
Critical Value 1%: -3.434908816804013  
Critical Value 5%: -2.863553406963303  
Critical Value 10%: -2.5678419239852994  
Conclusion: Non-Stationary

ADF Test for Premium Rooms  
ADF Statistic: -2.1359470749871265  
p-value: 0.2303078418058474  
Critical Value 1%: -3.434911997169608  
Critical Value 5%: -2.863554810504947  
Critical Value 10%: -2.567842671398422  
Conclusion: Non-Stationary

Differenced Time Series



ADF Test for Standard Rooms  
ADF Statistic: -4.650429185341465  
p-value: 0.00010417359492157454  
Critical Value 1%: -3.4349151819757466  
Critical Value 5%: -2.863556216004778  
Critical Value 10%: -2.5678434198545568  
Conclusion: Stationary

ADF Test for Premium Rooms  
ADF Statistic: -6.091009300062941  
p-value: 1.0365104637060615e-07  
Critical Value 1%: -3.4349151819757466  
Critical Value 5%: -2.863556216004778  
Critical Value 10%: -2.5678434198545568

Conclusion: Stationary

- Confirms that both time series are non-stationary

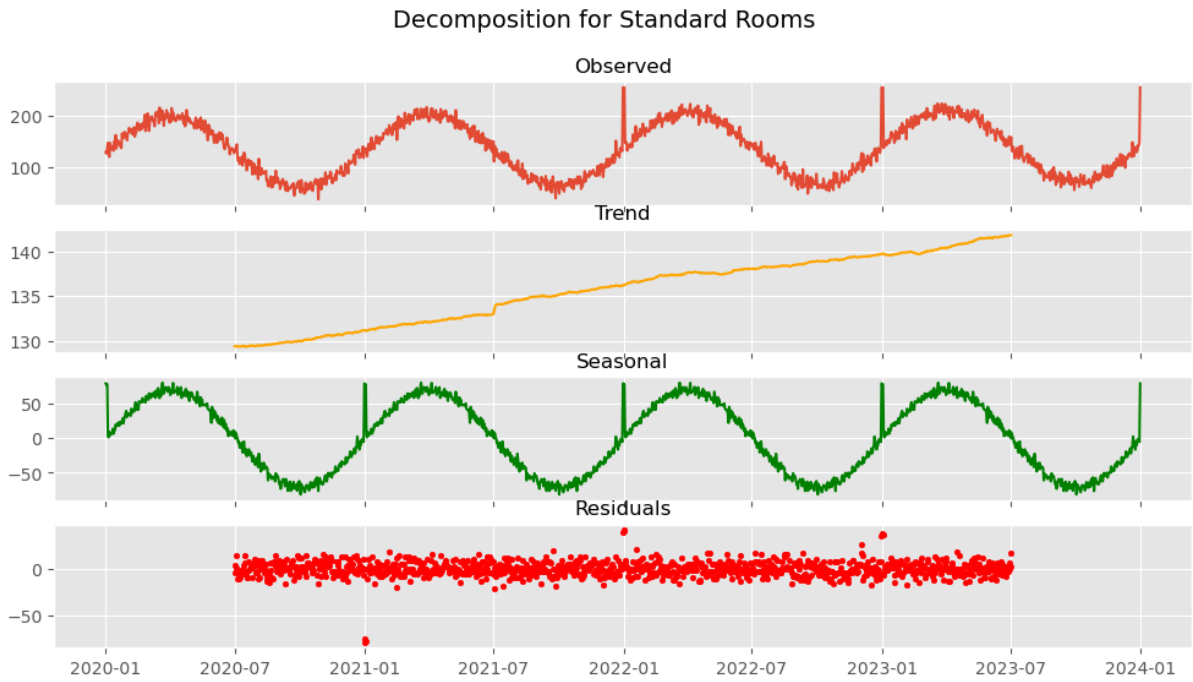
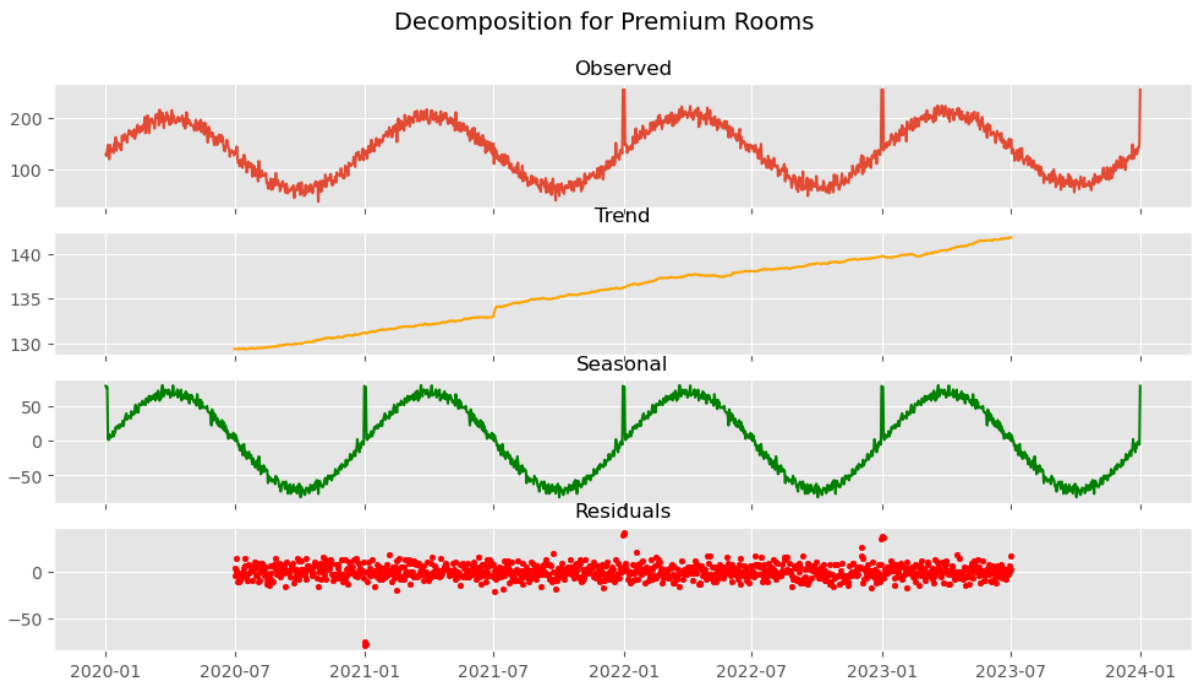


