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Revenue management forecasting: The resiliency of advanced booking methods given dynamic booking windows

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ABSTRACT

Forecasting is the initial component of the hospitality revenue management (RM) cycle. The accuracy of the forecast is critical for RM systems to make appropriate recommendations to optimize revenue. Over recent years the industry has cited shifting booking windows due to a variety of macro (e.g., technology and economy) and micro (e.g., promotion) factors. These shifts pose challenges for RM forecasting algorithms particularly in the domain of pick-up based techniques. In this paper, we review the literature on hotel RM forecasting, particularly with respect to popular techniques used in practice. We then introduce a neural network approach to the advance booking environment to address issues related to booking window shifts. The models are estimated and tested for accuracy, and then re-tested years later after the booking window has shifted. The results are synthesized with discussion as to which models are more suitable for forecasting in dynamic booking windows.

1. Introduction

Since its introduction in the 1980′s hotel revenue management (RM) has successfully improved the revenues and profitability of hospitality companies (Relihan, 1989; Choi and Kimes, 2002). Characterized by perishable inventory, revenue management systems (RMS) generate forecasts that serve as inputs to optimization algorithms, with the goal of maximizing revenues (Schwartz, 1998; Phillips, 2005). Forecasting, the initial component of the RM cycle, is critical as these estimates drive many subsequent decisions, with inaccurate predictions leading to suboptimal RM recommendations (Bosworth, 2019; McCracken, 2019). It has been suggested that a 20 % reduction in forecasting error may translate to a 1% gain in revenues (Pölt, 1998 cited in Talluri and Van Ryzin, 2006, p.407). For these reasons revenue management forecasting has received significant attention in the hospitality literature (Schwartz and Hiemstra, 1997; Rajopadhye et al., 2001; Weatherford et al., 2001; Weatherford and Kimes, 2003; Chen and Kachani, 2007; Tse and Poon, 2015; Pereira, 2016; Weatherford, 2016; Lee, 2018; Fiori and Foroni, 2020).

In recent years, it appears that the booking behavior of customers has changed (Lee, 2013). Historically, travel agents provided customers with information regarding rates and availability among a range of options. In this setting, leisure travelers tended to book well in advance, while business travelers booked closer to the date of stay. However, the emergence of technology and online distribution has provided customers with unprecedented information regarding rates and availability. The evolution has enabled travelers to shift their booking behavior outside of their traditional booking window (reservation lead time), which presents numerous challenges for RM. Anecdotal evidence has suggested that the fluctuations are not one-sided and that the booking window may "grow" or "shrink" (Lee, 2013; Manley, 2016). These shifts cause changes in reservation patterns as bookings accumulate in a new fashion than they have historically and the data used to generate forecasts is inherently different (Schwartz et al., 2016; Webb, 2016). From a pricing perspective, booking window shifts make it more difficult to price discriminate based on time as leisure travelers may book up until the date of stay.

As such, this study aims to address these challenges by estimating new and traditional forecasting methods which are tested on booking window shifts. Specifically, the study makes two main contributions.

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First, it assesses the potential of neural networks, specifically multilayer perceptron models to enhance the performance of advanced booking forecasting techniques. A unique approach utilizing neural networks for pattern recognition is applied following the curve similarity approach suggested by Schwartz and Hiemstra (1997). Second, it identifies forecasting algorithms that are more resilient given the challenges introduced by dynamic booking windows (DBW). Traditional forecasting research tends to focus on data from only one time period to compare model results and assess performance. Our approach estimates and tests the neural network-based technique against six models commonly found in the hotel RM forecasting literature, using data from multiple hotels located in or around National Parks in the US. For robustness, the models are then retested, years later, after the booking window has shifted. The consistency of model accuracy between the two periods is compared to identify which techniques are most adept to handle booking window shifts commonly present in today's dynamic booking environment.

The paper proceeds with a review of the literature on the evolution of booking behavior and forecasting in revenue management, and then formulates two research hypotheses regarding the efficacy of focal methods developed in this study. The methodology section discusses several models commonly found in the RM literature and also provides a brief overview of the multi-layer perceptron (MLP) neural network commonly used for forecasting. The models are then tested and results are presented with theoretical implications for the revenue management literature and practical implications for industry professionals.

2. Literature review

2.1. The evolution of travel purchases and the dynamic booking window

The introduction of the online booking environment changed the distribution of hospitality products in the late 1990′s (Barthel and Perret, 2015). Traditional reservation methods relied on travel agents or direct property inquiries to obtain information regarding rates and availability. However, the emergence of online distribution made travel shopping more efficient by allowing prices and availability to be readily accessible with the ability to make a purchase at any time (O'Connor and Frew, 2002). These online intermediaries effectively reduced the information gap for customers but also mitigated uncertainty associated with travel decisions through reviews and recommendations (Barthel and Perret, 2015; Gasdia, 2015; Thakran and Verma, 2013; Worgull, 2013; Spektor, 2018). The outcome was a superior shopping experience that has led to the sustained success of online travel agencies (OTAs). Research has indicated that the Internet is now the most important information source for trip planning (Toh et al., 2011; Xiang and Gretzel, 2010; Xiang et al., 2015a, b). In 2017, it was estimated that Expedia experienced a room night growth of 15 % while Booking.com attained 21 % (McIlwain, 2017). In 2015, TravelClick found that OTA, Brand.com and GDS channels all experienced growth greater than 3.5 %, while hotel direct calls and call centers decreased by 7.2 % and 4.4 % respectively (TravelClick, 2016). Similar trends were found in the 2018 report, indicating a continued decline of traditional channels (TravelClick, 2019). Furthermore, channel shifts should be expected to continue as industry reports state an increased preference for mobile reservations in the online environment (Harold, 2017; Mullan, 2018).

The increased prevalence of online reservation platforms generates advantages for travelers and hospitality organizations alike, but also challenges revenue management with regards to the booking window. Prior to online intermediaries, leisure travelers tended to book well in advance due to a lack of information. Conversely, business travelers booked closer to the date of stay due to the nature of business. This booking behavior allowed revenue managers to develop time based price discrimination strategies centered on a higher willingness to pay, closer to the date of stay (Phillips, 2005). However, online intermediaries shifted information back to the travelers with an instantaneous booking process, where customers can choose to book at the time they perceive to be optimal. Schwartz (2000, 2006, 2008) discusses the factors (e.g., price, sell out risk, search cost, cancellation policies etc.) that influence a traveler's decision regarding the optimal time to buy and shows that these factors are dynamic over time.

