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Occupancy forecasting methods and the use of expert judgement in hotel revenue management

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Occupancy forecasting methods and the use of expert judgement in hotel revenue management

by

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ABSTRACT

This dissertation presents two studies of the forecast of occupancy in the United States' hotel industry. The first is a quantitative study of the forecast accuracy performance of moving average, simple exponential smoothing, additive, and multiplicative Holt-Winters method, and Box-Jenkins forecasting procedures on weekly aggregated occupied room data from 10 geographic markets in the United States. In addition, this researcher also examined the performance of combined forecasts. The additive Holt-Winters method was found to be the most accurate in forecasting in seven of the 10 markets, even though it was not the most accurate in the training set. In three of the markets, the seasonal autoregressive integrated moving average method produced the highest level of accuracy.

The second study is a qualitative study designed to understand how the sample of revenue management experts uses their tacit knowledge of future demand in specific markets to modify statistically based forecasts of hotel occupancy. The researcher interviewed revenue managers. Four of these were working on a revenue management team, which supported groups of franchised hotels for a major global brand. These managers worked directly with the multiple hotels they supported in their assigned geographies. The remaining six revenue managers were located on the property they supported. Two of these managers also supported one or more properties in their geographic area in addition to their property. Marriott International, Hilton Worldwide, Starwood Hotels and Resorts Worldwide, Intercontinental Hotels Group, and Wyndham Hotels and Resorts were in the sample. The revenue managers oversaw the revenue management function in the limited and select service, full service, and luxury quality tiers.

Each of the revenue managers did use external sources of information to adjust forecasts based upon their local markets; however, there was little training or consistency in how this process occured. This results in a sub-optimal situation in which the knowledge, skills, and abilities in the application of expert judgement vary widely. There appears to be no consistent process, training, or knowledge transfer capabilities in place for this human element.

This presents an opportunity for forecast accuracy improvement across each of the major brands represented in the sample. Much of the literature has demonstrated that rule-based forecasting results in more accurate forecasts, particularly when there is good domain knowledge and that knowledge has a significant impact (Armstrong, 2006). Standardizing practices that result in greater accuracy and creating a more robust structure across brands could prove to be quite beneficial.

CHAPTER 1. GENERAL INTRODUCTION

Although researchers studied the topic of forecasting methods and the use of expert judgement for decades, application to the hotel industry has been relatively limited. 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 lodging facility. The production and consumption of the service experience are simultaneous and may not be inventoried, and the opportunity perishes every night (Zeithaml, Parasuraman, & Berry, 1985).

With the advent of internet based purchasing channels and the resulting transparency of room rates, the discipline of revenue management has become an extremely important role in the hotel industry. Before this, hotels set their rates independently and without much regard to what their competition was charging because it was very difficult for guests to shop around. Today, both the technology and the level of expertise required to function as a revenue manager effectively is increasing quickly. The major global brands continue to significant investments in revenue management and booking engine technology—including forecasting systems and the ability to continually scan the room rates the competition is displaying.

Dissertation Organization

The researcher organized the dissertation in a manner that presents each of two papers in a complete and cohesive manner. Chapter 1 introduces the importance and measurement of market share in the hotel industry, the importance of accurate forecasts of occupancy, the role of the revenue manager, and of the current methods used to forecast occupancy.

Chapter 2 presents a review of literature in four primary areas: (a) time series forecasting methods in general, (b) forecasting studies in the hospitality industry and (c) studies of expert judgement in general and in the hospitality industry in particular

Chapters 3 and 4 each consist of a self-contained paper prepared for publication in an academic journal. As such, each includes an introduction, literature review, hypothesis, methodology, results, conclusion, and discussion section.

Chapter 3 consists of a paper entitled “Effective Methods of Forecasting Occupied Rooms.” Chapter 4 consists of a paper entitled “The Application of Expert Judgement to Statistically Based Forecasts in the U.S. Hotel Industry.” Chapter 5 presents general conclusions from the two papers and identifies recommendations for future research on the topic of time series forecasting methods and the use of expert judgement by revenue managers to adjust these forecasts and improve forecast accuracy.

Market Share

The hotel industry is somewhat unique in that room nights are sold on a multitude of channels including the hotel or hotel brand website, third party intermediaries such as traditional and online travel agencies and through the direct solicitation of groups and large corporate transient and group businesses. Today it is possible for an individual traveler to book a room in virtually any hotel in the United States at least 360 days before arrival and in some cases 550 days before arrival. Hotels must be able to price these future dates based on their knowledge of the likely future demand. As demand or the rate positioning of the competitor hotels in a market change, a hotel must be able to adjust their pricing quickly in response (Chen & Schwartz, 2008).

The primary driver of room rates in transparent transient channels is competitive positioning. Transient guests typically view a hotel room within the same quality tier and general location as a commodity, and, as a result, pricing becomes a very heavily weighted component of the buying decision. The rates available to transient guests for a destination market are easily accessible on third party travel agency sites like Expedia, Travelocity, or Orbitz and it is simple to compare, shop, and book a room. Also, meta-search engines such as Kayak or Trivago aggregate the pricing displayed on hundreds of channels in one location making it even easier for travelers to shop multiple sites at a single time. It is of critical importance for a hotel to maintain their transient transparent rates in close range to their competition always or face losing business to the competition. Historically this has been a manual process, but today most major brands have the technology to scan competitive hotel pricing for all future dates immediately respond by changing rates. As a result, the transient rates are updated continuously to the date of arrival (Chen & Schwartz, 2008).

