BUAN 5510 Capstone Project

Hotel Demand Forecasting

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1. Introduction

Within the hotel industry, revenue management means selling the right room to the right client at the right moment, for the right price, through the right distribution channel, with the best cost efficiency. As a business practice, it is primarily concerned with optimizing financial results. The first step in creating a revenue management strategy is to forecast future demand. Demand is critical for revenue managers to understand future demand in order to project occupancy, revenue and operational needs (Weatherford & Kimes, 2003). Critically, demand forecasting predicts how many rooms would be booked on a given day if there are no constraints.

The ability to accurately forecast the number of occupied rooms for any given night is an important component in maximizing guest service and profitability in a hotel. The superior forecasting accuracy can be incredibly useful for hotel managers, because it allows them to predict future performance. This, in turn, means they can make more measured financial decisions, better prepare themselves for any financial problems and make adjustments in order to maximize revenue and minimize damage. In the short term of 3 to 10 days, a forecast of room demand is needed to schedule appropriate staff in both the rooms and other departments of a hotel and as a basis for the purchases of supplies. Profitability and guest service in hotel are optimized when these resources are carefully matched with the number of occupied rooms (Johns & Lee-Ross, 1996). In intermediate time horizons of 10 to 365 days, the forecast of occupied rooms informs pricing decisions to maximize average rate and segment availability (Zakhary et al., 2009). In the long term, forecasts of hotel room demand and average rate inform investment decisions (Newell & Seabrook, 2006). On the other hand, Inaccurate predictions lead to suboptimal decisions about the rate and availability recommendations produced by the RM system, that in turn have a negative effect on hotel revenue. Accurate forecasting can also help hotels in better staffing, purchasing and budgeting decisions. Lee (1990) found that a 10% increase in forecast accuracy in the airline industry increased revenue by 0.5-3.0% on high demand flights.

Hotel bookings are characterized mainly with two dimensions of time: book day and arrival day (Wang & Duggasani, 2017). The book day of a booking by a guest is the day when the booking is reserved by the guest, while the arrival day is the day when the guest plans to arrive and check in. For each arrival day, the bookings that it has are reserved at different book days prior to or at the arrival day. The total number of bookings for an arrival day is thus the sum of bookings over the individual book days. On the other hand, for each book day, the bookings that it has correspond to different arrival days in a future horizon, that is, all of the bookings are reserved on this same book day.

RM forecasting methods are commonly grouped into three types (Lee, 1990): historical booking models, advanced booking models and combined models. Historical booking models consider only the final number of rooms or arrivals on a particular stay night. Advanced booking models include only the buildup of reservations over time for a particular stay night. Combined models can be built by doing regression or assign a weighted average of historical models and advanced booking models to develop forecasts.

In this research, we tested a variety of different forecasting methods on data from three hotels. The accuracy of the various methods was determined and methods providing the most accurate and robust forecast were identified. Accuracy measurement of the model is based on MAE, MAPE and MASE. MASE was used as the determining error metric to compare with naive forecasts and between models. By having this information, hotels can use their revenue management systems more effectively and profitably.

2. Literature Review

2.1 Historical and Advanced Booking methods

Accurate forecasting of occupancy in the hotel industry is essential. The management team or data analyst is typically responsible for creating these forecasts. Many hotel revenue management systems rely on the approaches of exponential smoothing (Holt-Winters), moving average methods (simple and weighted), or linear regression to forecast demand based on historical arrivals (Weatherford & Kimes, 2003). Method comparison have been done by other researchers previously. It is debatable if there is a single best method that outperforms all other models in all conditions. In 1995, Wickham used airline data to study historical forecasting methods and pickup based forecasting methods and found that generally, pickup based forecasting yield higher accuracy. In 1998, Weatherford found that additive methods and regression out-performed multiplicative methods on airline data. Seven different forecasting models were examined by Weatherford and Kimes (2003). The methods included simple exponential smoothing, moving average, linear regression, logarithmic linear regression, additive and multiplicative, and Holt's double exponential smoothing. The results show that exponential smoothing, pickup methods and moving average models are the most robust. These models had varying degrees of forecasting accuracy, much dependent on the time horizon. Weatherford, Lawrence, Kimes, and Scott (2001) also tested the accuracy of aggregated and disaggregated forecasting methods for two large Marriott hotels over a 2-year period and found that the disaggregated forecasts outperformed the various aggregated methods. Moreover, Zheng et al. (2012) found the simple moving average and single exponential smoothing methods outperformed ARIMA and artificial neural network methods on the weekly RevPar time series. Zakhary, Gayar and Atiya (2008) evaluated 8 variations of the pickup methods and compared the results of these variations using a variety of simulated hotel reservations data since no previous detailed comparisons on hotel reservations data were reported using different variations of the pick up method. Their results show that classical pickup variations have outperformed the advanced pickup methods. Also, the "Multiplicative, classical, Exponential, Exponential Smoothing: variation has showed the best results.

2.2 Neural Network Technique

The use of neural network (NN) techniques including feedforward neural networks (FNN), multilayer perceptron (MLP), deep neural network (DNN), convolutional neural network (CNN), have achieved state-of-the-art performance in various supervised and unsupervised ML applications. Law and Law (1999) propose a FNN model to forecast Japanese tourist arrivals in Hong Kong based on the data of service price, average hotel rate, foreign exchange rate, population, marketing expenses, and gross domestic expenditure. Experimental results show that the use of FNN model outperforms multiple regression, naive, moving average, and exponential smoothing. Law (2000) applies NN to tourism demand forecasting by incorporating the back-propagation learning process into a nonlinearly separable tourism demand data. Empirical results exhibit that utilizing a back-propagation NNN outperforms regression models, time series models, and FNN in terms of forecasting accuracy.

2.3 Combination of forecasting methods:

The idea of developing a more accurate forecast by combining the individual forecasts obtained by the use of separate methods has existed in the tourism industry for decades. In their study focusing on forecasting tourism demand in Singapore, Oh and Morzuch (2005) showed that the composite forecasts based on the simple average of four competing time-series methods always outperformed the poorest individual forecasts and sometimes performed better than the best individual model. Building on this study, Wong, Song, Witt, and Wu (2007) analyzed the use of combination methods in predicting Hong Kong inbound tourists. These forecasts were derived from four different forecasting models: autoregressive integrated moving average (ARIMA) model, autoregressive distributed lag model (ADLM), error correction model (ECM) and vector autoregressive (VAR) model. The study concluded that composite forecasts could outperform the least accurate individual forecasts. Research to date has not determined one best combination method (Shen et al., 2011); however, the M3 competition did have results indicating that the composite forecasts outperform, on average, the combined individual forecasts (Makridakis & Hibon, 2000). No known study into the use of methods of combining individual forecasts into a composite forecast for hotel occupied rooms has been identified.

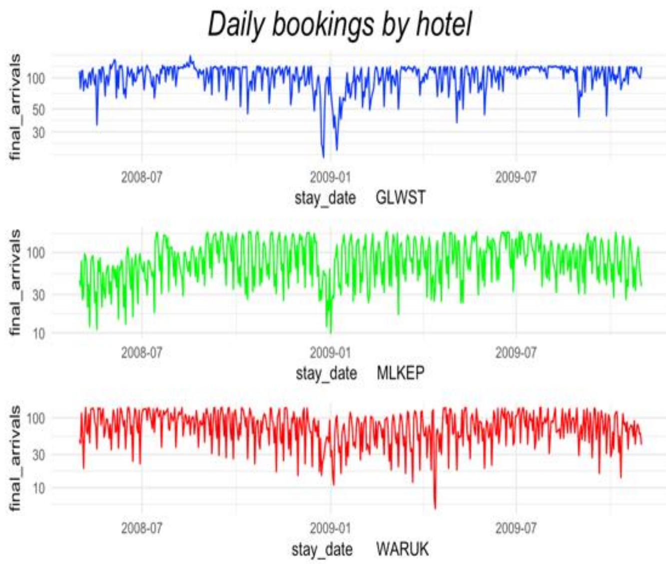
3. Data and EDA

3.1 Data Preprocessing

First of all, we removed unnecessary columns and checked missing values. We then aggregated booking of each day and added back records of all the dates between the first booking date and the final stay date filling booking value with zero, and then calculated for a new cum_booking (cumulative booking) column. We subtracted the CONF_DT from the stay_date column to create the days_prior(days of booking prior to the final stay date) column.There were two types of dataset used in our models: one dimension and two dimensions. Two dimensions of booking data: cumulative bookings on hand when the reservation was confirmed and final bookings on the stay date. The one-dimension data only consider the final bookings on the stay date, so we transformed the two-dimensional dataset by retrieving the cumulative bookings on the stay date where days_prior equals zero. Missing values were dropped when we transformed dataset from one dimension to two dimensions, and removed observations with NA when calculate the MAE, MAPE, MASE error matrix. Data were split into training dataset (2008-05-01 to 2009-10-31) and test dataset (2009-11-1 to 2010-4-30) and EDA are performed on training dataset.

3.2 Exploratory Data Analysis

3.2.1 Time series plot and Auto-correlation analysis



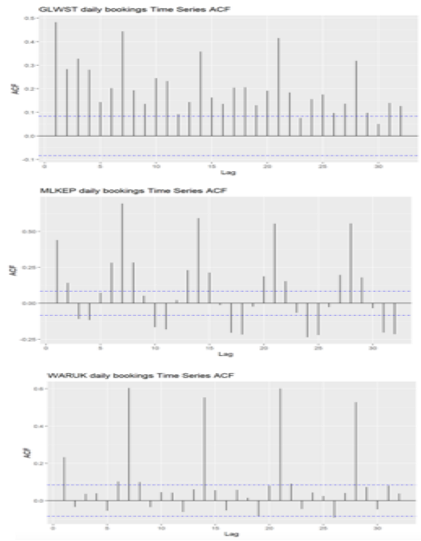


Fig. 1 Plots of total number of bookings on each stay date over the full training time range for each hotel

Fig. 2 ACF plots for each hotel

The number of final booking for each day trough at around the beginning of 2009 for all three hotels which might be due to Global Financial Crisis during that time that reduced the consumers' spending power (Fig.1). The ACF plots show that there is a periodic pattern that most likely corresponds to a weekly cycle. For hotel GLWST, the pattern repeated every 7, 14 and 21 days, and there is more randomness in the data compared to the other two hotels. Data for MLKEP and WARUK show a cyclic pattern in the ACF plots (Fig.2).