As reservations transitioned to online intermediaries, hotel professionals began to use these channels to sell distressed inventory close to the date of stay (O'Connor and Frew, 2002; Dacko, 2004). This, coupled with the consumer notion of lower prices online, has altered consumer search behaviors to include adaptive search patterns, learning elements and changes to their expectations (Worgull, 2013). What has emerged has been termed a "deal seeking culture" in which travelers continuously check rates and availability in hopes of finding a better deal (Dacko, 2004). Schwartz and Chen (2012) suggest the process of searching for rates while attempting to outsmart service providers may be a process that travelers actually enjoy. In their model, travelers gain additional utility from a hedonic motivation during the search process, captivated by the possibility of obtaining a better deal (Schwartz and Chen, 2012). Research has shown that the propensity to book increases as the date of stay draws near and, however, decreases with lower expected future rates (Chen and Schwartz, 2013). It follows that, in a search-friendly-environment, consumers are likely to delay purchase if rates decline. Toh et al. (2011) tracked 13 properties' daily quoted rates and concluded that in the first 14 weeks, rates were higher than in the last three. This outcome was attributed to the shortened booking window and distressed inventory, which lead decision makers to lower prices in response to a slower accumulation in reservations. This example illustrates the conflict for RM professionals as lower prices may allow for the hotel to capture more of the market, but may also cause a revenue loss as there may have been no change in demand, simply a shift in booking behavior.

Anecdotal evidence suggests that the booking window is constantly evolving and conflicting reports indicate that shifts are not one-sided, that is, they grow ***and*** shrink (Lee and Lein, 2013; Martz, 2016; Clausing, 2019). David Sangree, president of Hotel & Leisure Advisors stated that "the booking window for groups is decreasing as many group bookings are being done in a shorter timeline than historically" (Koss-Feder, 2019). Similarly, Weinsheimer (2015) found that while "the path-to-purchase, from first search to final booking, is lengthening" the "booking lead times", are "**getting shorter**". In comparison, TravelClick (2012) has previously reported a booking window **expansion** for both group and leisure travelers across 25 North American markets. At a company level, Denihan Hospitality Executive Vice President Tom Botts, was quoted stating that the average booking window increased to 39 days compared to 35 the previous year (Worgull, 2013), and Pleasant Holidays president and CEO Jack Richards stated an increase in 10 % of vacations booked more than 151 days in advance, compared to 2016 (Clausing, 2019). Finally, Manley (2016) reports that "there's been an **increase** in booking windows, with guests starting to book further out".

Ultimately, booking window lead time may vary from period to period depending on several macro and micro factors (Tse and Poon, 2015). Specifically, macro factors such as the economy (e.g., unemployment and exchange rates) or technology (e.g., adoption of OTAs and mobile APPs) may influence booking behavior globally. At the same time, property specific decisions such as changes in target market, channel choice or marketing strategy may impact the rate of booking at a micro level. These compounding factors make it incredibly difficult to anticipate directional shifts and adequately derive accurate forecasts to make optimal RM decisions.

2.2. Forecasting in revenue management

Forecasting is dependent on the data available to derive the prediction. In hotel revenue management, the three data types that are readily available to every property include historical reservations, current (on-the-book) reservations and exogenous information (Schwartz et al., 2016). Historical data is comprised of bookings that have occurred on similar days in the past. This includes reservation totals for the same day year over year. Current data consists of reservations on hand for a date of stay in the future. These reservations make up the pace report that track current reservation information for decision making (Hernandez, 2018). The third element, exogenous information, identifies events that revenue management systems are unlikely to identify as significantly different than traditional patterns. These may include concerts or events that are unlikely to occur again, typically characterized as outliers. Proper identification of these days allows for forecasting adjustments that will deviate from the pre-programmed techniques.

Forecasters use these data types in a variety of techniques that fall under one of three subclasses (Weatherford and Kimes, 2003). The first subclass focuses on the historical data and involves a time series approach. The inclination is that past observations will likely repeat due to the seasonality of travel patterns. The second subclass generates forecasts using current data. As bookings accumulate for a particular date of stay, the algorithms attempt to extrapolate the current bookings on hand to determine how many additional rooms will be picked up. Finally, the last subclass includes the industry standard of combining the historical and current data models to produce the final forecast (Weatherford and Kimes, 2003). While these approaches generate an estimate for projected demand, revenue managers may also use subjective adjustments based on their experience or outside knowledge. When the date of stay is far in advance (greater than 90 days) the historical information tends to receive a higher weight as reservations have yet to accumulate. However, as the date of stay approaches, bookings begin to occur more frequently and the current data techniques receive more weight. This is where the ability to yield rate levels becomes strategically important as the optimization algorithms open and close booking limits and recommend prices based on the current reservations and forecasted demand (Chen and Kachani, 2007; Phillips, 2005).

2.3. Forecasting methods

Several studies have attempted to identify which forecasting techniques are most accurate for revenue management. The applied techniques come from a variety of research streams and include methods such as exponential smoothing, moving average, Holt-Winters double exponential smoothing, linear regression, log-linear regression, additive pick-up, multiplicative pick-up, times-series, polynomial approximations and curve similarity approaches, as well as weighted combinations of the above (Schwartz and Hiemstra, 1997; Rajopadhye et al., 2001; Weatherford et al., 2001; Weatherford and Kimes, 2003; Chen and Kachani, 2007; Tse and Poon, 2015; Pereira, 2016; Weatherford, 2016). The general conclusion is that the most accurate methods will vary by property (Weatherford and Kimes, 2003), forecasting horizon, and type of error measure used (see Koupriouchina et al., 2014 for further discussion). These differences can largely be attributed to the notion that some algorithms will work better under different circumstances, such as market or reservation patterns that are property specific.

With the goal of increasing accuracy, research has expanded outside of traditional methods and begun to explore the incorporation of new data points. Studies have attempted to add consumer pulse data such as search queries or visits to travel websites to traditional time series models (Pan et al., 2012; Yang et al., 2014; Li et al., 2017). This information provides signals of potential demand patterns ahead of the date of stay. The results find increased performance compared to similar models not utilizing this information and may be valuable in many RM applications. Schwartz et al. (2016) suggest leveraging market knowledge by using a combination of forecasts from a competitive set. In their approach each hotel submits a forecast to be shared with the properties competitive set. These forecasts are then used as an input for each property's future forecasts.

Researchers have also explored the development of new models as a way to improve accuracy in hospitality RM. Pereira (2016) tested a trigonometric extension of the BATS model (TBATS) that allows for multiple seasonal periods and can improve accuracy. Lee (2018) tested several stochastic models including a Non-Homogenous Poisson Process and two Poisson Mixture Models (Negative Binomial and Multinomial) demonstrating increased accuracy over regression in the advanced booking environment. More recently, Fiori and Foroni (2020) reference actuarial techniques to suggest a model of stochastic pickups using both distribution-free and parametric generalized linear model (GLM) approaches.