Market share is one of the most critical metrics in the hotel industry. The major global brands compete fiercely for market share across all quality tiers. Owner/developers are likely to select a brand for a hotel based on that brand's ability to deliver high levels of market share. Market share is measured by three main indexes. Each of these indexes is determined by dividing the subject hotel's metric by the average of the competition's metric. Most hotels subscribe to a third-party service to which they report their metrics and receive in return the indexes which represent their performance against a local competitive set, a sub-market competitive set—an airport area of a larger metropolitan area, a market, or regional and national averages for hotels in the same quality tier. Of these, the most important is usually the local competitive set of 5 to 7 hotels. The confidentiality of the individual hotel data is carefully secured and thus individual hotels are encouraged to participate to gain access to the competitive data (STR Global, 2017).

Market share is measured for room revenue in three ways. Average daily rate, occupancy percentage, and revenue per available room (RevPar). RevPar is the product of multiplying the average daily rate by the occupancy percentage and represents the overall market share combining both underlying metrics. Market share is normally reported to STR Global daily, and STR Global reports back on a daily, weekly, and monthly basis.

Profitability

A hotel typically has a relatively large fixed cost. The ability to manage variable costs becomes a crucial determinant of overall profitability. An accurate short-term forecast (between 3 and 30 days) is important for hotel management to be able to properly staff and purchase supplies. Overstaffing or over ordering creates excessive costs for the occupancy and revenue. Understaffing or under ordering can create guest service problems and or run out of necessary operating supplies. Profitability and guest service in lodging are optimized when these workers match resources with the number of occupied rooms (Johns & Lee-Ross, 1996).

In addition to managing variable costs, the ability to increase the average daily rate and RevPar in periods of high demand has a large impact on profitability. As most of the variable costs do not change based on the room rate charged, increases in average rate flow through to increased profit, for example, the labor costs or the supply costs.

Over time periods of 30 to 365 days from the date of arrival, the forecast of occupied rooms informs pricing decisions to maximize average rate and segment availability (Zakhary, Atiya, Sishiny, & Gayar, 2009). In forecasts beyond 365 days, forecasts of occupancy and average rate are used primarily to inform investment decisions (Newell & Seabrook, 2006).

The Nature of Hotel Demand

The demand for hotel rooms in a given market varies on a daily basis and does not necessarily have a strong recurring pattern. There are many factors that influence demand for a given night. Group business meets when and where the group needs to meet. Corporate groups may meet in an easily accessible regional destination to limit travel costs of the meeting participants. State and regional associations typically meet in a geographical rotation, selecting a different market each year. Conventions may also meet in different destinations each year.

Transient travelers travel to destinations for a host of reasons, and may or may not ever return to a destination. A market may be host to a special event, which drives demand on a certain date or dates. Examples of this are sporting events, entertainment events, and cultural events. This fluctuation in demand creates challenges in forecasting occupancy and pricing for future periods.

Over multi-year time horizons, the underlying demand may also change based on changes to the market itself, including increased competition, movement of companies and their related travel into or out of a market, changes in airline capacity into a market, the expansion or closing of sporting and event venues and convention facilities, and the relative attractiveness of a destination to other destinations. The general economic conditions overshadow these conditions. Travel is highly discretionary and therefore subject to even minor changes in general economic conditions.

The Use of Time Series Methods in the Forecast of Hotel Occupancy

Time series based forecasting is defined as the extrapolation of patterns from historical data to obtain an approximation of the future demand over a time horizon (Cheikhrouhou, Marmier, Ayaidi, & Weiser, 2011). Time series forecasting assumes that the patterns identified in a time series repeat themselves in the future and then, when extrapolated, used for the development of forecasting models.

The time series models studied in the academic literature about hospitality and tourism include autoregressive integrated moving average (ARIMA) model, autoregressive distributed lag model (ADLM), error correction model (ECM), vector autoregressive (VAR) model (Wong, Song, Witt, & Wu, 2007) Box-Jenkins procedure (ARIMA Models), and smoothing methods such as simple moving average, single exponential smoothing, and Holt-Winters (Zheng, Bloom, Wang, & Schrier, 2012). 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).

The Use of Expert Judgement in the Forecast of Hotel Occupancy

Statistical forecasting methods can detect systematic patterns rapidly in large sets of data and can filter out noise, but they can be unreliable when data are scarce or have little relevance for future events. When historical time series patterns are disrupted by foreseeable special or non-reoccurring events as is the case in the hotel demand environment, judgmental modifications of statistical forecasts may improve accuracy by allowing the estimated effects of these events to be incorporated into the forecast. (Goodwin, 2000). Sanders and Manrodt

(2006) found from a large survey of 240 U.S. corporations, 60% indicated they routinely adjusted the forecasts based on their judgment.

Research Questions.

This dissertation explores two questions. The first is a quantitative study of the performance of various methods of forecasting hotel occupancy. In comparison to studies of forecasting arrivals into a destination and the forecast of RevPar, researchers have not fully explored this area.

The second study explores how practicing revenue managers obtain and use tacit contextual information about future demand in a market to adjust the time series based forecast baseline. This study will be a benefit to academe by highlighting the differentiation of forecasting methods and as basis for father study of expert judgement and the process of adjusting forecasts of hotel occupancy. The studies will also be of benefit to practitioners in the hotel industry who seek to improve their forecasting accuracy continually.