3.2.2 Average Demand by Time Analysis

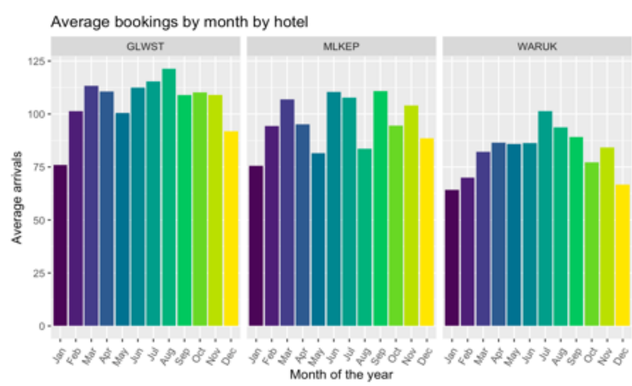


Fig 3 and Fig 4: Average bookings by Day of Week (DOW) and month

Fig. 3 and Fig 4 show that Saturdays appear to be the most popular days for hotel GLWST which is as expected. Tuesdays and Wednesdays are as popular as Saturdays for MLKEP and WARUK.Sundays have the lowest numbers of average bookings for all three hotel.

The demand is also varied by time within a year. Summer usually has the highest numbers of bookings and winter has the lowest demand.

3.2.3 Booking Curve Analysis

A booking curve is a chart of booking on hand (BOH) for a given day, recorded at regular intervals. These intervals might be months before arrival (MBA), weeks before arrival (WBA), or days before arrival (DBA) (Orkin, 1998). Based on historical data, this curve provides information about general tendencies in booking behavior that can be very useful in forecasting future bookings. In this case, we calculated the mean percentage of cumulative bookings to the final arrivals for all the stay dates grouping by days_prior and plot the bookings curve. The booking window below were restricted up to 90 days prior to arrival date for easier comparison.

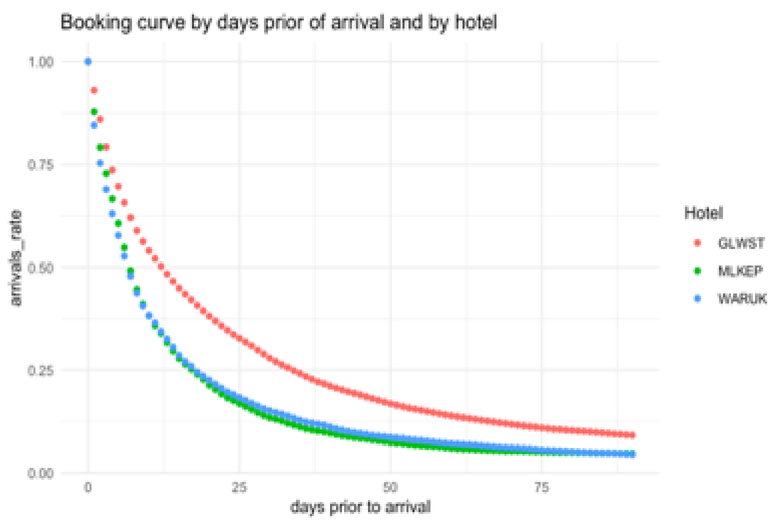


Fig. 5: Booking curve by days prior to stay date across 3 hotels

For all the hotels, the cumulative bookings increase at an increasing rate as the arrival day approaches which means guests tend to make reservations at dates closer to the final stay date.The pickup rate is flat 50 days before Day 0, and the pickup rate is much faster 30 days before Day 0. For GLWST, almost 80% of the bookings happen within 50 days of arrival. For MLKEP and WARUK,almost 90% of the bookings happen within 50 days of arrival. For all three hotels, booking within 30 days prior accounts for over 75% of the total bookings.

The same analysis was done for each day of the week (DOW) by each hotel separately and found that the same trend appears in day of the week (Fig. 6). By plotting the percentage of the cumulative bookings-on-hand against final arrivals for Day 0 group by DOW and days_prior,we noticed that Friday, Saturday and Sunday stand out across all three hotels, which means bookings on those days were picked up quicker. In addition, guests arrive on Saturdays, Fridays and Sundays tend to book earlier than those arrive on other days.

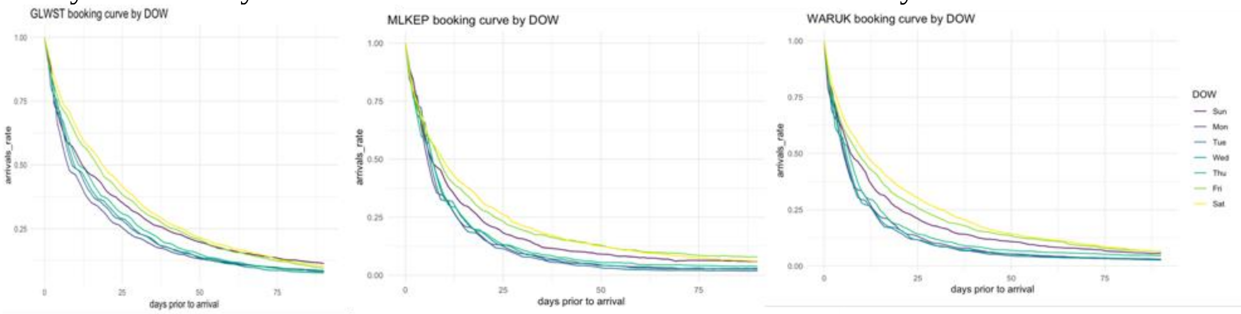


Fig. 6: Booking curve by DOW of the stay date across 3 hotels

3.2.4 Final Arrivals Distribution Analysis

The distribution of the final bookings for each DOW and month of the year were also examined. Figure 8 and Figure 9 show that for hotel GLWST and WARUK, booking data were more concentrated on Tuesdays and Saturdays. For hotel MLKEP, the bookings data are more concentrated on Mondays, Wednesdays and Sundays. The hotel GLWST have more concentrated booking from July to October that means the numbers of room booked in those months are consistent. However, for hotel MLKEP and WAURK, there are more variations in numbers of room booked.

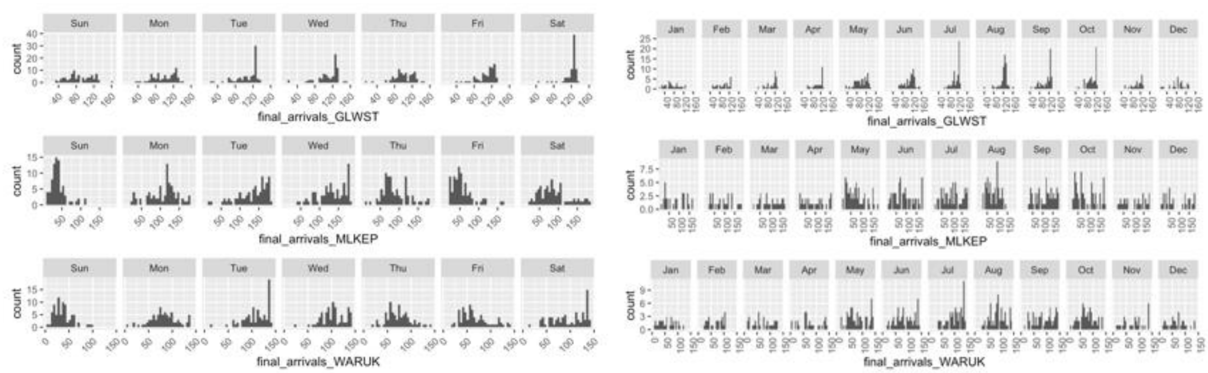


Fig. 8. and Fig. 9: Final Arrivals distribution across 3 hotels by Days of Week and Month of Year.

4. Model Descriptions and Methodology

The purpose of this study is to test the performance of additive and multiplicative advanced booking model, simple and double exponential smoothing, additive and multiplicative Holt-Winters method, seasonal and non-seasonal ARIMA models and neural network model on daily aggregated occupied room data from 3 hotels. Also, this study also examines the performance of combined forecasts. Table 1 lists the abbreviations of our chosen models and their descriptions.

Table 1. Model abbreviations and descriptions

Model Abbreviation	Method Explaination
add	Advanced additive booking model
mul	Advanced multiplicative booking model
add_mDOW	Advanced additive booking model (groupby month and Day of Week buckets)
add.hw_a__DOW	Combination of Advanced booking model (additive) and Holt-Winters' additive model split by DOW bucket
add_mDOW.hw_a__DOW	Combination of Advanced additive booking model (groupby month and Day of Week buckets) and Holt-Winters' additive model by DOW bucket
add_mDOW.hw_m__DOW	Combination of Advanced additive booking model (groupby month and Day of Week buckets) and Holt-Winters' multiplicative model split by DOW bucket
add.fc_hw_a__dpr	Combination of Advanced additive booking model (groupby month and Day of Week buckets) and Holt-Winters' additive model split by Days prior bucket
add_mDOW.hw_a__dpr	Combination of Advanced additive booking model (groupby month and Day of Week buckets) and Holt-Winters' additive model by Days prior bucket
add_mDOW.hw_m__dpr	Combination of Advanced additive booking model (groupby month and Day of Week buckets) and Holt-Winters' multiplicative model split by Days prior bucket
nn	Neural Network
glm_st	Ensemble Model using generalize linear model and stacking method
ses	Single exponential smoothing using a single factor Alpha considering the past observations without considering trend or seasonality
holt	Double exponential smoothing using Alpha and Beta considering the past observations and trend without considering seasonality
hw_add	Holt-Winters' model using Alpha, Beta and Gamma considering the past observations, trend and seasonality and use additive method to calculate seasonality
hw_mul	Holt-Winters' modeL using Alpha, Beta and Gamma considering the past observations, trend and seasonality and use multiplicative method to calculate seasonality
Arima	AutoRegressive Integrated Moving Average method
Sarima	Sesonal AutoRegressive Integrated Moving Average method

4.1 Advanced Booking Model

The advance bookings model considers the increase in the number of reservations over a relatively short period of time, usually days, for a particular day in a hotel(Weatherford & Kimes, 2003). We assume that the number of reservations in a hotel increases gradually and use additive or multiplicative models to forecast room occupancy in the future.

4.1.1 Simple Addictive Model

The simple additive method adds the current bookings to the average historical pickup in bookings from the reading day (Day n) to the actual night of the stay (Day 0):

Forecast at Day 0 = bookings at Day n + average pickup (Day n to Day 0)

In this model, we assumed that the Final Arrival (FA) is depending on the Cumulative bookings(CB) for 1,2,3…days prior to final stay date and the average remaining bookings remains the same for different stay dates if the booking date n share the same days prior numbers with the accordant final stay date. The training data were grouped by days prior for all the stay date and calculate the historical average Remaining Booking (RB= FA – CB). Finally, we applied that to the test to forecast the Final Arrivals, (FA = CB + RB) and calculated the error matrix.