In addition to these techniques, the recent emergence of big data and machine learning algorithms have prompted researchers to investigate techniques such as neural networks. Hospitality research has leveraged neural networks for tourism forecasting and revenue management applications as early as the 1990′s (Law, 1998; Law and Au, 1999; Uysal and El Roubi, 1999; Weatherford and Kimes, 2003; Tsai et al., 2009; Padhi and Aggarwal, 2011; Azadeh et al., 2013; Claveria et al., 2015; Silva et al., 2019). Specifically, in revenue management, Weatherford et al., 2003 demonstrated better accuracy when forecasting weekly airline reservations with a multi-layer perceptron (MLP) model over traditional methods including smoothing and regression.

Neural networks provide several advantages when compared to traditional techniques in that they are self-adaptive, non-parametric and require few a priori assumptions (Garson, 2014; Zhang et al., 1998). They also have the ability to capture any functional form and incorporate nonlinear relationships, which provides advantages over standard time series models (linear processes) (Vellido et al., 1999; Zhang et al., 1998). However, there are also a few drawbacks as their architecture makes it difficult to pinpoint casual inferences and presents a risk of overfitting (Garson, 2014; Hyndman and Athanasopoulos, 2014). The models must allow for adequate holdout samples and is largely data-driven, requiring several training iterations (Hyndman and Athanasopoulos, 2014).

Multi-Layer Perceptron models are the most commonly used neural network for forecasting (Vellido et al., 1999). The algorithm is a feedforward network where inputs are introduced to the model and pass information to the hidden layers. The hidden layer communicates information forward to future layers until the output layer is reached (Correa et al., 2012; Garson, 2014; Hyndman and Athanasopoulos, 2014). In the estimation process the back-propagation technique is used, where errors in the output layer are fed back to earlier layers that update nodes to optimize a prediction (Correa et al., 2012; Garson, 2014); this process is conducted after each iteration. The typical estimation process is supervised, in other words, the inputs and outputs are known in advance and several iterations of training are used to estimate the model. The process continues until the error is minimized or reaches a predetermined threshold.

The use of MLP models has yet to be investigated in the advanced booking environment, while the model architecture presents several advantages. As reservations begin to occur, these observations serve as inputs to the neural network just as they would in traditional modeling algorithms. However, the MLP feeds the reservations information to the hidden layer, where important characteristics of booking curves can be recognized and unknown patterns can be identified. The combination of different booking accumulations over the course of the booking window can specify unique weights for different settings, which optimize the prediction. In comparison, traditional methods will generally take the input and adjust based on a fixed coefficient, these approaches don't allow for dynamic adjustments without the presence of interaction terms. This structure makes MLP models in the advanced booking environment very appealing, leading to our first hypothesis:

Hypothesis 1. Multi-Layer Perceptron models will be more accurate than traditional RM forecasting models in the advanced booking setting.

2.4. Forecasting in the dynamic booking environment (Macro and Micro factors)

When faced with dynamic booking windows, the challenge for revenue management forecasting is most evident with regards to current data techniques. Traditional pick-up methods that are not frequently adjusted for changes in consumer behavior may be problematic as pickup rates vary over time (Webb, 2016). Tse and Poon (2015) find that hotel industry professionals tend to focus on future pickups from a fixed point in time, ignoring how reservations accumulate. In their article, industry professionals state that "pickup rates at different times are different and thus the booking data in early days or weeks bear no relevance in forecasting." This argument is particularly problematic in the face of dynamic booking windows, as a shift in reservation lead times can greatly alter the pickups forecasted for future room nights. Ultimately, forecasting techniques focusing solely on the pickup rates from a fixed point in time are utilizing an approach that exhibits the Markov property. The Markov property states that future behavior of a process is not altered by the additional information of past behavior (Lee, 1990; Tse and Poon, 2015). This would imply that future bookings are independent from the current bookings on hand and how these reservations accumulate.

Accurate forecasting in a dynamic booking environment requires an understanding of what is dictating changes in the booking window and how to identify when these changes are occurring. Tse and Poon (2015) argue that booking lead time may be a good representation of the various macro and micro factors that affect room occupancy and may carry through the entire booking period (Tse and Poon, 2015). This argument would suggest that the accumulation of the booking curve is critical to accurate forecasts as this information may help to predict future reservations.

Traditional current data techniques such as additive and multiplicative pick-up, linear regression and log-linear regression estimate pick-ups following the Markov property based on a fixed point in time. Other traditional techniques such as polynomial approximations and the curve similarity approach leverage the booking curve in the forecast prediction (Schwartz and Hiemstra, 1997; Tse and Poon, 2015). In addition, recent studies have found increased accuracy in revenue management forecasting when utilizing models that incorporate early reservation patterns due to inter-temporal correlations between early reservations and future demand (Lee, 2018; Fiori and Foroni, 2020). These findings and differences in algorithmic patterns initiate our second hypothesis:

Hypothesis 2. Forecasting algorithms that utilize the booking curve are more robust over time compared to methods exhibiting the Markov Property.

2.5. Summary

Ultimately, the evolution of the booking environment has provided travelers with the ability to book at any time. The increased flexibility presents numerous challenges for revenue management in both forecasting and pricing. For instance, reservations may accumulate in a different fashion than they have historically and make it more difficult to forecast accurately. When this occurs, booking window contractions may cause inaccuracies due to a lack of data available to make accurate predictions, and erroneously categorize inventory as distressed due to a lack of reservations. Similarly, an expansion may over forecast demand due to early reservation patterns, which may lead to rate hikes that limit the ability of a property to capture demand later in the window. The more accurate the forecast, the more likely proper rate changes will be implemented to maximize revenue and profitability. By testing new methods and identifying which algorithms are most robust in dynamic booking environments, hospitality professionals may be able to implement models that require less maintenance and are more resilient to changes in the booking window.

3. Methodology

In order to test the research hypotheses, our methodology aimed to understand 1) whether a multi-layer perceptron model performs better than those commonly used in RM forecasting and 2) whether the same model shows robustness over time given the fluctuation in the booking window. Common models for forecasting with current data include additive pick-up, multiplicative pick-up, linear regression, log-linear regression, curves similarity and the polynomial curve fitting approach (Schwartz and Hiemstra, 1997; Weatherford and Kimes, 2003; Chen and Kachani, 2007; Tse and Poon, 2015). The formal derivations of each model are provided below. Models 1–4 estimate the number of reservations to be picked up from a fixed point in time, under conditions of the Markov property. Model 5, the polynomial approach, fits a quadratic function to each booking curve and then extrapolates that curve from the current horizon to the date of stay. In this derivation, the model follows Tse and Poon (2015) which fits the curve starting 90 days prior to the date of stay. The model is estimated based on t = (90-n) where n is the number of days before the date of stay. This transformation allows the number of days to increase as the date of stay draws near. Finally, the curve similarity derivation follows the approach of Schwartz and Hiemstra (1997) where the room nights on hand are compared every 10 days to identify historical dates of stay that have accumulated room nights following a similar pattern. The forecast is generated by averaging the final number of room nights of the 10 most similar curves.