Figure A.3: Occupancy Time Series Decomposition



- Both have a small positive trend with room occupancy increasing 5 to 105% pa
- Confirms both time series are seasonal, with annual peaks and troughs
- On top of the annual seasonality, there are regular spikes leading to 100% occupancy
- Close clustering of residuals with some outliers that correspond to the seasonal spikes

## A.4 Ordinary Least Squares (OLS) linear regression

- Unlikely to be a good model for forecasting given the strong seasonality, but examine to confirm

Durbin-Watson statistic: 0.07265854622866856

Durbin-Watson statistic: 0.24391749000237792

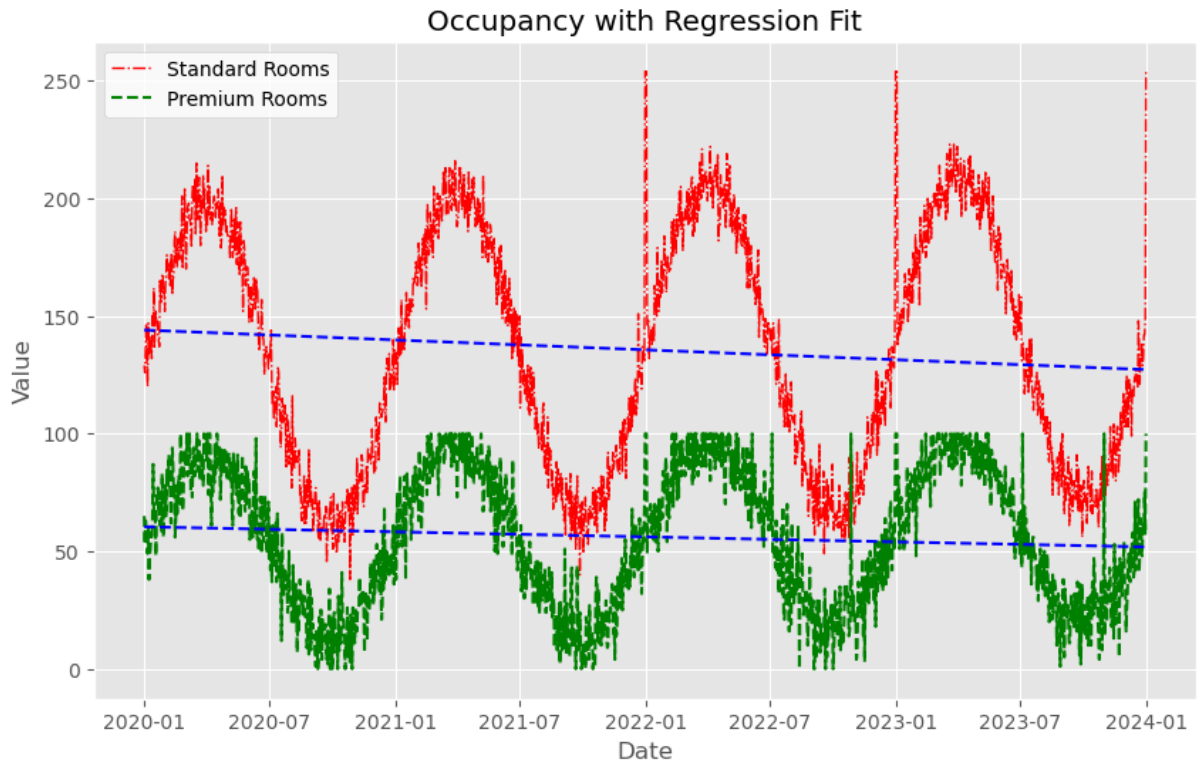


Figure A.4: OLS Linear Regression

- The two fitted lines do not capture any seasonality
- Also show a downward trend line, which is not consistent with the decomposition trend line
- The Durbin-Watson statistics for both time series are less than 1.5 which confirms evidence of autocorrelation

## A.5 SARIMA

## **B Customer Satisfaction & Loyalty**