4.1.2 Simple Multiplicative Model

The multiplicative method multiplies the current bookings by the average historical pickup ratio in bookings from the reading day (Day n) to the actual night of the stay (Day 0):

Forecast at Day 0 = bookings at Day n * average pickup ratio Day n to (Day 0)

In this model, we assume that the ratio for Final Arrival (FA) to Cumulative bookings(CB) is depending on the days (1,2,3… days) prior to the final stay and the average remaining bookings remains the same for different stay dates if the booking date n share the same days prior numbers with the accordant final stay date. The training data were grouped by days prior for all the stay date and the historical average Booking Rate. (BR =CB/FA) was calculated. Finally, we applied that to the test data to forecast the Final Arrivals, (FA = CB * RB) and calculated the error matrix.

4.1.3 Additive vs Multiplicative method variations

It is known that the hotel industry is characterized by seasonality. Depends on peak or low season, there may be large variation in booking demand domestically and internationally. The EDA also shows that the bookings of the three hotel fluctuates through a week and a year. However, all of the above simple advance booking methods used only the cumulative bookings-on-hand and days prior information (bookings at Day n prior Day 0), and overlooked the seasonality and features of the final stay date. In this model, we assumed that certain days of week or certain months of year would have different demand patterns so we included DOW and month and the combination of the two into the model. The training data were grouped in 3 ways, by 1) DOW and days prior (days of Day n prior Day 0) 2) month and days prior and 3) DOW and month and days prior, and then calculated average remaining bookings (RB) respectively. Then we applied that to the test data to forecast the Final Arrivals and calculated the error matrix. A similar way was used to include Month and DOW data into a new multiplicative model.

4.1.4 Key Findings

The results in Table 2 to Table 4 show the MASE of advanced booking methods forecasting. By days prior alone, for hotel GLWST and WARUK, the add_mDOW model outperforms all other models and naive model over all 6-time horizons. For hotel MLKEP, when forecast with more than 15 days prior to arrivals, performances of all the advanced booking models are worse than the naive model, with MASE larger than 1. As we expected, the accuracy of the short time horizon “1 to 7 days” forecast is the highest, and the results get worse as the time horizon are expended to medium and long term.

By days prior and DOW, add_mDOW model perform better for the hotel GLWST and WARUK. For hotel MLKEP, the forecast for Tuesday, Wednesday and Saturday are worse than the naive models across all the advance booking models. The result for Saturday have the lowest accuracy across three hotels, it may be due to large variations on bookings on those days of the week and make the demand hard to predict. In the current study, our advanced booking model only consider the current bookings-on-hand information, and forecast by simply aggregating mean RB and BR grouping by the combinations of days prior, DOW and month buckets. The omission of the historical arrivals data and trend may lead to the volatility of the model.

Table 2. MASE across Advance booking models for hotel GLWST by days prior categories

	days_prior_c	MASE_add	MASE_mul	MASE_add_m	MASE_mul_m	MASE_add_DOW	MASE_mul_DOW	MASE_add_mDOW	MASE_mul_mDOW
1	1 to 7_out	0.47	0.67	0.45	0.68	**0.44**	0.59	0.45	0.61
2	8 to 14_out	0.76	1.41	0.69	1.37	0.70	1.24	**0.69**	1.18
3	15 to 21_out	0.85	1.81	0.77	1.78	0.78	1.61	**0.76**	1.51
4	22 to 28_out	0.90	2.02	0.78	2.07	0.83	1.77	**0.76**	1.71
5	29 to 60_out	1.03	2.32	0.87	2.35	0.95	2.14	**0.79**	2.08
6	60 or more_out	1.18	3.04	1.06	3.67	1.04	2.98	**0.94**	3.82

Table 3. MASE across Advance booking models for hotel MLKEP by days prior categories

	days_prior_c	MASE_add	MASE_mul	MASE_add_m	MASE_mul_m	MASE_add_DOW	MASE_mul_DOW	MASE_add_mDOW	MASE_mul_mDOW
1	1 to 7_out	0.93	0.70	0.93	0.70	0.58	0.64	**0.56**	0.70
2	8 to 14_out	1.83	1.52	1.80	1.54	1.00	1.27	**0.89**	1.44
3	15 to 21_out	2.13	2.22	2.09	2.34	1.15	1.80	**1.03**	2.14
4	22 to 28_out	2.25	2.82	2.22	3.00	1.22	2.32	**1.09**	2.80
5	29 to 60_out	2.32	3.48	2.29	3.75	1.28	2.98	**1.14**	3.59
6	60 or more_out	2.26	3.24	2.17	3.69	1.42	2.94	**1.36**	4.03

Table 4. MASE across Advance booking models for hotel WARUK by days prior categories

	days_prior_c	MASE_add	MASE_mul	MASE_add_m	MASE_mul_m	MASE_add_DOW	MASE_mul_DOW	MASE_add_mDOW	MASE_mul_mDOW
1	1 to 7_out	0.62	0.51	0.58	0.48	0.42	0.44	**0.38**	0.47
2	8 to 14_out	1.11	1.12	1.04	1.05	0.71	0.86	**0.67**	0.89
3	15 to 21_out	1.25	1.31	1.16	1.29	0.87	0.99	**0.78**	1.10
4	22 to 28_out	1.31	1.44	1.19	1.45	0.94	1.06	**0.81**	1.18
5	29 to 60_out	1.38	1.54	1.23	1.46	1.04	1.30	**0.87**	1.37
6	60 or more_out	1.41	1.92	1.28	1.78	1.13	1.67	**0.95**	1.86

Table 5. MASE across Advance booking models for hotel GLWST by day of week categories

	DOW	MASE_add	MASE_mul	MASE_add_m	MASE_mul_m	MASE_add_DOW	MASE_mul_DOW	MASE_add_mDOW	MASE_mul_mDOW
1	Sun_out	1.24	1.76	1.09	1.78	**0.80**	1.89	0.82	2.02
2	Mon_out	0.98	2.94	0.87	2.36	0.92	2.83	**0.84**	2.46
3	Tue_out	1.10	2.63	0.88	2.20	1.14	2.58	**0.76**	2.65
4	Wed_out	0.90	2.62	0.72	2.10	0.89	2.48	**0.68**	2.38
5	Thu_out	1.12	2.06	1.00	2.08	1.08	1.98	**0.95**	1.97
6	Fri_out	**0.89**	2.64	0.86	4.50	0.88	2.46	0.92	3.92
7	Sat_out	1.20	3.84	1.17	6.29	**1.04**	3.49	1.06	5.81

Table 6. MASE across Advance booking models for hotel MLKEP by day of week categories

	DOW	MASE_add	MASE_mul	MASE_add_m	MASE_mul_m	MASE_add_DOW	MASE_mul_DOW	MASE_add_mDOW	MASE_mul_mDOW
1	Sun_out	3.60	1.44	3.81	1.40	**0.71**	1.52	0.82	1.74
2	Mon_out	1.32	2.41	1.12	2.00	1.07	2.04	**0.87**	2.14
3	Tue_out	3.30	4.62	3.00	4.02	1.91	3.41	**1.73**	4.30
4	Wed_out	2.83	4.08	2.65	4.05	1.69	3.68	**1.41**	4.40
5	Thu_out	0.84	2.05	**0.76**	2.02	0.87	2.07	0.91	1.84
6	Fri_out	3.75	2.62	4.19	4.82	1.07	2.22	**0.92**	3.93
7	Sat_out	1.46	2.64	1.51	4.04	**1.26**	2.26	1.26	4.08

Table 7. MASE across Advance booking models for hotel WARUK by day of week categories

	DOW	MASE_add	MASE_mul	MASE_add_m	MASE_mul_m	MASE_add_DOW	MASE_mul_DOW	MASE_add_mDOW	MASE_mul_mDOW
1	Sun_out	5.79	1.37	4.84	1.76	1.38	1.17	**0.68**	1.60
2	Mon_out	0.74	1.49	0.69	1.30	0.80	1.22	**0.94**	1.68
3	Tue_out	1.19	2.50	1.31	2.22	0.92	1.91	**0.91**	2.00
4	Wed_out	0.84	1.85	0.95	1.69	0.91	1.58	**0.92**	1.56
5	Thu_out	1.13	1.35	0.97	1.19	0.94	1.31	**0.87**	1.21
6	Fri_out	1.75	0.97	1.36	1.05	1.14	0.81	**0.75**	0.82
7	Sat_out	0.99	1.13	0.75	1.21	1.25	1.06	**0.74**	1.20

4.2 Exponential Smoothing

We then looked at one of the most popular historical models for demand forecasting: the exponential smoothing method which is used to forecast future data based on past observations. In this method, previous observations are discounted such that recent observations are given more weights and observations further in the past are given less weight. The weights decrease by a constant ratio, and thus lie on an exponential curve. There are three main types of exponential smoothing time series forecasting methods. A simple method that assumes no systematic structure, an extension that explicitly handles trends, and the most advanced approach that add support for seasonality.

4.2.1 Single Exponential Smoothing

Time series data for each hotel were split into training and test data where training data contains final hotel room demand from April 30, 2009 to October 31, 2009 and test data are those from November 1, 2009 to April 30, 2010. We forecasted for the next 6 months, 3 months and 1 months. The first forecast is to use the final demand from 364 days ago as naive forecasting. We then apply single exponential smoothing (SES) to our hotel data using the ses function from forecast package. SES is a time series forecasting method for univariate data without a trend or seasonality. It requires a single parameter or the smoothing factor, alpha. This parameter controls the rate at which the influence of the observations at prior time steps decay exponentially. Alpha is often set to a value between 0 and 1. Large values means that the model pays attention mainly to the most recent past observations, whereas smaller values mean more of the history is taken into account when making a prediction. We kept alpha as default in which the function automatically optimizes it and h parameter is set to the length of days in 1 month, 3 months and 6 months. The alpha for 3 hotels are shown in Table 9 below. The algorithm generally give historical data more weight when we do long term forecasting as the alpha is closer to 0 and gives more weight to the most recent observation for short term forecasting as alpha is closer to 1.