Benchmark Models

1 **Additive PU**

$$Forecast_t = Current\ Reservations\ on\ Hand + Avg\ Pickup\ at\ Horizon$$

2 **Multiplicative PU**

$$Forecast_t = (Current\ Reservations\ on\ Hand)^*\ Avg\ Pickup\ Ratio$$

3 **Linear Regression**

$$Forecast_t = a + b * Current\ Reservations\ on\ Hand$$

4 **Log-Linear Regression**

$$Log(Forecast_t) = a + b * Log(Current\ Reservations\ on\ Hand)$$

5 **Polynomial Curve Fit**

$$Forecast_t = a + bt + ct^2$$

Where t is defined as t = (90-n), and n is the number of days before the date of stay.

6 **Curves Similarity**

$$Dissimilarity = \sqrt{(R_t - C_t)^2 + ... + (R_{40} - C_{40})^2 + .. + (R_{110} - C_{110})^2 + (R_{120} - C_{120})^2}$$

Where R is a historical booking curves reservations at time t and C is the current booking curves reservations at time t.

Final Forecast

$$Forecast_t = Average\ 10\ most\ similar\ curves$$

The multi-layer perceptron (MLP) model was designed with a network architecture similar to the curves similarity approach, using the

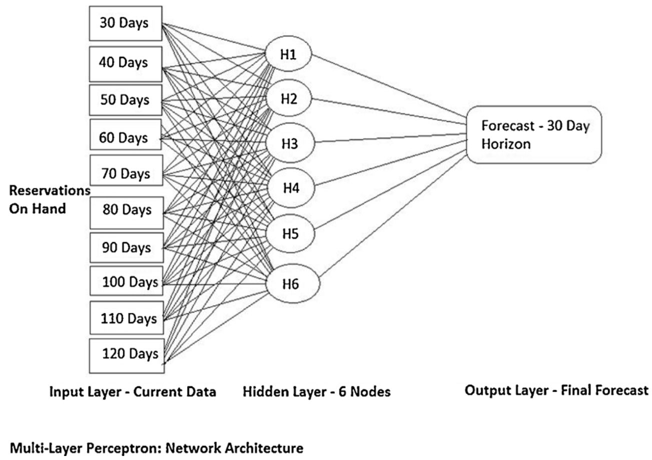

Fig. 1. Multi-Layer Perceptron Model.

reservations on hand every 10 days beginning 120 days in advance (Schwartz and Hiemstra, 1997). For example, the network architecture for a 30-day horizon is provided in Fig. 1, with inputs of the number of reservations on hand at days 30, 40, 50, 60, 70, 80, 90, 100, 110 and 120 days prior to the date of stay. All input variables were standardized in the range of (-1, 1). One hidden layer was used as research suggests that only one hidden layer is necessary to account for non-linear relationships and should be sufficient for most forecasting problems (Zhang, 1998). The architecture was identified using the growth method similar to Azadeh et al. (2013). The number of nodes in the hidden layer began with 2 and increased until 10 with the optimal architecture identified based on the model that minimized the average error and provided the best model fit based on the AIC and BIC criterion. The tangent hyperbolic function was used as the hidden layer activation function which was found to be preferable for the majority of MLP applications by Karlik and Olgac (2011). The identity function was chosen as the target activation function. To ensure the models reached a global solution, each model was estimated 100 times (using different starting points) with a maximum of 1000 iterations in each run. The iterations continue until there is no further improvement in the objective function. The best performing model in this architecture provided our final model.

Evaluating the most accurate forecasting method across all techniques can be challenging as outlined by Koupriouchina et al. (2014). Different models may perform better at different horizons, for this reason each property, model and sample were estimated on 3 different horizons of 7 days, 14 days, 30 days prior to the date of stay. The best forecast can also be misleading depending on the error measure used. Different error measures can produce different outcomes due to discrepancies in how the metrics are formulated. For this reason, the study implemented three commonly accepted error measures for comparison, specifically, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE). In addition, each of the forecasts errors were statistically tested using the Wilcoxon Signed Rank Test, a non-parametric technique at the 0.05 level of significance. The test allows for the comparison of each model against one another to statistically imply the most accurate method by ranking the difference in results (Flores, 1989). As such, Hypothesis 1 regarding the efficacy of MLP is operationalized as follows:

H_{1a}: $M_d = 0$ *No significant difference between forecasting errors*

H_{1b}: $M_d \neq 0$ *A significant difference between forecasting errors*

Where

M_d *is the sum of the signed ranks of the forecasting error metrics*

To statistically identify the consistency of forecast accuracy over time (i.e., resiliency to changes in the booking window), the Wilcoxon Rank Test was implemented to compare the error measures in both periods. The differences between error metrics were measured at the 0.05 level of significance. It is important to note that the more robust techniques will not have a significant difference between the two time periods. Therefore, Hypothesis 2 regarding algorithm resilience is operationalized as follows:

Wilcoxon Rank Test

H_{2a}: *the distibution of errors are equal*

H_{2b}: *the distribution of errors are not equal*

3.1. Data

Reservations data spanning multiple years was collected from four properties located in or around National Parks in the United States. The locations were chosen due to their focus on leisure travelers. This market segment has the greatest opportunity for observing fluctuations in reservation patterns as their travel needs provide more flexibility. The first two properties were located on the West Coast, while the third was located in the North West and the fourth in the Mid-West United States. The average lead days for each quarter and year are displayed in Table 1.

In general, the booking window appears to be increasing over time. A model estimation period was selected for each property in early years that contained the shorter accumulation periods. For Properties 1 and 2, the estimation sample was 2012 and 2013, for Property 3 the estimation period was 2013 and 2014, and for Property 4, 2010 and 2011 were used.

For each estimation period a holdout sample was selected to provide validity of the model estimates. A holdout sample of 20 % was used in each of these time periods as suggested by Granger (1993) for forecasting models. The number of observations in each sample are displayed in Table 2. The derivation of the estimate and hold out samples was conducted using stratified random sampling in SAS with strata selected based on the arrival month and day of week. This ensured that all months and days of week were included in each sample. A third sample was selected following the same procedure, years later after the booking window had shifted. These time periods are also shown in Table 2. Properties 1–3 used 2016, while property 4 was selected from 2015.

In summary, the sample selection process allowed for model estimation and validation in one period to identify performance and create a benchmark. Then the same estimated model is tested again on a future sample, years later, to determine if booking window shifts may cause model accuracy to deteriorate.

Table 1
Avg Lead Days.