Glossary of Terms

The following terms are commonly used in the hotel industry

Available Room Night: One room available for sale for a single night.

Available Rooms: The number of physical rooms available for sale.

Average Rate: Room revenue divided by the number of rooms occupied for the same period.

Franchised: A hotel which is not owned by the brand organization. The vast majority of hotels in the United States are franchised. Franchised hotels may or may not be operated by the brand organization.

Full Service: A hotel featuring full service food and beverage and meeting facilities.

General Manager: The management position with overall responsibility for a hotel operation. All other managers in a hotel report up to this position, either directly or through department managers.

Limited Services: A hotel that offers limited facilities and amenities, typically without a full-service restaurant or meeting space.

Occupancy: The number of rooms occupied divided by the number of rooms available for the same period.

Occupied Room: One room occupied for one night.

Revenue Management: The forecasting, pricing, and management of the distribution channels rooms are sold through for a hotel. Revenue management seeks to optimize revenue per available room and profitability.

RevPar: Room revenue per available room. RevPar combines both the average rate and occupancy percentage into a single statistic.

STR Global: A company which provides competitive data and analytics to the hotel industry globally. The vast majority of hotels in the United States participate in STR global reporting.

CHAPTER 2. REVIEW OF LITERATURE

Introduction

Any discussion of forecasting in the hotel industry should begin with a discussion regarding the general business literature that addresses the accuracy of time series foreasting models and the application of expert judgement in adjusting these models to produce increased forecast accuracy. As the two studies contained herein are single-industry focused, a review on the literature relative to the hospitality and tourism industries is appropriate. Finally and as a means for leading directly to the research questions, a discussion of the research into hotel revenue management professionals—though very limited—is included.

Forecasting in Business

Accurate forecasts are essential to successful to organizational planning (Fildes & Goodwin, 2007). While statistical forecasting methods may lead to a reliable demand forecast in some industries by extrapolating regular patterns in a time series, demand in a market is subject to many non-recurring events and unpredictable changes which interrupt historical patterns (Cheikhrouhou, Marmier, Ayaidi, & Weiser, 2011). This limits the accuracy even the best-fit time series models.

There have been decades of academic research focused on time series analysis (Fildes & Makridakis, 1995), improving statistical methods of forecasting (Fildes, Goodwin, & Lawrence, 2006) and the use of judgmental approaches to adjust these forecasts (Lawrence, Goodwin, O’Connor, & Onkal, 2006).

Also, the idea of developing a more accurate forRevenue ManagementMean Secast by combining the individual forecasts obtained by the use of separate methods has existed in the tourism industry for decades. Bates and Granger (1969) combined two different sets of airline passenger forecasts to form a new forecast. Their work analyzed some different methods of combining these individual forecasts, generally seeking a method of weighting each forecast so that the composite forecast error resulted in the lowest mean squared error. Their groundbreaking findings were that composite forecasts could yield lower mean square error than individual forecasts.

Research to date has not determined one best combination method (Shen, Li, & Song, 2011); however, the M3 competition did have results indicating that the composite forecasts outperform, on average, the combined individual forecasts (Makridakis & Hibon, 2000). Shen et al. (2011) determined that the accuracy of a composite forecast is directly related to the performance consistency of the individual forecasts of which it is composed. No known study into the use of methods of combining individual forecasts into a composite forecast for hotel occupied rooms has been identified.

Time Series Forecasting

Time series based forecasting is defined as the extrapolation of patterns from historical data to obtain an approximation of the future demand over a time horizon (Cheikhrouhou et al., 2011). Time series forecasting assumes that the patterns identified in a time series repeat themselves in the future and then when extrapolated may be used for the development of forecasting models.

Time series models have been used in both research and practice as the inputs into the model are based on historical observations; data collection and model construction are comparatively inexpensive (Song & Li, 2008). There are many different mathematical and statistical methods (Makridakis, Wheelwright, & Hyndman, 1998) used in time series forecasting. Studies, including the M-Competitions, have concluded that the accuracy of various methods of time series forecasting varies based on the time horizon (Makridakis et al., 1998; Makridakis & Hibon, 2000).

Forecasting in Hospitality and Tourism

The ability to accurately forecast arrivals to a tourist destination is important to minimize the financial and environmental costs of excess capacity or the opportunity costs of unfulfilled demand (Chu, 2011). The time series models studied in the academic literature about hospitality and tourism include autoregressive integrated moving average (ARIMA) model, autoregressive distributed lag model (ADLM), error correction model (ECM), vector autoregressive (VAR) model (Wong, Song, Witt, & Wu, 2007), Box-Jenkins Procedure (ARIMA models), and smoothing methods such as simple moving average, single exponential smoothing, and Holt-Winters (Zheng, Bloom, Wang, & Schrier, 2012).

To date, the literature which is specific to hospitality and tourism has focused primarily on tourist arrival forecasts for specific destinations using time series models, econometric models, and methods of forecast combination. Time series models examine historical trends and seasonal patterns and predict the future based on the trends and patterns recognized in the model. Various studies of arrivals into Hong Kong (Chan, Witt, Lee, & Song, 2010; Cho, 2003; Song, Lin, & Zhang, 2011) used different time series forecast and forecast combination methods and reported mixed results in improving accuracy. Econometric models attempt to predict the impact of outside factors such as guests' income, exchange rates, and competitors' prices on demand (Song & Li, 2008).