Table 9. The optimal alpha parameter identified by ses function for each hotel

	forecast_period	alpha_G	alpha_M	alpha_W
1	6m_Nov-Apr_out	0.188	0.086	0.044
2	3m_Nov-Jan_out	0.188	0.086	0.044
3	3m_Dec-Feb_out	0.184	0.084	0.043
4	3m_Jan-Mar_out	0.199	0.107	0.052
5	3m_Feb-Apr_out	0.211	0.108	0.053
6	1m_Nov_out	0.188	0.086	0.044
7	1m_Dec_out	0.184	0.084	0.043
8	1m_Jan_out	0.199	0.107	0.052
9	1m_Feb_out	0.253	0.132	0.053
10	1m_Mar_out	0.213	0.103	0.054
11	1m_Apr_out	0.206	0.096	0.054

1

4.2.2 Double Exponential Smoothing (Holt's Linear Trend Method)

Double exponential smoothing is an extension to SES that explicitly adds support for trends in the univariate time series. In addition to alpha, an additional smoothing factor is added to control the decay of the influence of the change in trend called beta. We then applied double exponential smoothing method in the following manner. Both alpha and beta kept as default in which the function automatically optimizes it and h is set to the length of days in 1 month, 3 months and 6 months. The alpha and beta show in Table 10 below. A small beta indicates that there is no obvious trend in the data.

Table 10. The optimal alpha and beta parameters identified by holt function for each hotel

	forecast_period	alpha__G	beta__G	alpha_M	beta_M	alpha_W	beta_W
1	6m_Nov-Apr_out	0.1921	1e-04	0.0881	1e-04	0.0634	1e-04
2	3m_Nov-Jan_out	0.1921	1e-04	0.0881	1e-04	0.0634	1e-04
3	3m_Dec-Feb_out	0.1882	1e-04	0.0844	1e-04	0.0612	1e-04
4	3m_Jan-Mar_out	0.2024	1e-04	0.1093	1e-04	0.0681	1e-04
5	3m_Feb-Apr_out	0.2142	1e-04	0.1104	1e-04	0.0685	1e-04
6	1m_Nov_out	0.1921	1e-04	0.0881	1e-04	0.0634	1e-04
7	1m_Dec_out	0.1882	1e-04	0.0844	1e-04	0.0612	1e-04
8	1m_Jan_out	0.2024	1e-04	0.1093	1e-04	0.0681	1e-04
9	1m_Feb_out	0.2572	1e-04	0.1328	1e-04	0.0815	1e-04
10	1m_Mar_out	0.2158	1e-04	0.1052	1e-04	0.0699	1e-04
11	1m_Apr_out	0.2084	1e-04	0.0982	1e-04	0.0691	1e-04

4.2.3 Triple Exponential Smoothing (Holt-Winters' Seasonal Method)

Triple exponential smoothing or Holt-Winters' exponential smoothing captures seasonality. Another parameter called gamma is added to controls the influence on the seasonal component. The seasonality may be modeled as either an additive or multiplicative process for a linear or exponential change in the seasonality. For longer range or multi-step forecasts, the trend may continue on unrealistically. As such, it can be useful to dampen the trend over time. Dampening means reducing the size of the trend over future time steps down to a straight line. We next applied holt-winters' exponential smoothing method. Both "additive" and "multiplicative" structure were implemented as the additive model is best used when the seasonal trend is of the same magnitude throughout the data set, while the multiplicative Model is preferred when the magnitude of seasonality changes as time increases. Alpha, beta and gamma kept as default in which the function automatically optimizes it. Similar to SES and Holt's method, all three parameters are constrained to 0 to 1. Damped is set to TRUE in order to reduce the size of the trend over future time steps down to a straight line, and h is set to the length of 1 month, 3 months and 6 months. The alpha, beta and gamma show in the Table 11 and Table 12 below. The identified alpha for hotel GLWST and MLKEP are much higher than those in previous two circumstances indicating more weight are put to recent observations. A small beta and gamma indicate that there is no obvious trend and seasonality exited in the data which was consistent with our EDA findings.

Table 11. The optimal alpha, beta and gamma parameters identified by holt winters' additive method for each hotel

	forecast_period	alpha_G	beta_G	gamma_G	alpha_M	beta_M	gamma_M	alpha_W	beta_W	gamma_W
1	6m_Nov-Apr_out	0.4651	1e-04	1e-04	0.44	1e-04	1e-04	0.077	1e-04	0.104
2	3m_Nov-Jan_out	0.4651	1e-04	1e-04	0.44	1e-04	1e-04	0.077	1e-04	0.104
3	3m_Dec-Feb_out	0.4676	1e-04	1e-04	0.4203	1e-04	2e-04	0.0674	1e-04	0.1352
4	3m_Jan-Mar_out	0.5012	1e-04	1e-04	0.4626	1e-04	1e-04	0.0868	1e-04	0.1379
5	3m_Feb-Apr_out	0.4832	1e-04	2e-04	0.4641	1e-04	1e-04	0.0995	1e-04	0.1485
6	1m_Nov_out	0.4651	1e-04	1e-04	0.44	1e-04	1e-04	0.077	1e-04	0.104
7	1m_Dec_out	0.4676	1e-04	1e-04	0.4203	1e-04	2e-04	0.0674	1e-04	0.1352
8	1m_Jan_out	0.5012	1e-04	1e-04	0.4626	1e-04	1e-04	0.0868	1e-04	0.1379
9	1m_Feb_out	0.5251	1e-04	1e-04	0.4881	1e-04	2e-04	0.143	1e-04	4e-04
10	1m_Mar_out	0.4711	1e-04	2e-04	0.476	1e-04	1e-04	0.0962	1e-04	0.1388
11	1m_Apr_out	0.4631	1e-04	1e-04	0.4568	1e-04	1e-04	0.097	1e-04	0.1334

Table 12. The optimal alpha, beta and gamma parameters identified by holt winters' multiplicative method for each hotel

	forecast_period	alpha_G	beta_G	gamma_G	alpha_M	beta_M	gamma_M	alpha_W	beta_W	gamma_W
1	6m_Nov-Apr_out	0.4008	1e-04	1e-04	0.5514	0.0011	1e-04	0.0339	1e-04	0.1513
2	3m_Nov-Jan_out	0.4008	1e-04	1e-04	0.5514	0.0011	1e-04	0.0339	1e-04	0.1513
3	3m_Dec-Feb_out	0.3818	1e-04	1e-04	0.4789	1e-04	1e-04	0.0298	1e-04	0.1586
4	3m_Jan-Mar_out	0.4472	1e-04	1e-04	0.4457	1e-04	1e-04	0.0508	1e-04	0.1447
5	3m_Feb-Apr_out	0.4455	1e-04	1e-04	0.5764	0.0042	1e-04	0.0602	1e-04	0.1517
6	1m_Nov_out	0.4008	1e-04	1e-04	0.5514	0.0011	1e-04	0.0339	1e-04	0.1513
7	1m_Dec_out	0.3818	1e-04	1e-04	0.4789	1e-04	1e-04	0.0298	1e-04	0.1586
8	1m_Jan_out	0.4472	1e-04	1e-04	0.4457	1e-04	1e-04	0.0508	1e-04	0.1447
9	1m_Feb_out	0.3814	1e-04	1e-04	0.5401	1e-04	0.0254	0.098	1e-04	0.0432
10	1m_Mar_out	0.4446	1e-04	1e-04	0.5719	1e-04	1e-04	0.0596	1e-04	0.1464
11	1m_Apr_out	0.4228	1e-04	0.0054	0.5871	0.001	1e-04	0.0591	1e-04	0.1407

4.2.4 Key Findings

Table 13 to 15 show the forecasting results for each hotel. For hotel GLWST, the MASE show that, among all the exponential smoothing methods, the holt-winters' additive method produces an overall best result. However, it only outperforms the naive forecast at 4 time period: the forecasting for November, February, March and from February to April. There are more better results for one-month forecasting than three and six months since exponential smoothing is better at forecasting short time frame as it put more weight on the most recent observations. For hotel MLKEP, all exponential smoothing models yield worse results than naive forecasts except for February forecast. The holt-winters' additive method produces an overall best result and the MASE for February forecast is 0.22. For hotel WARUK, the two holt winters' models are relatively better than SES and holt method, although they both have only 4 forecasts outperform naive forecasts. The best results for all the model is the February forecast. Exponential smoothing method is known for its short-term forecasting accuracy. It is not a convenient way for forecasting for a long-term time horizon, i.e. the accuracy of the exponential smoothing is getting worse if the forecast for medium- or long-term time horizon is required. This is consistent with our results in which the accuracy for 1-month forecasting is higher than 3- and 6-month forecasting. Exponential smoothing model is relatively simple and inflexible in terms of using few statistical data for the prediction of the future value. In our case, the only information used was the historical hotel final demands. This lack of adequate variables regarding other factors that could influence the future demand may affect the forecasting accuracy. In the current study, the smoothing parameters were automatically determined by the function optimizing them for minimum forecasting error. We could set the smoothing parameter manually based on our experience and the dataset in order to find a better result.

Table 13. MASE across exponential smoothing models for hotel GLWST

	forecast_period	MASE.ses	MASE.holt	MASE.hw_add	MASE.hw_mul
1	6m_Nov-Apr_out	1.51	1.57	1.25	1.27
2	3m_Nov-Jan_out	1.91	1.95	1.59	1.62
3	3m_Dec-Feb_out	1.85	1.85	1.84	1.79
4	3m_Jan-Mar_out	1.23	1.26	1.31	1.16
5	3m_Feb-Apr_out	1.11	1.14	0.99	0.86
6	1m_Nov_out	0.99	1.00	0.69	0.70
7	1m_Dec_out	1.49	1.49	1.42	1.40
8	1m_Jan_out	1.47	1.46	2.33	2.13
9	1m_Feb_out	0.95	0.84	0.72	0.78
10	1m_Mar_out	0.87	0.88	0.69	0.74
11	1m_Apr_out	0.95	0.96	1.09	1.11

Table 14. MASE across exponential smoothing models for hotel MLKEP

	forecast_period	MASE.ses	MASE.holt	MASE.hw_add	MASE.hw_mul
1	6m_Nov-Apr_out	2.42	2.41	2.15	2.46
2	3m_Nov-Jan_out	2.50	2.51	2.26	2.43
3	3m_Dec-Feb_out	2.94	3.05	1.99	1.87
4	3m_Jan-Mar_out	3.15	3.17	4.53	3.79
5	3m_Feb-Apr_out	2.24	2.23	1.04	1.61
6	1m_Nov_out	2.48	2.47	2.40	2.71
7	1m_Dec_out	2.63	2.69	2.03	1.91
8	1m_Jan_out	2.84	2.85	3.82	3.09
9	1m_Feb_out	0.68	0.62	0.22	0.32
10	1m_Mar_out	2.52	2.50	1.15	1.34
11	1m_Apr_out	1.73	1.73	1.17	1.10