	Quarter	2010	2011	2012	2013	2014	2015	2016
Property 1	Q1			32	34	39	39	42
	Q2			67	68	69	85	73
	Q3			89	92	91	92	94
	Q4			53	51	61	58	62
Property 2	Q1			24	28	26	32	32
	Q2			69	76	83	93	93
	Q3			104	109	123	126	137
	Q4			42	38	50	53	61
Property 3	Q1				27	20	23	26
	Q2				40	47	50	61
	Q3				79	90	112	117
	Q4				31	37	31	41
Property 4	Q1	23	21	25	28	26	36	
	Q2	33	36	39	44	44	46	
	Q3	49	50	50	56	63	67	
	Q4	37	34	36	40	44	40	

Table 2
Sample.

Hotel	Sample Period		Number of Observations		
	Initial	Booking Window	Estimate	Hold Out	Booking Window
Property 1	2012 – 2013	2016	563	168	168
Property 2	2012 – 2013	2016	555	168	168
Property 3	2013 – 2014	2016	554	166	168
Property 4	2010 – 2011	2015	562	168	168

4. Results

The accuracy of the forecasting models are provided in Table 3 for Property 1. The results of the models for the other locations can be made available upon request. The table reports the accuracy of each technique, across the three-error metrics, three horizons and the three samples. For instance, the estimate table provides the baseline metric of each model's performance. The second set measures the performance of the models in the hold out sample, during the same period but not used in estimation. Finally, the last set contains the same models retested years later after the booking window had shifted.

The results of the Wilcoxon Signed-Rank Test generated pairwise comparisons between models across all properties (4), error metrics (3), and horizons (3), generating 36 comparisons among techniques and compiling 756 comparisons in total. The outcome of each result was tabulated to identify the number of times a model was found to be statistically superior, inferior or exhibit no difference in performance compared to the competing model at a 0.05 level of significance.

Table 4
MLP - Wilcoxon Signed Rank Test Results.

Model	MLP	No Difference	Competing
Regression	18	18	0
Log Regression	4	26	6
Additive PU	15	21	0
Multiplicative PU	12	24	0
Curve Similarity	3	32	1
Polynomial Approx.	36	0	0

Several models performed consistently well across all settings. Specifically, the multi-layer perceptron, log-regression and curve similarity techniques were the most accurate compared to the other models. The results of the Wilcoxon Signed-Rank Test for the neural network (MLP) are provided in Table 4. Specifically, the first column of the table shows the number of times the MLP significantly outperformed the other techniques. The no difference column counts the instances where there were no significant differences between results, while the competing column shows when the comparison model performed better. The results in Table 4 indicate that the neural network was rarely outperformed, except when compared to the log regression and curve similarity approaches. In these instances, the models were fairly comparable. The results show support for Hypothesis 1, that neural networks may prove a viable approach for forecasting in the advance booking environment.

The results of the Wilcoxon Rank Test for similar error distributions over time are reported in Table 5. The models with the most consistent

Table 3
Property 1 Forecasting Results.

Property 1 Estimate: 2012 – 2013									
	Horizon 7			Horizon 14			Horizon 30		
Model	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE
Regression	14.5	8.4%	28.9	19.7	12.4%	34.1	33.5	26.8%	57.0
Log Regression	13.7	6.8%	28.6	18.2	9.3%	33.4	28.8	16.5%	56.7
Additive PU	14.2	7.3%	29.0	19.3	10.2%	34.3	30.8	20.1%	57.0
Multiplicative PU	16.0	7.9%	30.2	21.8	11.2%	36.0	33.6	16.8%	62.4
Curve Similarity	15.4	7.9%	30.1	18.5	9.5%	33.9	30.7	21.8%	56.8
Polynomial Approx.	19.5	9.8%	34.0	24.1	12.3%	40.3	38.7	19.4%	70.0
MLP	12.5	6.4%	27.4	16.6	9.1%	29.8	27.5	20.3%	48.5
Property 1 Hold Out: 2012 – 2013									
	Horizon 7			Horizon 14			Horizon 30		
Model	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE
Regression	17.3	10.9%	38.7	21.5	15.6%	41.1	37.6	35.7%	66.2
Log Regression	16.0	7.6%	38.2	19.7	10.4%	40.1	31.4	19.6%	65.4
Additive PU	17.1	9.1%	38.7	21.1	12.3%	41.1	34.1	26.1%	65.9
Multiplicative PU	18.4	8.7%	39.3	23.7	12.5%	42.1	37.3	18.8%	72.4
Curve Similarity	17.5	8.6%	38.2	20.6	11.3%	40.6	32.4	27.3%	68.1
Polynomial Approx.	22.9	11.2%	42.0	27.0	13.9%	45.4	45.6	21.3%	89.9
MLP	15.4	7.4%	38.1	21.7	12.6%	40.8	34.4	26.9%	67.9
Property 1 Booking Window: 2016									
	Horizon 7			Horizon 14			Horizon 30		
Model	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE
Regression	11.3	4.7%	26.9	15.4	6.6%	31.4	29.8	13.7%	54.9
Log Regression	11.3	4.6%	26.9	15.1	6.3%	31.1	28.9	12.1%	56.3
Additive PU	11.5	4.6%	27.0	15.4	6.3%	31.4	30.1	12.5%	57.3
Multiplicative PU	15.0	5.9%	29.1	20.2	8.4%	33.8	37.8	16.8%	62.2
Curve Similarity	17.0	7.4%	30.4	19.6	8.4%	35.0	28.8	12.8%	50.8
Polynomial Approx.	18.3	7.7%	33.0	23.2	10.0%	44.0	48.5	20.2%	74.7
MLP	13.2	5.8%	28.1	20.1	9.5%	34.4	30.9	15.2%	52.5

Table 5
Wilcoxon Rank Test.

Forecasting Technique	Significant	Insignificant	% Significant
Regression	13	23	36%
Log Regression	12	24	33 %
Additive PU	13	23	36%
Multiplicative PU	13	23	36%
Curve Similarity	9	27	25 %
Polynomial Approx.	12	24	33 %
MLP	4	32	11 %

Method Classification	Significant	Insignificant	% Significant
Pick Up Methods	51	93	35%
Curve Based Methods	25	83	23%
Estimate with Historical Curves	13	59	18 %

error metrics were the Curve Similarity, Polynomial and MLP models. The Curve Similarity exhibited significant differences 25 % of the time, while the errors of the neural network shifted on only 11 % of instances. The polynomial model had shifts in 33 % of the tests, however the 12 significant differences were tied for the best among the remaining models. Overall, the polynomial approach was the least accurate model in the study, likely due to the structure of curve estimation from 90 days out. This approach was chosen to follow the initial structure tested by Tse and Poon (2015), however as they suggest, re-estimation with shorter intervals such as 30 days in advance, or sooner, may provide more accurate results and better performance during shifts. Tabulating the results across methods reveals that not all methods perform consistently among shifts to the booking window providing support for Hypothesis 2. The most resilient models that exhibit the least change in accuracy over time all use the booking curve in the estimation process.