As to the emergence of forecast combination methods, 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 et al. (2007) analyzed the use of combination methods in predicting Hong Kong inbound tourists. These forecasts derived from four different forecasting models: ARIMA model, ADLM, ECM, and VAR model. The study concluded that composite forecasts could outperform the least accurate individual forecasts. A review of recent literature suggests it remains very challenging to identify a "best" forecasting method (Song & Li, 2008).

Forecasting in Hotels

Accurate forecasting of occupancy in the hotel industry is essential. The position of revenue manager or general manager is typically responsible for creating these forecasts. While there has been significant research into revenue management as a discipline in the hotel industry (Guilet & Mohammed, 2015), there has been little research published on forecasting occupancy in hotels specifically.

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).

The basic concept of revenue management is to maximize revenues through demand-based variable pricing (Choi & Matilla, 2004) based on a forecast of demand for each future date (Emeksiz, Gursoy, & Icoz, 2006). Revenue management is most effective in transactions which involve variable demand and relatively fixed, highly perishable inventories (Cetin, Demirciftci, & Bilgihan, 2016). 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 lodging facility. The production and consumption of the service experience are simultaneous and may not be inventoried, and the opportunity perishes every night (Zeithaml, Parasuraman, & Berry, 1985).

Hotel management uses forecasts of occupancy to price, to schedule staff, to purchase supplies and to manage cash flow (Johns & Lee-Ross, 1996). The contribution of revenue management techniques on profits has been acknowledged and proven beneficial in a range of industries (Cross, Higbie, & Cross, 2009) and specifically the hospitality industry (Deighton & Shoemaker, 2001).

Over time periods of between 3 and 30 days from arrival, a forecast of occupancy is needed to appropriately schedule staff in both the rooms and other departments of a lodging facility and as a basis for the purchases of supplies. Profitability and guest service in lodging are optimized when these resources are carefully matched with the number of occupied rooms (Johns & Lee-Ross, 1996). Over time periods of 30 to 365 days from the date of arrival, the forecast of occupied rooms informs pricing decisions to maximize average rate and segment availability (Zakhary, Atiya, Sishiny, & Gayar, 2009). In forecasts beyond 365 days, forecasts of occupancy and average rate are used primarily to inform investment decisions (Newell & Seabrook, 2006).

Recent research has examined several types of time series forecasts of revenue per available room night (RevPar) using aggregated weekly U.S. lodging industry data and concluded that the simpler methods might perform better (Zheng et al., 2012).

Seven different forecasting models were examined by Weatherford and Kimes (2003). The methods included simple exponential smoothing, moving sverage, liner regression, logarithmic linear regression, additive and multiplicative, and Holt’s double exponential smoothing. 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.

Additional studies have included daily occupancy, ADR, and Revpar in a sample of hotels in Milan (Baggio & Sainaghi, 2011); a single hotel in Ankara, Turkey (Yüksel, 2007) and a sample of international tourist hotels in Taiwan (Chen & Yeh, 2012). The forecast accuracy of the approaches in these studies is mixed. 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.

Expert Judgement

Statistical forecasting methods can detect systematic patterns rapidly in large sets of data and can filter out noise, but they can be unreliable when data are scarce or have little relevance for future events. On the other hand, judgmental forecasters can anticipate the effects of special events, but they are subject to a range of cognitive and motivational biases (Lawrence et al., 2006). When historical time series patterns are disrupted by foreseeable special or non-reoccurring events as is the case in the hotel demand environment, judgmental modifications of statistical forecasts may improve accuracy by allowing the estimated effects of these events to be incorporated into the forecast (Goodwin, 2000). Sanders and Manrodt (2006) found from a large survey of 240 U.S. corporations, 60% indicated they routinely adjusted the forecasts based on their judgment.

In their meta study, Goodwin and Wright (1993) concluded that most research suggests that judges in possession of continuously available contextual information that has predictive validity can outperform statistical time series methods either by adjusting these forecasts of making forecasts independently. A second meta study in judgmental forecasting concluded that there is now an acceptance of the role of judgements and a desire to learn how to blend judgements with statistical methods to estimate the most accurate forecasts (Lawrence et al., 2006).

A third meta study covering 25 years of published research found that forecasts adjusted by judgmental input have been found to be more accurate than those unaided judgements and proposed a method of "judgmental bootstrapping" as a model of regressing expert forecasts against the information the expert used (Armstrong, 2006).

Much of the research focused on rules based forecasting (RBF), which uses judgmental coding to select and weight extrapolation techniques (Adya, Collopy, Armstrong, & Kennedy, 2001). Studies have also focused on the use of panel and Delphi approaches to expert judgements (Archer, 1980).

Of course, the use of expert judgement has challenges. Polanyi (1958) distinguished between explicit and tacit knowledge. Explicit knowledge is open and codifiable. Tacit knowledge refers to all intellectual capital or physical capabilities and skills than an individual cannot fully articulate, represent, or codify. Tacit knowledge is thus difficult to measure and represent but is described as a critical asset for an individual, group, and organizational performance (Styhre, 2004). The use of tacit knowledge is common in the forecast of occupancy.