Table 15. MASE across exponential smoothing models for hotel WARUK

	forecast_period	MASE.ses	MASE.holt	MASE.hw_add	MASE.hw_mul
1	6m_Nov-Apr_out	1.31	1.27	0.94	0.98
2	3m_Nov-Jan_out	1.42	1.37	1.03	1.09
3	3m_Dec-Feb_out	1.61	1.57	1.24	1.23
4	3m_Jan-Mar_out	1.78	1.96	1.91	1.50
5	3m_Feb-Apr_out	1.29	1.33	0.84	0.91
6	1m_Nov_out	1.12	1.11	0.71	0.69
7	1m_Dec_out	1.21	1.18	1.17	1.16
8	1m_Jan_out	1.51	1.45	1.24	1.15
9	1m_Feb_out	0.54	0.59	0.35	0.37
10	1m_Mar_out	1.30	1.30	0.87	0.89
11	1m_Apr_out	0.86	0.87	0.56	0.57

4.3 ARIMA and Seasonal ARIMA

4.3.1 ARIMA

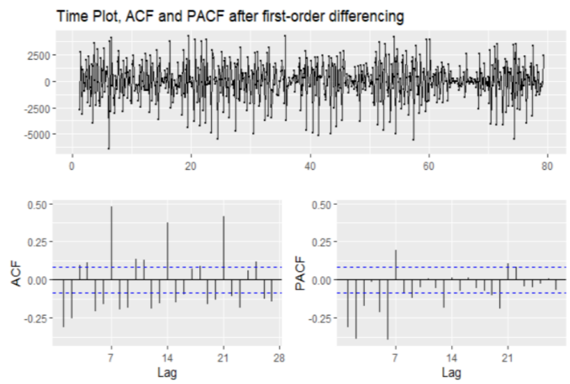
ARIMA is an acronym that stands for AutoRegressive Integrated Moving Average, which is one of the most popular models for time series forecasting analysis, has been originated from the autoregressive model (AR), the moving average model (MA) and the combination of the AR, the MA, and the ARMA models (Blanchard and Desrochesrs, 1984). It explains a given time series based on its own past values, that is, its own lags and the lagged forecast errors, so that equation can be used to forecast future values. An ARIMA model is characterized by 3 terms: p, d, q, where p is the order of the 'Auto Regressive' (AR) term which refers to the number of lags of Y to be used as predictors. q is the order of the 'Moving Average' (MA) term which refers to the number of lagged forecast errors that should go into the ARIMA model. d is the number of differencing required to make the time series stationary. ARIMA models first turn unstable time series into stable time series by d differences and then regress dependent values on lag values and the random error's present and lag values. In our study, we developed both ARIMA and seasonal ARIMA models for each hotel. The hotel room final booking time series data were first split into in-sample and out-sample data where in-sample data was used to find the applicable parameter and fit the model. The out-sample data was used as test dataset. We check if the data is stationary by looking at the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Box-Cox transformation was then used to stabilise the variance to make the data stationary. A unit root test was used to determine whether more differencing is required. In order to find the AR term (p), we inspected the PACF plot. Any autocorrelation in a stationarized series can be rectified by adding enough AR terms. So, we initially take the order of AR term to be equal to as many lags that crosses the significance limit in the PACF plot. The ACF plot shows how many MA terms are required to remove any autocorrelation in the stationarized series.

4.3.2 Seasonal ARIMA

A seasonal model is formed by including additional seasonal terms (P,D,Q) in the ARIMA models. The seasonal part of an AR or MA model was also determined by examining the PACF and ACF plot. The modelling procedure is almost the same as for non-seasonal data, except that we need to select seasonal AR and MA terms as well as the non-seasonal components of the model.

4.3.3 Key Findings

We considered a large number of ARIMA and seasonal ARIMA models by considering values for p,q,P and Q and their performances were compared using the AIC, AICc and BIC. Residual from our chosen model were examined by plot the ACF of the residuals. We used the autoplot, ACF and PACF in Figure 10 to 15 to decide on the p,d,q and P,D,Q parameters for our chosen models for each hotel. The chosen ARIMA and seasonal ARIMA models for each hotel and their AIC, AICc and BIC values are listed in below table. The results show that for each hotel, AIC, AICc and BIC for seasonal ARIMA models have smaller values than those of ARIMA models indicates that seasonal ARIMA models fit the data better than ARIMA models.



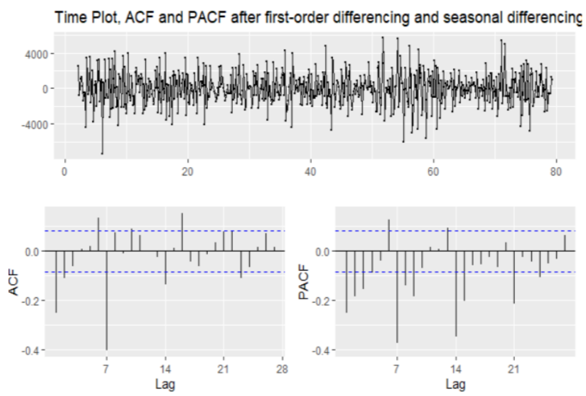
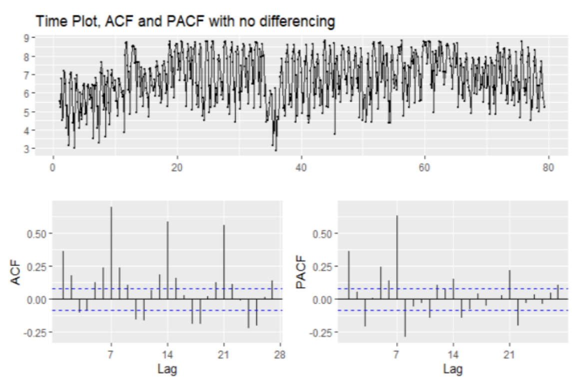


Fig. 10 and Fig. 11: Time Plot, ACF and PACF plots to find the p,d,q and P, D, Q parameters for hotel GLWST's ARIMA and seasonal ARIMA model



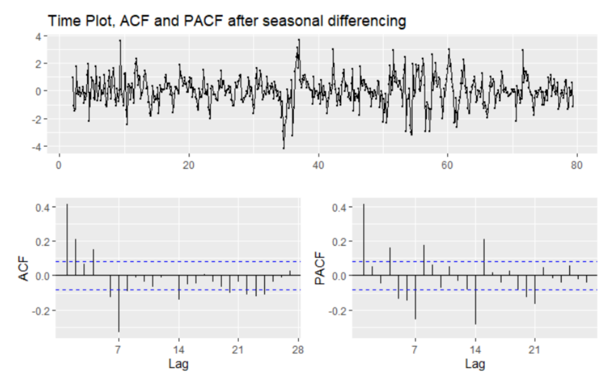
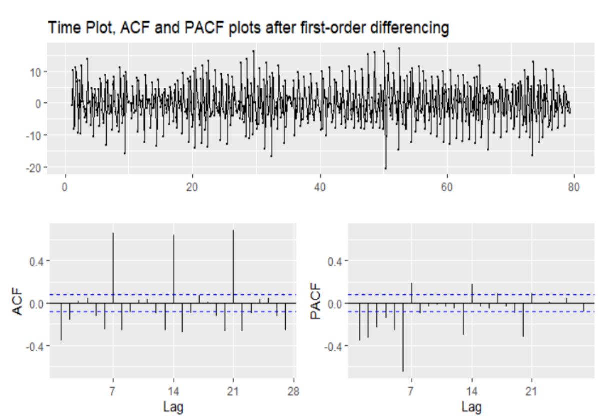


Fig. 12 and Fig. 13: Time Plot, ACF and PACF plots to find the p,d,q and P, D, Q parameters for hotel MLKEP's ARIMA and seasonal ARIMA model



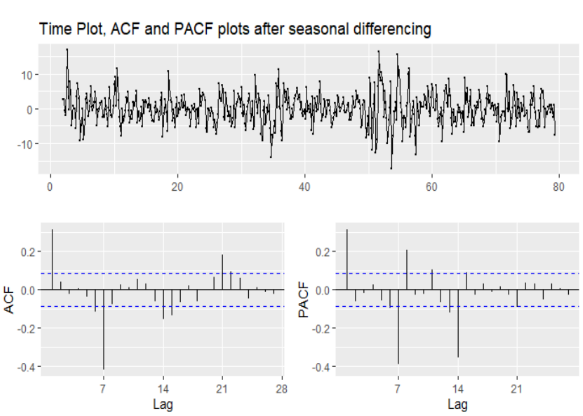


Fig. 14 and Fig. 15: Time Plot, ACF and PACF plots to find the p,d,q and P, D, Q parameters for hotel WARUK's ARIMA and seasonal ARIMA model

Table 16. p, d, q, P, D, Q, m (number of observations per year) parameters and AIC, AICc and BIC values of chosen ARIMA and seasonal ARIMA models for three hotels

		Parameters of the Model							Error Matrix		
Hotel	**Model**	**p**	**d**	**q**	**P**	**D**	**Q**	**m**	**AIC**	**AICc**	**BIC**
GLWST	Arima	7	1	2					9509.39	9509.8	9552.45
	Sarima	3	1	1	3	1	1	7	9315.14	9315.48	9353.78
MLKEP	Arima	1	0	21					1484.68	1486.97	1588.07
	Sarima	7	0	0	0	1	2	7	1230.09	1230.5	1273.04
WARUK	Arima	6	1	1					3050.49	3050.76	3084.94
	Sarima	8	0	1	2	1	1	7	2819.05	2819.74	2874.89

We forecasted in-sample and out-sample for the next 6 months, 3 months and 1 months. Table 17 to 19 show the forecasting results for each hotel. In general, ARIMA and seasonal ARIMA models do not provide satisfactory results. For hotel GLWST, the ARIMA model outperform naive forecasts 4 out of 11 times. Seasonal ARIMA only have 3 MASE values that are smaller than 1. For hotel MLKEP, both ARIMA and seasonal ARIMA model outperform naive forecast when forecasting demand in February. For hotel WARUK, ARIMA model is better at forecasting February and April; seasonal ARIMA model outperforms naive forecasts for periods November to April, February to April, November, February, March and April. Seasonal ARIMA, in general, provide better results than ARIMA models as they take into account the seasonality of dataset. In addition to examine the error measurement, an estimate of how much the actual demand is likely to vary around the single forecast number were also determined, so that the ARIMA model will estimate the upper and lower values around the forecast where there is only a 5% chance that the real value will not be in that range. The results shown in Table 20 to 22. Just as exponential smoothing methods, ARIMA model place heavy emphasize on the recent past rather than the distant past, it is advisable to run the model after obtaining each new observation, so that fresh forecasts can be generated for the next period. This might explain why our model perform better for one month forecasting. Also note that ARIMA simply approximates historical patterns and therefore does not aim to explain the structure of the underlying data mechanism.