Considering the models in further detail, the MLP and Curve Similarity approaches specifically map the booking curve to information based on historical curves, while the polynomial approach fits an approximation to the current curve. If we restrict the booking curve group to only the two models that utilize information from historical curves, significant changes in accuracy due to shift occur only 18 % of the time. The results further indicate the importance of incorporating how reservations accumulate for improved accuracy over time. Specifically, leveraging historical information from previous curves may be critical to accurate forecasting in the advance booking environment.

4.1. Robustness

There is no clear approach for defining the optimal model architecture for estimating neural networks and numerous possibilities exist. While our initial approach selected the models that minimized error as well as AIC and BIC, Anders and Korn (1999) suggest potential limitations of this approach. Robustness of the presented model architecture was further investigated with a k-fold cross validation as suggested by Anders and Korn (1999) and utilized in many neural network applications (Azadeh et al., 2013; Lado-Sestayo and Vivel-Búa, 2019). The estimation technique allows each observation to partake in both the estimation and validation sets. A 5-fold cross validation was employed where each model was estimated 5 times with 80 percent of the sample used in estimation and 20 % used in validation. The 5-fold samples were constructed using stratified random sampling similar to the initial sample splits. The model errors were then averaged across the five estimates in each run. The architectures were tested with various combinations of hidden and target activation functions (TanH, Cos, Identity), with neurons ranging from 2 to 10. In all tests and horizons the variance in errors for MAE were less than one room across architectures. Therefore, we felt our original model that minimized error, AIC and BIC, provided a robust architecture.

Further validation of the MLP models robustness was conducted by plotting the actuals vs predicted values for our estimate and hold out samples similar to Lado-Sestayo and Vivel-Búa (2019). This approach allows for visual inspection of any patterns in the data that may not have been captured in the estimation process. It also allows for visual inspection that estimation and hold out samples perform similarly to ensure the model is not over fit. Visual inspection of the twelve models revealed similar performance across estimation and hold out samples with an expected positive linear trend. In addition, correlations were calculated between predicted and actual values, with all estimates greater than 0.8, further indicating model reliability.

5. Discussion

Forecasting in dynamic booking windows presents significant challenges to RM practitioners because these forecasts feed RM optimization algorithms and dictate rate decisions. Any forecast inaccuracies may lead to inaccurate recommendations and sub-optimal results. For instance, under-forecasting due to a booking window contraction may cause management to erroneously implement rate reductions or promotions when demand hasn't changed, however the booking window has only shifted. Conversely, early reservation patterns may cause systems to over-forecast and suggest rate hikes that may sacrifice future occupancy. Therefore, the importance of an accurate forecast cannot be overstated as accuracy can contribute to significant revenue increases (Polt, 1998 cited in Talluri and Van Ryzin, 2006; Koupriouchina et al., 2014; Bosworth, 2019; McCracken, 2019).

The first investigation tested the forecasting performance of neural networks in the advance booking environment. While other studies have leveraged neural networks and more specifically MLP models in a variety of ways, this is the first study to use reservation accumulations over time as an input vector. The results show that the MLP performs as accurately as the best performing techniques in these tested scenarios, implying that neural network-based methods may provide a viable forecasting approach in the advanced booking environment. Neural networks also provide increased flexibility that other models may not exhibit when assessing underlying assumptions required for model formulation or the inclusion of exogenous information. For instance, they can easily include other data points such as economic indicators or consumer search behaviors not readily incorporated into other models such as additive or multiplicative PU techniques. In addition, depending on network architecture, the models can learn and improve over time (Garson, 2014). For these reasons, neural networks should be considered as a viable option for forecasting in hotel revenue management especially within the context of a changing environment that requires an adaptive approach.

While it is recommended that practitioners evaluate a range of methods for forecasting in dynamic booking windows, the results show that models using the booking curve might be less impacted by changes in reservation lead time and should provide practitioners with sustained accuracy over a longer duration. These results are likely attributed to the fact that how the reservations accumulate prior to the forecast help to depict the current consumption climate, as well as the many macro and micro factors that may be influencing the pace of booking. Leveraging information from previous curves that follow the same pattern, allows for model estimation on data from bookings that may have occurred under similar conditions in the past, and are less susceptible to sudden changes. The results of this study suggest that industry professionals who fit an accurate, curve-based approach may experience more consistent forecast accuracy over time. These techniques will require less re-estimation in comparison to the traditional pick up methods, thus providing a more autonomous forecasting system. In addition, the improved accuracy will likely lead to better decisions, generating superior performance.

6. Limitations and future research

The study has several limitations as the models were estimated on only four properties located around national parks. The accuracy of the models may provide different results for properties located in different geographic locations with different target markets. The use of national parks data allowed for the models to be tested on leisure travelers with shifts in booking behavior, however, further investigation in other settings such as urban markets may alter the outcomes found here.

Further investigation into the booking window and forecasting accuracy may help to identify which shifts are more detrimental to revenue management decisions. For instance, over-forecast errors are capped at capacity and may have less implications than situations that underestimate demand. Another avenue for RM forecasting with neural networks is to use utilize the modeling technique to optimize the weighted combination of separate forecasts using historical and current data. Research has traditionally minimized error by deriving optimal weighted averages of different techniques to construct the final forecast. Neural networks may be able find several optimal combinations of the data, under different circumstances (in the hidden layer) without having to estimate and test combinations of all the different models and horizons. In this instance, neural networks may provide a better solution for combining forecasting techniques together. Researchers could also explore the flexibility of neural networks to combine the three data types (historical, current and exogenous information) into one forecasting model and eliminate the need for historical and current (pickup) forecast estimates.

Finally, numerous machine learning applications exist. While neural networks and specifically multi-layer perceptron models were utilized here, future research may apply other machine learning techniques such as decision trees, random forests, support-vector machines or k-nearest neighbor to minimize forecast error in the advanced booking environment. These techniques present modeling advantages and allow for the incorporation of big data outside of traditional reservations. Incorporating new information (similar to Yang et al., 2014) that may indicate customer demand and improve forecast accuracy would be beneficial to researchers and practitioners. As machine learning applications become more accessible due to open source software, all hotels can begin to experiment with various machine learning approaches to improve accuracy over time as shown here.

References

Anders, U., Korn, O., 1999. Model selection in neural networks. Neural Netw. 12 (2), 309–323.

Azadeh, S., Labib, R., Savard, G., 2013. Railway demand forecasting in revenue management using neural networks. Int. J. Revenue Manage. 7 (1), 18–36.