Erouglu and Croxton (2010) examined the impact of judgmental bias in the adjustment process and found that the forecasters' personal and motivational orientations have a significant effect. Sanders and Ritzman (2001) proposed that forecasters should consider six principles in deciding when and how to use judgement in adjusting statistical forecasts: (a) adjust statistical forecasts if there is important domain knowledge, (b) adjust statistical forecasts in situations with a high degree of uncertainty, (c) adjust statistical forecasts when there are known changes in the environment, (d) structure the judgmental adjustment process, (e) document all judgmental adjustments made and periodically relate to forecasting accuracy, and (f) consider mechanically integrating judgmental and statistical forecasts over adjusting.

Expert Judgement In Hotel Revenue Management Forecasts

Forecasting systems used in hotels are not able to predict or recognize non-recurring events from historical data and rely on inputs based on the revenue managers' knowledge to improve the accuracy of forecasts (Radjopadhye, Mounir, Wang, Baker, & Eister, 2001). Although there have been improvements in forecasting systems in the hotel industry, human judgement is still an important factor. (Chiang et al., 2007). There has been little research into the perspectives of revenue management professionals (Kimes, 2011).

Radjopadhye et al. (2001) reviewed the problems of forecasting unconstrained room demand and the challenges with various traditional forecasting methods and concluded that incorporating expert knowledge into a forecast is one of the most important objectives of improving forecast accuracy. Revenue and other hotel managers have partial knowledge of future events, and it is typical that this knowledge is used to adjust the statistically generated forecast to improve forecast accuracy.

As with the broader research into the application of expert judgement, Schwartz and Cohen (2008) pointed out the subjectivity of forecasting occupancy using a simulation methodology in a survey of revenue management professionals and found that experience and gender both affect the level of forecast uncertainty.

CHAPTER 3. EFFECTIVE METHODS OF FORECASTING OCCUPIED ROOMS

Introduction

The ability to accurately forecast arrivals to a tourist destination is important to minimize the financial and environmental costs of excess capacity or the opportunity costs of unfulfilled demand (Chu, 2011). Similarly, 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 lodging facility. The production and consumption of the service experience are simultaneous and may not be inventoried, and the opportunity perishes every night (Zeithaml, Parasuraman, & Berry, 1985). In the short term of 3 to 10 days, a forecast of occupied rooms is needed to schedule appropriate staff in both the rooms and other departments of a lodging facility and as a basis for the purchases of supplies. Profitability and guest service in lodging 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, Atiya, Sishiny, & Gayar, 2009). In the long term (multiple years), forecasts of occupied rooms and average rate inform investment decisions (Newell & Seabrook, 2006). A search of literature suggests that no known study has applied various methods of forecasting occupied rooms.

The purpose of this study is to test the performance of moving average, simple exponential smoothing, additive and multiplicative Holt-Winters method, and Box-Jenkins forecasting procedures on weekly aggregated occupied room data from ten geographic markets in the United States. Also, this study also examines the performance of combined forecasts. This study found that the simple exponential smoothing method (SES) produced the best degree of accuracy as measured by mean absolute percentage error and mean standard error in each of the 10 different geographic markets in the training sets, however. The results of the simple average combination method produced the most accurate combined forecast in most markets.

Review of Literature

Forecasting in the lodging industry.

The lodging industry is one in which accurate forecasting of occupied rooms is essential. Unlike industries that produce and inventory a tangible product, the lodging industry produces intangible experiences that are produced and consumed simultaneously. The need to align production resources with occupied rooms is essential to both efficient operation and guest satisfaction. Radjopadhye, Mounir, Wang, Baker, and Eister (2001) reviewed the problems of forecasting unconstrained room demand and the challenges with various traditional forecasting methods. Schwartz and Cohen (2004) pointed out the subjectivity of forecasting using a simulation methodology in a survey of revenue management professionals. Seven different forecasting models were examined by Weatherford and Kimes (2003). These models had varying degrees of forecasting accuracy. Weatherford, Kimes, and Scott (2001) also tested the accuracy of aggregated and disaggregated forecasting methods and found that the disaggregated forecasts outperformed the various aggregated methods. Zheng, Bloom, Wang, and Schrier (2012) found in the forecasting of RevPar, simple moving average and single exponential smoothing methods outperformed ARIMA and artificial neural networks. A review of recent literature suggests it is very challenging to identify a "best" forecasting method (Song & Li, 2008).

Forecasting models used in the hospitality industry.

Time series models

Time series models examine historical trends and seasonal patterns and forecast the future periods based on the trends and patterns recognized in the model. Various studies of arrivals into Hong Kong (Chan, Witt, Lee, & Song, 2010; Cho, 2003; Song, Lin, Witt, & Zhang, 2011); retail sales (Alon, Qi, & Sadowski, 2001); and a small sample of Choice and Marriott hotels in the United States (Weatherford & Kimes, 2003) found that exponential smoothing, pickup, and moving average models were the most robust; daily occupancy, ADR, and RevPar in a sample of hotels in Milan (Baggio & Sainaghi, 2011) confirmed the complex nature of the destination and its tendency towards a chaotic state. A single hotel in Ankara, Turkey (Yüksel, 2007), was used for a study invoving adjustment by an analytical heirarcy process and concluded that the process might help improve forecast accuracy; a sample of international tourist hotels in Taiwan (Chen & Yeh, 2012) was considered and concluded that demand uncertainty affects hotel failures, and the aggregated weekly RevPar of the U.S. lodging industry (Zheng et al., 2012) concluded that the simpler forecasting methods might be more accurate.