Table 17. MASE of ARIMA and seasonal ARIMA models for hotel GLWST

	forecast_period	MASE.Arima	MASE.Sarima
1	6m_Nov-Apr_out	1.51	1.40
2	3m_Nov-Jan_out	1.91	1.74
3	3m_Dec-Feb_out	1.96	1.82
4	3m_Jan-Mar_out	1.21	1.16
5	3m_Feb-Apr_out	1.12	1.92
6	1m_Nov_out	0.99	0.74
7	1m_Dec_out	1.48	1.39
8	1m_Jan_out	1.74	1.68
9	1m_Feb_out	0.78	1.15
10	1m_Mar_out	0.82	0.77
11	1m_Apr_out	0.82	0.89

Table 18. MASE of ARIMA and seasonal ARIMA models for hotel MLKEP

	forecast_period	MASE.Arima	MASE.Sarima
1	6m_Nov-Apr_out	2.39	1.41
2	3m_Nov-Jan_out	2.49	1.71
3	3m_Dec-Feb_out	2.41	1.62
4	3m_Jan-Mar_out	2.50	1.43
5	3m_Feb-Apr_out	2.20	1.02
6	1m_Nov_out	2.37	1.45
7	1m_Dec_out	1.83	1.76
8	1m_Jan_out	2.95	1.66
9	1m_Feb_out	0.52	0.21
10	1m_Mar_out	2.18	1.06
11	1m_Apr_out	1.63	0.79

Table 19. MASE of ARIMA and seasonal ARIMA models for hotel WARUK

	forecast_period	MASE.Arima	MASE.Sarima
1	6m_Nov-Apr_out	1.20	0.96
2	3m_Nov-Jan_out	1.20	1.07
3	3m_Dec-Feb_out	1.45	1.24
4	3m_Jan-Mar_out	1.85	1.58
5	3m_Feb-Apr_out	1.11	0.92
6	1m_Nov_out	1.01	0.70
7	1m_Dec_out	1.02	1.21
8	1m_Jan_out	1.51	1.26
9	1m_Feb_out	0.44	0.38
10	1m_Mar_out	1.02	0.89
11	1m_Apr_out	0.76	0.55

Table 20. Actuals within 95 interval of forecast of ARIMA and seasonal ARIMA models for hotel GLWST

	forecast_period	Arima_in_95pc	SArima_in_95pc
1	6m_Nov-Apr_in	0.91	0.99
2	6m_Nov-Apr_out	0.85	0.99
3	3m_Nov-Jan_in	0.83	0.97
4	3m_Nov-Jan_out	0.99	0.96
5	3m_Dec-Feb_in	1.00	0.83
6	3m_Dec-Feb_out	1.00	1.00
7	3m_Jan-Mar_in	0.87	0.94
8	3m_Jan-Mar_out	0.97	0.90
9	3m_Feb-Apr_in	1.00	0.89
10	3m_Feb-Apr_out	0.97	0.97
11	1m_Nov_in	1.00	1.00
12	1m_Nov_out	0.91	0.99
13	1m_Dec_in	0.85	0.99
14	1m_Dec_out	0.83	0.97
15	1m_Jan_in	0.99	0.96
16	1m_Jan_out	1.00	0.83
17	1m_Feb_in	1.00	1.00
18	1m_Feb_out	0.87	0.94
19	1m_Mar_in	0.97	0.90
20	1m_Mar_out	1.00	0.89
21	1m_Apr_in	0.97	0.97
22	1m_Apr_out	1.00	1.00

Table 21. Actuals within 95 interval of forecast of ARIMA and seasonal ARIMA models for hotel MLKEP

	forecast_period	Arima_in_95pc	SArima_in_95pc
1	6m_Nov-Apr_in	0.97	0.96
2	6m_Nov-Apr_out	0.95	0.91
3	3m_Nov-Jan_in	0.93	0.89
4	3m_Nov-Jan_out	0.96	0.98
5	3m_Dec-Feb_in	1.00	0.99
6	3m_Dec-Feb_out	1.00	1.00
7	3m_Jan-Mar_in	0.94	0.81
8	3m_Jan-Mar_out	0.87	0.94
9	3m_Feb-Apr_in	1.00	1.00
10	3m_Feb-Apr_out	1.00	0.97
11	1m_Nov_in	0.97	0.97
12	1m_Nov_out	0.97	0.96
13	1m_Dec_in	0.95	0.91
14	1m_Dec_out	0.93	0.89
15	1m_Jan_in	0.96	0.98
16	1m_Jan_out	1.00	0.99
17	1m_Feb_in	1.00	1.00
18	1m_Feb_out	0.94	0.81
19	1m_Mar_in	0.87	0.94
20	1m_Mar_out	1.00	1.00
21	1m_Apr_in	1.00	0.97
22	1m_Apr_out	0.97	0.97

Table 22. Actuals within 95 interval of forecast of ARIMA and seasonal ARIMA models for hotel WARUK

	forecast_period	Arima_in_95pc	SArima_in_95pc
1	6m_Nov-Apr_in	1.00	0.93
2	6m_Nov-Apr_out	1.00	0.87
3	3m_Nov-Jan_in	1.00	0.90
4	3m_Nov-Jan_out	0.93	0.94
5	3m_Dec-Feb_in	1.00	0.98
6	3m_Dec-Feb_out	1.00	0.97
7	3m_Jan-Mar_in	1.00	0.77
8	3m_Jan-Mar_out	0.84	0.90
9	3m_Feb-Apr_in	1.00	0.96
10	3m_Feb-Apr_out	1.00	1.00
11	1m_Nov_in	0.93	0.90
12	1m_Nov_out	1.00	0.93
13	1m_Dec_in	1.00	0.87
14	1m_Dec_out	1.00	0.90
15	1m_Jan_in	0.93	0.94
16	1m_Jan_out	1.00	0.98
17	1m_Feb_in	1.00	0.97
18	1m_Feb_out	1.00	0.77
19	1m_Mar_in	0.84	0.90
20	1m_Mar_out	1.00	0.96
21	1m_Apr_in	1.00	1.00
22	1m_Apr_out	0.93	0.90

4.4 Neural Networks

4.4.1 Neural Network

We also investigated the feasibility of incorporating a neural network model, which is a machine learning algorithm that simulates the human intelligence to deduce or learn from a data set, to forecast hotel room demand for 3 hotels. Neural networks are capable of representing knowledge based on massive parallel processing and pattern recognition based on past experience or examples (Law, 1996). The pattern recognition ability of a neural network makes it a good alternative classification and forecasting tool in business applications. An additional advantage of applying a neural network to forecasting is that a neural network can capture the nonlinearity of samples in the training set (Wang & Sun, 1996). The non-linear factor handling ability makes a neural network different from time-series models. A neural network consists of an input layer, an output layer, and usually one or more hidden layers. Each of these layers contains nodes, and these nodes are connected to nodes at adjacent layer(s). Each node in a neural network is a processing unit that contains a weight and summation function. A weight return a mathematical value for the relative strength of connections to transfer data from one layer to another layer; whereas a summation function computes the weighted sum of all input elements entering a processing unit. Nodes in the input layer represents independent variables of the problem. The hidden layer is used to add an internal representation of handling non-linear data. The output of a neural network is the solution to a problem.

In this study, a dependent variable is the final demand for each future date. On-the-book for each stay date, days prior to stay date, and 10 final demands from previous days were used as features. The 10 final demands are from 1 day, 2 day, 3 day, 4 day, 5 day, 6 day, 7 day, 14 day, 21 day and 364 day ago. According to the results from preliminary modeling runs, autocorrelation and partial autocorrelation functions, considering components like trend, seasonality, cyclic and residual, we found that the present value might be related with these past values. On-the-booking and days prior provide information on booking process. As the arrival day is approaching, days prior increases while on-the-book increases. The dataset was scaled before split into training and test datasets. Among the 66,206 entries of data, 36,595 were used as training data which contains stay date from April 30, 2009 to October 31, 2009. The other 29,611 were used for accuracy testing which contains stay date from November 1, 2009 to April 30, 2010. The input layer contained the 12 nodes and the output variables used in this study was the number of hotel rooms booked for each stay date. We forecasted for the next 6 months, 3 months and 1 months. Value greater than 1 means worse than naive forecasts; smaller than 1 means outperform naive forecasts. During the training of neural networks, we tuned the number of hidden layers (0,1,2 and 3) and number of neurons in each layer, (e.g., [20], [10, 10], [15,15,15]). We used the sum of squared errors as the error function and the resilient backpropagation with weight backtracking as the learning algorithm. We also tested different activation functions including *logistic, tangent, softplus and relu*, and noticed that zero hidden layer yield the best result.

4.4.2 Key Findings

The results in Table 23 show that for hotel GLWST. The neural network model outperforms naive forecast over all the time horizon. For hotel MLKEP, only forecast for November and April outperform naive forecasting (Table 24). For hotel WARUK (Table 25), except for forecast for January, February and 3 month forecast from January to March, the rest is outperform naive forecasting. The chosen model is a neural network with no hidden layer. Zero hidden layer means that inputs connect directly to the outputs through a single layer of weights which can only be used to represent linearly separable functions. We speculate that there is a linear relationship between independent variables and dependent variable as the simplest neural network performs a least squares regression. In addition to that, the success of FNNs is highly dependent upon the assumption of independence among the training and test data (Lipton et al., 2015). The data in a time series, however, usually depend on each other, implying that the independence assumption will no longer hold anymore. Long time dependence is in fact the basis for time series forecasting. As a result, FNNs will degrade performance due to their insufficient capability of modeling long-term dependencies. To further improve our forecasting results, we may want to use nnetar function from the forecast package in R which is designed for forecasting univariate time series.