Barthel, J., Perret, S., 2015. OTAs – A Hotel'S Friend or Foe? How Reliant Are Hotels on OTAs? Hospitality Net http://www.hotelleriequebec.com/wp-content/uploads/2015/07/HVS-OTAs-–-A-Hotels-Friend-Or-Foe.pdf.

Bosworth, P., 2019. Building and Accurate Forecast: The Lifeblood of Any Hotel Revenue Manager. Viewed on August 30, 2019. Lodging Magazine. https://lodgingmagazine.com/building-an-accurate-forecast-the-lifeblood-of-any-hotel-revenue-manager/.

Chen, C., Kachani, S., 2007. Forecasting and optimisation for hotel revenue management. J. Revenue Pricing Manage. 6 (3), 163–174.

Chen, C.C., Schwartz, Z., 2013. On revenue management and last minute booking dynamics. Int. J. Contemp. Hosp. Manage. 25 (1), 7–22.

Choi, S., Kimes, S.E., 2002. Electronic distribution channels' effect on hotel revenue management. Cornell Hotel Restaur. Adm. Q. 43 (3), 23–31.

Clausing, J., 2019. Luxury Tour Operators Report Longer Booking Windows. viewed on 29 July 2019. Travel Weekly. https://www.travelweekly.com/Travel-News/Tour-Operators/Luxury-tour-operators-report-longer-booking-windows.

Claveria, O., Monte, E., Torra, S., 2015. Tourism demand forecasting with neural network models: different ways of treating information. Int. J. Tour. Res. 17 (5), 492–500.

Correa, A., Gonzalez, A., Nieto, C., Amezquita, D., 2012. Constructing a credit risk scorecard using predictive clusters. SAS Global Forum Vol. 128.

Dacko, S.G., 2004. Marketing strategies for last-minute travel and tourism: profitability and revenue management implications. J. Travel Tour. Mark. 16 (4), 7–20.

Fiori, A.M., Foroni, I., 2020. Prediction accuracy for reservation-based forecasting methods applied in Revenue Management. Int. J. Hosp. Manag. 84, 102332.

Garson, D., 2014. Neural Network Models. Statistical Associates, pp. 1–144.

Gasdia, Marcello, 2015. Mobile Travel Shopping Hits Tipping Point – but PC Still Dominates Booking. Phocuswright. http://www.phocuswright.com/Travel-Research/Research-Updates/2015/Mobile-Travel-Shopping-Hits-Tipping-Point-But-PC-Still-Dominates-Booking.

Granger, C.W., 1993. Strategies for modelling nonlinear time-series relationships. Econ. Rec. 69 (3), 233–238.

Harold, K., 2017. Mobile Drives Growth of Online Travel Bookings. Viewed on August 30, 2019. Travel Market Report. https://www.travelmarketreport.com/articles/Mobile-Drives-Growth-Of-Online-Travel-Bookings.

Hernandez, R., 2018. 3 Pace Report Metrics That Will Reveal Hidden Revenue. Viewed on August 30, 2019. Origin World Labs. https://www.forsmarthotels.com/2018/02/15/3-pace-reports-that-will-reveal-hidden-revenue/.

Hyndman, R.J., Athanasopoulos, G., 2014. Forecasting: Principles and Practice. OTexts.

Karlik, B., Olgac, A.V., 2011. Performance analysis of various activation functions in generalized MLP architectures of neural networks. International Journal of Artificial Intelligence and Expert Systems 1 (4), 111–122.

Koss-Feder, L., 2019. Shorter Group Booking Window Has Trickle-down Effect. Hotel News Now. viewed on 29 July 2019. < http://www.hotelnewsnow.com/Articles/295890/Shorter-group-booking-window-has-trickle-down-effect > .

Koupriouchina, L., van der Rest, J.P., Schwartz, Z., 2014. On revenue management and the use of occupancy forecasting error measures. Int. J. Hosp. Manag. 41, 104–114.

Lado-Sestayo, R., Vivel-Búa, M., 2019. Hotel profitability: a multilayer neural network approach. J. Hosp. Tour. Technol.

Law, R., 1998. Room occupancy rate forecasting: a neural network approach. Int. J. Contemp. Hosp. Manage. 10 (6), 234–239.

Law, R., Au, N., 1999. A neural network model to forecast Japanese demand for travel to Hong Kong. Tour. Manag. 20 (1), 89–97.

Lee, A.O., 1990. *Airline Reservations Forecasting: Probabilistic and Statistical Models of the Booking Process*. Flight Transportation Laboratory, Dept. of Aeronautics and Astronautics, Massachusetts Institute of Technology, Cambridge, Mass [1990].

Lee, T., 2013. Top 10 Trends of The Next Generation of Travel: The Millennials. available at:. Hotel Online. http://www.hotelonline.com/News/PR2013_2nd/Apr13_MillennialTrends.html.

Lee, M., 2018. Modeling and forecasting hotel room demand based on advance booking information. Tour. Manag. 66, 62–71.

Lee, J., Lein, S., 2013. Shortened Booking Windows – the New Normal? *Hotel Online*. viewed on 25 November 2018. < https://www.hotel-online.com/press_releases/release/shortened-booking-windows-the-new-normal-by-jenny-lee-and-sandra-lien > .

Li, X., Pan, B., Law, R., Huang, X., 2017. Forecasting tourism demand with composite search index. Tour. Manag. 59, 57–66.

Manley, B., 2016. Business Travel: an Evolution in Progress. available at:. *Hotel News Now*. http://hotelnewsnow.com/Articles/48528/Business-travel-An-evolution-in-progress.

Martz, R., 2016. The Urban Hotel Market Challenge. viewed on 18 July 2019. Lodging. https://lodgingmagazine.com/the-urban-hotel-market-challenge/.

McCracken, S., 2019. The Top Issues Facing Select-service Revenue Management. Viewed on August 30, 2019. *Hotel News Now*. http://www.hotelnewsnow.com/Articles/296022/The-top-issues-facing-select-service-revenue-management.

McIlwain, L., 2017. OTA Commissions Are up, but You're Still Winning. Here's why. Triptease. viewed on 7 January 2018. < https://www.triptease.com/blog/direct-vs-otas/ > .

Mullan, C., 2018. Travel Booking Trends: Mobile and Online Booking Dominant. Viewed August 30, 2019. IMRG. https://www.imrg.org/blog/travel-booking-trends-mobile-online-dominant/.

O'Connor, P., Frew, A.J., 2002. The future of hotel electronic distribution: expert and industry perspectives. Cornell Hotel Restaur. Adm. Q. 43 (3), 33–45.

Padhi, S.S., Aggarwal, V., 2011. Competitive revenue management for fixing quota and price of hotel commodities under uncertainty. Int. J. Hosp. Manag. 30 (3), 725–734.