Researchers have used time series models in both research and practice. As the inputs into the models are based on historical observations, data collection and model construction are comparatively inexpensive (Song & Li, 2008). Many hotel revenue management systems rely on fairly simple 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).

Econometric models

Econometric models attempt to predict the impact of outside factors such as guest income, exchange rates, and competitors' prices on demand (Song & Li, 2008). While many tourism studies (Hsieh & Li, 2010; Radjopadhye, Ghalia, Wang, Baker, & Eister, 2001; Shen, Li, & Song, 2011; Song et al., 2011; Song, Witt, & Jensen, 2003) have been focused in this area, no known study has been identified that examined the use of econometric modeling for hotel occupied room forecasts. Forecasting systems used in hotels are not able to predict or recognize non-recurring events from historical data and rely on inputs based on the revenue managers' knowledge to improve the accuracy of forecasts (Radjopadhye et al., 2001). Yüksel (2007) conducted a study which combined time series forecasts with two Delphi based inquiry panels. Pan (2012) conducted a study using search engine data to forecast hotel room demand in Charleston, South Carolina.

Emergence of combination 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. Bates and Granger (1969) combined two different sets of airline passenger forecasts to form a new forecast. Their work analyzed some different methods of combining these individual forecasts, generally seeking a method of weighting each forecast so that the composite forecast error resulted in the lowest mean squared error. Their groundbreaking findings were that composite forecasts could yield lower mean square error than individual forecasts. 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.

The question then arises as to what and how many single method forecasts should be used to make up a composite forecast. 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). Shen et al. (2011) determined that the accuracy of a composite forecast is directly related to the performance consistency of the individual forecasts of which it is composed. No known study into the use of methods of combining individual forecasts into a composite forecast for hotel occupied rooms has been identified.

Data and Methods

Data.

This study used 5 years of weekly occupancy data from 2007 through 2011. The researcher selected convenience sample of 10 major U.S. metropolitan markets. Each of these 10 markets contained weekly data for an aggregated set of five hotels. STR Global (STR Global, 2013) provided the data. To be included in the sample, each hotel must have had a similar number of available rooms and the same brand for the entire time period. Also, each hotel must have a primarily transient individual (as opposed to group) business. This distinction is important in that the purpose of this study is to focus on the forecasting of transient occupied rooms. Forecasting group occupied rooms is less difficult for a hotel, as this business is contracted well in advance.

The weekly data for the period from Monday, January 1, 2007, through Sunday, December 26, 2010, were used as the in-sample training set for model fitting, and the weekly data for the period from Monday, December 27, 2010, through Sunday, December 25, 2011, were used as holdout data to validate the forecasts and calculate forecast accuracy.

Table 1

Descriptive Statistics (Occupied Rooms)

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
In-sample training set										
Minimum	1,672	2,531	2,696	2,688	2,433	3,919	2,280	3,068	2,569	2,019
Maximum	6,404	7,139	7,068	7,663	4,463	6,221	5,541	5,199	6,686	6,086
Mean	4,160	5,090	5,046	5.002	3,540	5,222	3,683	4,313	4,143	3,664
Standard Deviation	744	1,180	1,134	997	463	480	623	466	856	902
N	208	208	208	208	208	208	208	208	208	208
Hold out set										
Minimum	2,633	3,172	3,536	3,404	2,582	4,441	2,661	3,185	3,060	2,483
Maximum	6,350	7,213	6,851	7,616	4,197	6,369	5,444	5,143	6,077	5,466
Mean	4,617	5,604	5,227	5,260	3,398	5,472	3,906	4,469	4,013	3,681
Standard Deviation	660	1,136	951	944	420	393	601	543	799	825
N	53	53	53	53	53	53	53	53	53	53

Forecast methods.

This study will first examine models identified as more accurate in prior forecasting studies. First, the study builds on the work of Weatherford and Kimes (2003) by testing the methods of moving average and single exponential smoothing. Next, building on prior tourism arrival studies, the study tests both the additive and multiplicative Holt-Winters methods. Finally, a Box-Jenkins procedure will be tested building on the work of Zheng et al. (2012).

While there are various measurements of error available and frequently used, which of them to use is a subjective decision. In this study, mean absolute error (MAE) and mean absolute percentage error (MAPE) were used as the primary measurement of error as they reflect a meaningful value to practitioners in the same units as the forecast.

Moving average (MA) method

For the moving average method, the single parameter *n* that minimizes the mean absolute error of the in-sample training set is held constant for the forecast of the holdout set. The method can be demonstrated using the formula

$$\hat{Y}_t = (Y_{t-1} + Y_{t-2} + \ldots + Y_{t-n})/n$$

where Y_{t-1} = the actual value in a time series at time period t-1 and $\hat{Y}_t$ is the forecast of the time series for time period t. For this study, Excel was used to test n between 1 and 52. It is important to note that each time series may have error minimized by a unique n. A concern with the moving average method is that when forecasting, the forecast will stabilize at the value of the last data point in only a few periods and remain constant for the duration of the forecasting horizon.