Table 23. MAE, MAPE and MAPE of neural network forecasting for hotel GLWST

	forecast_period	MAE_nn	MAE_naive	MAPE_nn	MASE_nn
1	6m_Nov-Apr_out	14.78	17.96	0.21	0.82
2	3m_Nov-Jan_out	15.01	18.64	0.25	0.81
3	3m_Dec-Feb_out	15.24	16.90	0.25	0.90
4	3m_Jan-Mar_out	15.76	16.65	0.21	0.95
5	3m_Feb-Apr_out	14.87	21.05	0.18	0.71
6	1m_Nov_out	11.68	17.33	0.13	0.67
7	1m_Dec_out	17.09	21.42	0.34	0.80
8	1m_Jan_out	14.65	15.74	0.25	0.93
9	1m_Feb_out	10.56	13.25	0.13	0.80
10	1m_Mar_out	18.15	26.94	0.23	0.67
11	1m_Apr_out	12.97	22.20	0.16	0.58

Table 24. MAE, MAPE and MAPE of neural network forecasting for hotel MLKEP

	forecast_period	MAE_nn	MAE_naive	MAPE_nn	MASE_nn
1	6m_Nov-Apr_out	20.57	19.36	0.36	1.06
2	3m_Nov-Jan_out	20.11	19.65	0.37	1.02
3	3m_Dec-Feb_out	27.39	18.43	0.41	1.49
4	3m_Jan-Mar_out	20.79	15.92	0.26	1.31
5	3m_Feb-Apr_out	18.60	16.19	0.25	1.15
6	1m_Nov_out	17.51	20.67	0.20	0.85
7	1m_Dec_out	30.09	20.23	0.61	1.49
8	1m_Jan_out	27.42	16.68	0.36	1.64
9	1m_Feb_out	18.43	13.75	0.21	1.34
10	1m_Mar_out	17.99	17.13	0.23	1.05
11	1m_Apr_out	21.58	24.00	0.30	0.90

Table 25. MAE, MAPE and MAPE of neural network forecasting for hotel WARUK

	forecast_period	MAE_nn	MAE_naive	MAPE_nn	MASE_nn
1	6m_Nov-Apr_out	19.17	22.11	0.36	0.87
2	3m_Nov-Jan_out	18.61	24.09	0.40	0.77
3	3m_Dec-Feb_out	17.45	19.84	0.37	0.88
4	3m_Jan-Mar_out	17.82	15.76	0.30	1.13
5	3m_Feb-Apr_out	17.45	17.89	0.25	0.98
6	1m_Nov_out	18.91	26.87	0.36	0.70
7	1m_Dec_out	15.24	26.33	0.43	0.58
8	1m_Jan_out	17.43	17.32	0.37	1.01
9	1m_Feb_out	15.73	13.18	0.25	1.19
10	1m_Mar_out	15.68	17.94	0.23	0.87
11	1m_Apr_out	20.78	31.53	0.52	0.66

4.5 Ensemble (combined) models

Ensemble or combination is the art of combining diverse set of learners (individual models) together to improve the stability and predictive power of the model (Kincade, 2019). Since different models using different algorithms and hypothesis for predictions, they are supposed to make varied predictions on final arrivals. Now we can take the predictions of all the previous models into account while making the final decision. This combining has great potential to reduce the variability that arises in the forced action of selecting a single model, and make our final result more robust, accurate and less likely to be biased. Also, we can use ensembling to capture linear and non-linear complex relationships in the data. Some methods to apply the ensembling are Averaging, Majority vote, Weighted average,regression or some machine learning algorithms like neural network, svm etc (Singh, 2018).

As shown in Figure15 below, the top layer model f() make decisions for the final arrivals based on the outputs of the models in layers below it. In this case, the generalized linear model (glm) was used as the ensembling function, then we chose individual models that are robust and accurate when applied individually and stacked them together as the bottom layer models (m1, m2, m3… m11). Each bottom model carry their forecasted final arrivals output from the original input features(x). Finally, Top layer model used the output of the bottom layer models (m1, m2, m3.. m11) as its input and predicts the final output.

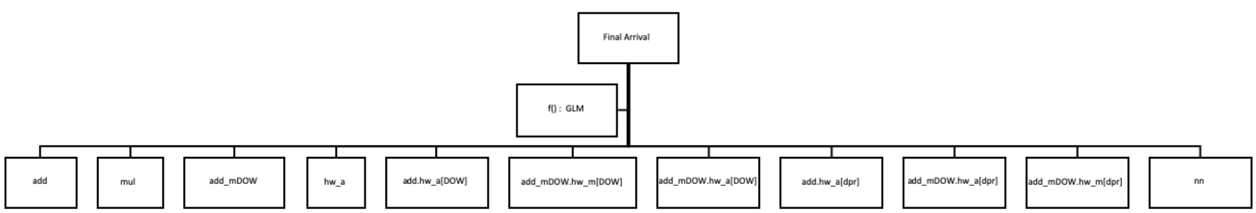


Fig. 15 : models and methods used in the ensemble model

The results in Table 26 to Table 28 indicate the results for three hotels, for hotel GLWST, all the results perform better than the naive model. In general, the forecast with closer time horizon perform better than the longer horizon. However, the ensemble model doesn’t improve the forecast accuracy for hotel MLKEP and WARUK, with more than half of the time horizons with MASE bigger than 1. Comparing between different time horizon, the model didn’t perform well for December to February, which may be due to the change of demands without pattern.

There is a limitation with ensembling model. It is hard to interpret the result as it involves combination of the result of different model. Also, the selection of models for creating an ensemble is an art which is hard to master.

Table 26. MAE, MAPE and MAPE of ensemble model forecasting for hotel GLWST

	forecast_period	MAE_glm_st	MAPE_glm_st	MASE_glm_st
1	6m_Nov-Apr_out	14.32	0.22	0.80
2	3m_Nov-Jan_out	14.79	0.26	0.79
3	3m_Dec-Feb_out	14.70	0.26	0.87
4	3m_Jan-Mar_out	13.56	0.19	0.81
5	3m_Feb-Apr_out	13.94	0.18	0.66
6	1m_Nov_out	9.58	0.10	0.55
7	1m_Dec_out	14.24	0.31	0.66
8	1m_Jan_out	13.71	0.23	0.87
9	1m_Feb_out	8.46	0.10	0.64
10	1m_Mar_out	13.74	0.16	0.51
11	1m_Apr_out	10.78	0.13	0.49

Table 27. MAE, MAPE and MAPE of ensemble model forecasting for hotel MLKEP

	forecast_period	MAE_glm_st	MAPE_glm_st	MASE_glm_st
1	6m_Nov-Apr_out	24.12	0.49	1.21
2	3m_Nov-Jan_out	24.34	0.51	1.24
3	3m_Dec-Feb_out	24.92	0.52	1.30
4	3m_Jan-Mar_out	19.22	0.30	1.18
5	3m_Feb-Apr_out	17.74	0.25	1.10
6	1m_Nov_out	13.32	0.15	0.64
7	1m_Dec_out	28.83	0.75	1.43
8	1m_Jan_out	20.68	0.40	1.24
9	1m_Feb_out	11.85	0.14	0.86
10	1m_Mar_out	17.41	0.22	1.02
11	1m_Apr_out	14.76	0.22	0.62

Table 28. MAE, MAPE and MAPE of ensemble model forecasting for hotel WARUK

	forecast_period	MAE_glm_st	MAPE_glm_st	MASE_glm_st
1	6m_Nov-Apr_out	26.60	0.64	1.19
2	3m_Nov-Jan_out	26.44	0.70	1.10
3	3m_Dec-Feb_out	27.64	0.74	1.39
4	3m_Jan-Mar_out	33.82	0.81	2.15
5	3m_Feb-Apr_out	26.17	0.51	1.46
6	1m_Nov_out	19.91	0.48	0.74
7	1m_Dec_out	22.56	0.66	0.86
8	1m_Jan_out	37.05	1.14	2.14
9	1m_Feb_out	24.62	0.49	1.87
10	1m_Mar_out	26.26	0.56	1.46
11	1m_Apr_out	19.90	0.50	0.63

5. Model Evaluation and Comparison:

In this research, we tested 16 different forecasting methods on 3 hotel booking data. We will report the results on a summarized basis. The model name and detailed descriptions can be referred to Table 1. Table 29 to 31 show the MASEs across all the methods for 3 hotels. MASE smaller than 1 means the model outperforms naive forecasts. The smaller the MASE value the better the forecasting.

As Table 29 shown, for hotel GLWST, there is no single method outperforms others. Combined models have the highest overall accuracy. For long-term, medium time horizon, January and April, the ensemble model have the smallest MASE value. Among the short-term time horizon forecasting, the add_mDOW.hw_m__dpr combined model yield the best result for November forecasting, the add_mDOW.hw_m__DOW combined model yield the best result for December forecasting, the add.hw_a__DOW yield the best result for March forecasting. The advanced booking model using additive method with month and Day of Week outperform for February. This model along with neural network and ensemble model outperform naive forecasting on all the time horizon. Seasonal ARIMA has the lowest accuracy which only outperforms naive forecasts 3 times. The most robust method as measured by lowest standard deviation of MASE are neural network and ensemble model.

As Table 30 indicated, for hotel MLKEP, there is no single method outperforms others. There is mixed results across all models. Combined models have the highest overall accuracy. The neural network is better at forecasting long-term horizon. For medium time horizon, except for 3 forecasts from add_mDOW, add_mDOW.hw_a__dpr adn add_mDOW.hw_m__dpr slightly outperform naive forecasts. All the models fail to give satisfactory results. Among the short-term time horizon forecasting, the add_mDOW.hw_m__dpr combined model yield the best result for November forecasting. The advanced booking multiplicative method yield the best result for December forecasting, the seasonal ARIMA model yield the best result for January forecasting. add_mDOW.hw_m__dpr outperform others for February forecasting and add_mDOW outperform others for March forecasting. Finally, add_mDOW.hw_m__DOW yield the better result for April forecasting. None of the models outperform naive forecasting on all the time horizon. The two advanced booking methods have the lowest accuracy with no forecastings outperform naive model. The most robust method as measured by lowest standard deviation of MASE are neural network and ensemble model.

The results in Table 31 indicate that, for hotel WARUK, Combined models have the highest overall accuracy, especially the add_mDOW.hw_m__DOW performs the best at long-term and medium-term time horizon. For short-term horizon, combined models outperform other models for November, February, March and April forecasting. Neural network is better at forecasting December demand and holt winters' additive method provides better result for January demand. None of the models outperform naive forecasting on all the time horizon. As with hotel MLKEP, the two advanced booking methods have the lowest accuracy with least forecastings outperform naive model. The most robust method as measured by lowest standard deviation of MASE are add_mDOW, add_mDOW.hw_m__DOW, add_mDOW.hw_a__dpr and add_mDOW.hw_m__dpr.