Pan, B., Chenguang Wu, D., Song, H., 2012. Forecasting hotel room demand using search engine data. J. Hosp. Tour. Technol. 3 (3), 196–210.

Pereira, L.N., 2016. An introduction to helpful forecasting methods for hotel revenue management. Int. J. Hosp. Manag. 58, 13–23.

Phillips, R.L., 2005. Pricing and Revenue Optimization. Stanford University Press.

Rajopadhye, M., Ghalia, M.B., Wang, P.P., Baker, T., Eister, C.V., 2001. Forecasting uncertain hotel room demand. Inf. Sci. (Ny) 132 (1–4), 1–11.

Relihan III, W.J., 1989. The yield-management approach to hotel-room pricing. Cornell Hotel Restaur. Adm. Q. 30 (1), 40–45.

Schwartz, Z., 1998. The confusing side of yield management: myths, errors, and misconceptions. J. Hosp. Tour. Res. 22 (4), 413–430.

Schwartz, Z., 2000. Changes in hotel guests' willingness to pay as the date of stay draws closer. J. Hosp. Tour. Res. 24 (2), 180–198.

Schwartz, Z., 2006. Advanced booking and revenue management: room rates and the consumers' strategic zones. Int. J. Hosp. Manag. 25 (3), 447–462.

Schwartz, Z., 2008. Time, price, and advanced booking of hotel rooms. Int. J. Hosp. Tour. Adm. 9 (2), 128–146.

Schwartz, Z., Chen, C.C., 2012. Hedonic motivations and the effectiveness of risk perceptions–oriented revenue management policies. J. Hosp. Tour. Res. 36 (2), 232–250.

Schwartz, Z., Hiemstra, S., 1997. Improving the accuracy of hotel reservations forecasting: curves similarity approach. J. Travel. Res. 36 (1), 3–14.

Schwartz, Z., Uysal, M., Webb, T., Altin, M., 2016. Hotel daily occupancy forecasting with competitive sets: a recursive algorithm. Int. J. Contemp. Hosp. Manage. 28 (2), 267–285.

Silva, E.S., Hassani, H., Heravi, S., Huang, X., 2019. Forecasting tourism demand with denoised neural networks. Ann. Tour. Res. 74, 134–154.

Spektor, A., 2018. 5 Tips to Make Your OTA More Successful. Viewed on August 30, 2019. Hospitality Net. https://www.hospitalitynet.org/opinion/4089075.html.

Talluri, K.T., Van Ryzin, G.J., 2006. The Theory and Practice of Revenue Management Vol. 68 Springer Science & Business Media.
Thakran, K., Verma, R., 2013. The emergence of hybrid online distribution channels in travel, tourism and hospitality. Cornell Hosp. Q. 54 (3), 240–247.
Toh, R.S., DeKay, C.F., Raven, P., 2011. Travel planning: searching for and booking hotels on the internet. Cornell Hosp. Q. 52 (4), 388–398.
TravelClick, 2012. Business and Leisure Travelers Book Hotel Rooms Further in Advance. viewed on 21 August 2016. *TravelClick*. http://www.travelclick.com/en/news-events/press-release/business-and-leisure-travelers-book-hotel-rooms-further-advance.
TravelClick, 2016. Hotel News Resource – Digital and Mobile Channels Remain Driver of Hotel Bookings. Viewed on August 30, 2019. *Travel Click*. https://www.travelclick.com/insight/hotel-news-resource-digital-and-mobile-channels-remain-driver-of-hotel-bookings/.
TravelClick, 2019. GDS Booking and ADR Growth Drive Strong Q4 2018 RevPAR Performance in Hospitality. Viewed on August 30, 2019. Hospitality Net. https://www.hospitalitynet.org/performance/4092226.html.
Tsai, T.H., Lee, C.K., Wei, C.H., 2009. Neural network based temporal feature models for short-term railway passenger demand forecasting. Expert Syst. Appl. 36 (2), 3728–3736.
Tse, T.S.M., Poon, Y.T., 2015. Analyzing the use of an advance booking curve in forecasting hotel reservations. J. Travel Tour. Mark. 32 (7), 852–869.
Uysal, M., El Roubi, M.S., 1999. Artificial neural networks versus multiple regression in tourism demand analysis. J. Travel. Res. 38 (2), 111–118.
Vellido, A., Lisboa, P.J., Vaughan, J., 1999. Neural networks in business: a survey of applications (1992–1998). Expert Syst. Appl. 17 (1), 51–70.
Weatherford, L., 2016. The history of forecasting models in revenue management. J. Revenue Pricing Manage. 15 (3–4), 212–221.
Weatherford, L.R., Gentry, T.W., Wilamowski, B., 2003. Neural network forecasting for airlines: A comparative analysis. Journal of Revenue and Pricing Management 1 (4), 319–331.
Weatherford, L.R., Kimes, S.E., 2003. A comparison of forecasting methods for hotel revenue management. Int. J. Forecast. 19 (3), 401–415.
Weatherford, L.R., Kimes, S.E., Scott, D.A., 2001. Forecasting for hotel revenue management: testing aggregation against disaggregation. Cornell Hotel Restaur. Adm. Q. 42 (4), 53–64.
Webb, T., 2016. From travel agents to OTAs: how the evolution of consumer booking behavior has affected revenue management. J. Revenue Pricing Manage. 15 (3–4), 276–282.
Weinsheimer, K., 2015. For Hotels, a New Reality of Booking Lead Times and Path-to-purchase. *Travel Weekly*. viewed on 25 November 2018. < https://www.travelweekly.com/Kurt-Weinsheimer/For-hotels-a-new-reality-of-booking-lead-times-and-path-to-purchase > .
Worgull, S., 2013. Travelers' Trip-planning Habits Are Evolving. Hotel News Now. http://www.hotelnewsnow.com/Articles/20146/Travelers-trip-planning-habits-are-evolving.
Xiang, Z., Gretzel, U., 2010. Role of social media in online travel information search. Tour. Manag. 31 (2), 179–188.
Xiang, Z., Wang, D., O'Leary, J.T., Fesenmaier, D.R., 2015a. Adapting to the internet: trends in travelers' use of the web for trip planning. J. Travel. Res. 54 (4), 511–527.
Xiang, Z., Magnini, V.P., Fesenmaier, D.R., 2015b. Information technology and consumer behavior in travel and tourism: insights from travel planning using the internet. J. Retail. Consum. Serv. 22, 244–249.
Yang, Y., Pan, B., Song, H., 2014. Predicting hotel demand using destination marketing organization's web traffic data. J. Travel. Res. 53 (4), 433–447.
Zhang, G., Patuwo, B.E., Hu, M.Y., 1998. Forecasting with artificial neural networks:: the state of the art. Int. J. Forecast. 14 (1), 35–62.