<u>Single exponential smoothing (SES) method</u>

The formula for this method is:

$$\hat{Y}_t = \alpha Y_{t-1} + (1-a)\hat{Y}_{t-1}$$

where $Y_{t-1)}$ is the actual value in a time series at time period t-1; $\hat{Y}_t$ is the forecast of the time series for time period t; α is a smoothing constant, with a weight

$$(0 \le \alpha \le 1).$$

The value of α was estimated using JMP to minimize the mean absolute error of the in-sample training set, and then this value of α was applied to the hold out sample. Note that each data set may have a unique α (shown as "level smoothing weight) in the results section.

<u>Additive Holt-Winters method</u>

The additive Holt-Winters method is appropriate when a time series has a linear trend with an additive seasonal pattern for which the level, the growth rate, and the seasonal pattern may be changing (Bowerman, Bates, & Grainger, 2005). For this method the smoothing constants α, β, γ were determined by Excel solver to optimize the value that minimized the mean absolute error in the training set. The time series point forecast may be described by the following formula

$$\hat{y}_{T+\tau}(T) = \ell_T + \tau b_t + sn_{T+\tau-L}$$

where $sn_{T+\tau-L}$ is the "most recent" estimate of the seasonal factor for the season corresponding to time period $T+\tau$. (τ =1,2,…).

The estimate for level ℓ_T is given by

$$\ell_T = \alpha(y_T - sn_{T-L}) + (1-\alpha)(\ell_{T-1} + b_{T-1}).$$

The estimate for the growth rate b_T is given

$$b_T = \gamma(\mathrm{l}_T - \mathrm{l}_{T-1}) + (1-\gamma)b_{T-1}.$$

The estimate for the seasonal factor sn_T is given by

$$sn_T = \delta(y_T - \mathrm{l}_T) + (1-\delta)sn_{T-L}.$$

Where α is the data-smoothing factor, β is the trend-smoothing factor, and γ is the seasonal change-smoothing factor. Each of these factors may take on a value between 0 and 1. In this analysis, a least squared error regression is fitted to the training set. The intercept value of this regression is used as the initial value of the "level," and the slope value is used as the initial value of the "growth." Regression estimates are then calculated for each data point in the time series (both the in-sample training set and the forecast). The data is then detrended by dividing the actual value at each time *t* by the regression value. Seasonal factors are determined by averaging the detrended values over the in-sample period. For this data set, the researcher calculated the average detrended values for the 52-week season by averaging the detrended values using the formula

$$\frac{t_1 + t_{1+52} + t_{1+104} + t_{1+156}}{4}.$$

The smoothing formulas above are then used to calculate the level, growth, seasonal, and forecast values for each time period *t.* Solver was used to find the values of α, δ, and γ which minimized the mean absolute error in the training set. These values were then used in calculating the forecast for the hold-out sample.

<u>Multiplicative Holt-Winters method</u>

The multiplicative Holt-Winters method is appropriate when a time series has a linear trend with a multiplicative seasonal pattern for which the level, growth rate, and the seasonal pattern may be changing rather than fixed (Bowerman et al., 2005). Similar to the additive

Holt-Winters method, the estimate ℓ_T of the level, the estimate b_T for the growth rate, an estimate sn_T for the seasonal factor of the time series in time period T are given by the following smoothing equations:

$$\ell_T = \alpha(y_T / sn_{T-L}) + (1-\alpha)(\ell_{T-1} + b_{(T-1)})$$

$$b_T = \gamma(\ell_T - \ell_{T-1}) + (1-\gamma)b_{T-1}$$

$$sn_T = \delta\left(y_T / \ell_T\right) + (1-\delta)sn_{T-L}$$

where α, δ, and γ are smoothing constants between 0 and 1, which were optimized to minimize squared error using Excel solver, ℓ_{T-1} and b_{T-1} are estimates of the level and growth rate which are determined using a linear regression of the training set which minimizes root mean absolute error, and sn_{T-L} is the estimate in time period T-L for the seasonal factor, which is found using the same process as in the additive method. A point forecast made in time period T for $y_{T+\tau}$ is:

$$\hat{y}_{T+\tau}(T) = \left(\ell_T + \tau b_T\right)sn_{T+\tau-L}, \ (\tau = 1,2,\ldots)$$

Note that this process is used for each of the 10 geographic data sets, so unique initial values of the level, growth, and seasonal factors and unique optimized values for α, δ, and γ are used.

<u>Seasonal autoregressive integrated moving average (SARIMA) method</u>

A Box-Jenkins seasonal autoregressive integrated moving average (SARIMA) is an appropriate model to use for the data sets in this study. A requirement of this approach is that the time series must be transformed to stationarity if it is not stationary in raw form. Taking first differences of the non-stationary time series value most typically accomplishes this. In the Box-Jenkins methodology, the sample autocorrelation (SAC) and partial autocorrelation (SPAC) are examined and a model selected based on the behavior of these two diagnostic measures. As a result, the selection of a model may be highly subjective. The authors chose to use the JMP Time Series platform ARIMA Modeling in which JMP selected models using an iterative process that resulted in the minimum Akaike information criterion (AIC). AIC is a measurement of the relative quality of a statistical model and includes a penalty based on the number of estimated parameters. The models with the minimum AIC also generally had the lowest MAE for the training set. Each of these models also met the stability and invertibility requirements of the Box-Jenkins methodology. The iteratively selected model was then applied to the hold-out fifth year data.

Composite forecasts.