Table 29. MASE and MASE standard deviation for hotel GLWST forecasting methods across 11 time horizon

	Advance Booking model			Combined model					Machine learning model	Enseblem model	One dimentional Time series model						
forecast_period	add	mul	add_mDOW	add.hw_a_DOW	add_mDOW.hw_m__DOW	add.hw_a__dpr	add_mDOW.hw_a__dpr	add_mDOW.hw_m__dpr	nn	glm_st	ses	holt	hw_add	hw_mul	Arima	Sarima	best_model
1m_Nov_out	0.77	1.82	0.84	0.56	0.71	0.65	0.71	0.7	0.67	**0.55**	0.99	1	0.69	0.7	0.99	0.74	glm_st
1m_Dec_out	0.72	1.18	0.62	0.84	**0.62**	0.8	0.65	0.65	0.8	0.66	1.49	1.49	1.42	1.4	1.48	1.39	add_mDOW.hw_m__DOW
1m_Jan_out	0.89	1.75	**0.76**	1.32	0.89	1.26	0.8	0.79	0.93	0.87	1.47	1.46	2.33	2.13	1.74	1.68	add_mDOW
1m_Feb_out	0.86	1.82	0.85	0.96	0.91	0.82	0.8	0.8	0.8	**0.64**	0.95	0.84	0.72	0.78	0.78	1.15	glm_st
1m_Mar_out	0.46	0.94	0.41	**0.4**	0.41	0.46	0.44	0.45	0.67	0.51	0.87	0.88	0.69	0.74	0.82	0.77	add.hw_a_DOW
1m_Apr_out	0.59	1.56	0.47	0.54	0.46	0.56	**0.45**	0.45	0.58	0.49	0.95	0.96	1.09	1.11	0.82	0.89	add_mDOW.hw_m__dpr
3m_Nov-Jan_out	1.33	1.98	0.97	1.25	0.98	1.36	0.99	0.99	0.81	**0.79**	1.91	1.95	1.59	1.62	1.91	1.74	glm_st
3m_Dec-Feb_out	1.34	2.21	0.93	1.43	1.03	1.47	1.02	1.02	0.9	**0.87**	1.85	1.85	1.84	1.79	1.96	1.82	glm_st
3m_Jan-Mar_out	1.01	2.76	0.84	1.12	0.9	1.15	0.88	0.88	0.95	**0.81**	1.23	1.26	1.31	1.16	1.21	1.16	glm_st
3m_Feb-Apr_out	0.69	1.91	0.7	0.67	0.72	0.71	0.71	0.71	0.71	**0.66**	1.11	1.14	0.99	0.86	1.12	1.92	glm_st
6m_Nov-Apr_out	1.22	2.76	0.97	1.16	0.96	1.24	0.97	0.97	0.83	**0.8**	1.51	1.57	1.25	1.27	1.51	1.4	glm_st
Std	0.3	0.56	0.19	0.35	0.21	0.35	0.2	0.2	**0.12**	0.14	0.37	0.38	0.52	0.47	0.44	0.43	nn

Table 30. MASE and MASE standard deviation for hotel MLKEP forecasting methods across 11 time horizon

Advance Booking model				Combined model					Machine learning model	Enseblem model	One dimentional Time series model						
forecast_period	add	mul	add_mDOW	add.hw_a_DOW	add_mDOW.hw_m__DOW	add.hw_a__dpr	add_mDOW.hw_a__dpr	add_mDOW.hw_m__dpr	nn	glm_st	ses	holt	hw_add	hw_mul	Arima	Sarima	best_model
1m_Nov_out	1.79	1.86	0.68	1.21	**0.64**	1.69	0.67	0.67	0.85	0.64	2.48	2.47	2.4	2.71	2.37	1.45	add_mDOW.hw_m__DOW
1m_Dec_out	1.76	**1.31**	1.45	1.63	1.51	1.73	1.49	1.49	1.49	1.43	2.63	2.69	2.03	1.91	1.83	1.76	mul
1m_Jan_out	2.35	2.45	1.22	1.52	1.26	2.54	1.16	**1.14**	1.64	1.24	2.84	2.85	3.82	3.09	2.95	1.66	add_mDOW.hw_m__dpr
1m_Feb_out	2.27	2.44	0.71	1.06	0.81	1.31	0.74	0.73	1.34	0.86	0.68	0.62	0.22	0.32	0.52	**0.21**	Sarima
1m_Mar_out	1.83	2.06	**0.79**	0.9	1.13	1.11	0.85	0.85	1.05	1.02	2.52	2.5	1.15	1.34	2.18	1.06	add_mDOW
1m_Apr_out	1.43	1.43	0.54	0.67	0.63	0.94	0.51	**0.5**	0.9	0.62	1.73	1.73	1.17	1.1	1.63	0.79	add_mDOW.hw_m__dpr
3m_Nov-Jan_out	2.25	2.68	1.29	1.58	1.32	1.91	1.31	1.31	**1.02**	1.24	2.5	2.51	2.26	2.43	2.49	1.71	nn
3m_Dec-Feb_out	2.11	2.54	1.37	1.43	1.48	1.82	1.41	1.42	1.46	**1.3**	2.94	3.05	1.99	1.87	2.41	1.62	glm_st
3m_Jan-Mar_out	2.44	3.61	1.12	1.31	1.22	2.67	1.13	**1.1**	1.3	1.18	3.15	3.17	4.53	3.79	2.5	1.43	add_mDOW.hw_m__dpr
3m_Feb-Apr_out	2.34	3.86	**0.92**	1.17	1.12	1.58	0.96	0.96	1.15	1.1	2.24	2.23	1.04	1.61	2.2	1.02	add_mDOW
6m_Nov-Apr_out	2.16	2.58	1.26	1.51	1.33	1.8	1.29	1.29	**1.02**	1.21	2.42	2.41	2.15	2.46	2.39	1.41	nn
Std	0.32	0.79	0.31	0.31	0.31	0.53	0.32	0.32	**0.26**	0.27	0.68	0.71	1.24	0.98	0.64	0.47	nn

Table 31. MASE and MASE standard deviation for hotel WARUK forecasting methods across 11 time horizon

Advance Booking model				Combined model					Machine learning model	Enseblem model	One dimentional Time series model						
forecast_period	add	mul	add_mDOW	add.hw_a_DOW	add_mDOW.hw_m__DOW	add.hw_a__dpr	add_mDOW.hw_a__dpr	add_mDOW.hw_m__dpr	nn	glm_st	ses	holt	hw_add	hw_mul	Arima	Sarima	best_model
1m_Nov_out	1	1.06	0.56	**0.44**	0.55	0.78	0.56	0.57	0.7	0.74	1.12	1.11	0.71	0.69	1.01	0.7	add.hw_a_DOW
1m_Dec_out	1.08	0.89	0.72	0.94	0.72	0.87	0.72	0.72	**0.58**	0.86	1.21	1.18	1.17	1.16	1.02	1.21	nn
1m_Jan_out	1.6	1.67	0.52	0.87	0.5	1.04	**0.53**	0.53	1.01	2.14	1.51	1.45	1.24	1.15	1.51	1.26	add_mDOW.hw_m__DOW
1m_Feb_out	1.58	1.73	1.06	1.03	1.04	1.18	1.07	1.08	1.19	1.87	0.54	0.59	**0.35**	0.37	0.44	0.38	hw_add
1m_Mar_out	1.11	1.42	0.7	0.76	0.72	0.72	**0.69**	0.69	0.87	1.46	1.3	1.3	0.87	0.89	1.02	0.89	add_mDOW.hw_a__dpr
1m_Apr_out	0.71	0.88	0.55	0.46	0.54	**0.43**	0.56	0.56	0.66	0.63	0.86	0.87	0.56	0.57	0.76	0.55	add.hw_a__dpr
3m_Nov-Jan_out	1.43	1.24	0.75	0.91	**0.74**	1.02	0.74	0.75	0.77	1.1	1.42	1.37	1.03	1.09	1.2	1.07	add_mDOW.hw_m__DOW
3m_Dec-Feb_out	1.61	1.63	0.84	1.16	**0.83**	1.17	0.84	0.84	0.88	1.39	1.61	1.57	1.24	1.23	1.45	1.24	add_mDOW.hw_m__DOW
3m_Jan-Mar_out	1.67	2.48	0.89	1.04	**0.88**	1.45	0.88	0.89	1.13	2.15	1.78	1.96	1.91	1.5	1.85	1.58	add_mDOW.hw_m__DOW
3m_Feb-Apr_out	1.25	1.79	0.91	**0.81**	0.91	0.93	0.9	0.91	0.98	1.46	1.29	1.33	0.84	0.91	1.11	0.92	add.hw_a_DOW
6m_Nov-Apr_out	1.47	1.49	0.81	0.95	**0.79**	1.09	0.8	0.81	0.87	1.19	1.31	1.27	0.94	0.98	1.2	0.96	add_mDOW.hw_m__DOW
Std	0.31	0.46	0.17	0.23	0.17	0.27	**0.17**	0.17	0.19	0.53	0.34	0.36	0.41	0.32	0.38	0.35	add_mDOW.hw_a__dpr

6. Conclusion and Recommendations

In this study, we have presented 16 different forecasting methods. Experiments were conducted on datasets from 3 hotels. Each method was evaluated with 3 different error measures. Data from May 1, 2008 to October 31, 2009 were used as training data to forecast demand for 6 month, 3 month and 1 month out. Experimental results demonstrated that neural network and ensemble model are the most robust models for hotel GLWST and hotel MLKEP. The advanced booking models combined with holt winters' method yield the most robust results for hotel WARUK. The forecast combination technique seems to be an effective way to avoid series forecasting failure. In particular, our results show that the combined models are able to reduce forecasting risks and improve forecasting accuracy. We attempted to combine variations of advanced booking methods, exponential smoothing methods and neural networks in this study, other combinations or the same combination with different weights can be implemented in the future. Although did not find the single perfect method to forecast hotel room demand in all conditions, our findings shed light on the importance of being able to forecast in the hospitality sector in view of gaining a competitive advantage. In particular, our results show that even hotel with only historical booking data for a short period of time, time series forecasting methods such as exponential smoothing and ARIMA can help them predict future demand with a moderate level of accuracy, thus enhancing their revenue and profitability. Based on our results, we would suggest any one of the three most robust methods (neural network, ensemble model and combined model) to the hotel management team.

The current investigation is based on hotel-specific data provided by three establishments for a limited period of time. Further empirical work is needed to develop a more thorough understanding of specific demand features and possibly identify more sophisticated strategies that could be implemented in the context of hospitality. In particular, a number of socio-economic factors (including income, tastes and preferences etc.) and events nearby such as (conference, sports events and concert) may influence hotel room demand at an aggregate level. Those factors can be useful for algorithm with higher degree of flexibility such as neural network. Also, it has been observed that hotel managers are able to give very accurate forecasts within a period of 2-3 weeks of the arrival day. This is because they are able to supplement their experience with their knowledge of events, demand patterns etc. Incorporating their knowledge into the forecast may enable a better result.

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