Two weighting methods for combining forecasts that were found to be the most accurate overall from the Chan (2010) study will be used in this study. First, simple average (SA). In this method, equal weights are assigned to all single forecasts. If *p* single forecasting methods are used, each method will be assigned a weight of 1/*p*. In this study, there were five separate forecasts combined, and thus each was weighted at 0.20. Second, the forecasts will be combined using a fixed weighting (FW∞). In this method, the optimal weights are determined using Excel Solver to minimize the mean absolute error (MAE) in the training set, and fixed these weights for the entire holdout sample. Consistent with the error measurement throughout the study, the accuracy of these composite forecasts were measured based on MAE and mean absolute percentage error (MAPE).

Data Analysis and Results

Table 2

Results of the Moving Average Method

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
Accuracy										
Optimal *n*	4	2	4	4	4	4	4	4	4	4
MAE Training	449	454	400	433	180	271	275	213	228	280
MAPE Training	11.0%	9.5%	8.4%	8.9%	5.2%	5.3%	7.4%	5.1%	8.2%	7.7%
MAE Forecast	2,084	2,069	1,678	1,778	657	602	1,439	912	637	1,386
MAPE Forecast	43.6%	44.2%	29.6%	31.6%	18.2%	10.6%	35.1%	19.5%	13.9%	34.6%

Table 3

Results of Single Exponential Smoothing Method

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
Level Smoothing Weight	0.3677	0.7049	0.6743	0.6602	0.7266	0.4943	0.5938	0.6997	0.8386	0.7732
Accuracy										
MAE Training	421	433	386	419	172	269	267	202	317	269
MAPE Training	10.9%	9.0%	8.2%	8.5%	4.9%	5.2%	7.3%	4.8%	7.7%	7.3%
MAE Forecast	1,236	2,394	1,447	1,582	664	369	1,170	803	623	1,317
MAPE Forecast	25.8%	39.9%	25.4%	28.0%	18.4%	6.6%	28.2%	17.3%	13.9%	32.7%

Table 4

Results of the Additive Holt-Winters Method

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
Best Model Information										
Regression										
Intercept	4.416.69	4.835.07	-1.13223	-0.07192	-4.09365	-0.20914	-2.7062	-0.01724	-6.48724	-6.0286
Slope	-2.45549	2.44416	-1.13223	-0.07192	-4.09365	-0.20914	-2.70628	-0.01724	-6.48724	-6.0286
R^2	0.03942	0.01555	0.00361	0.00002	0.28295	0.00069	0.6839	0	0.20802	0.16193
Adjusted R^2	0.03476	0.01078	-0.00123	-0.00484	0.27947	-0.00416	0.06387	0.00485	0.20417	0.15786
Smoothing Coefficient										
Alpha	0.21927	0.44961	0.35905	0.35563	0.19076	0.26382	0.26382	0.23901	0.41117	0.37448
Delta	0.06810	0.10605	0.09506	0.08093	0.07367	0.07868	0.07546	0.07637	0.08136	0.09018
Gamma	0.00000	0.00000	0.23081	0.14565	0.15155	0.00000	0.00000	0.00000	0.00000	0.00000
Accuracy										
MAE Training	492.8	563.9	497.6	553.4	397.8	423.7	450.4	389.2	531.3	458.2
MAPE Training	12.8%	11.9%	10.7%	11.4%	11.2%	8.3%	12.3%	9.3%	13.1%	13.0%
MAE Forecast	399.4	494.0	381.7	541.3	275.0	317.6	360.0	307.4	394.5	344.9
MAPE Forefast	9.3%	9.3%	7.5%	10.1%	8.2%	5.9%	9.4%	7.3%	10.0%	9.3%

Table 5

Results of Holt-Winters Multiplicative Method

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
Best Model Information										
Regression										
Intercept	4,886.16	4,835.07	5,163.99	5,009.6 4	3,968.28	5,243.5 3	3,969.59	4,315.12	4,821.19	4,293.93
Slope	-9.9864	2.4442	-1.1322	-0.0719	-4.0937	- 0.20091	-2.7063	-0.0172	-6.4872	-6.0286
R^2	0.1707	0.0156	0.0036	0.0	0.2829	0.0007	0.6884	0.0	0.20800	0.16190
Adjusted R^2	0.1626	0.0108	-0.0012	-0.0048	0.2795	-0.0042	0.0639	-0.0048	0.2042	0.1579
Smoothing Coefficient										
Alpha	0.1195	0.3931	0.4469	0.1916	0.631	0.0532	0.1947	0.0000	0.3615	0.5921
Delta	0.0000	0.0000	0.0000	0.0000	1.0000	0.3489	0.0375	0.0000	0.0000	0.0000
Gamma	0.3102	0.2665	0.1519	0.2983	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Accuracy										
MAE Training	475.1	609.0	607.6	553.3	280.9	360.8	403.0	378.7	462.7	419.9
MAPE Training	12.7%	13.4%	1287%	11.7%	8.3%	7.1%	11.7%	11.7%	11.8%	12.2%
MAE Forecast	506.1	680.1	722.7	627.8	299.3	339.3	480.0	498.0	507.3	484.6
MAPE Forefast	12.2%	14.0%	15.3%	12.4%	9.0%	6.3%	13.4%	11.6%	12.9%	14.4%

Table 6

Results of Seasonal Autoregressive Integrated Moving Average Method

	Best SARINA Model	Akaike Information	Accuracy			
			MAE Training	MAPE Training	MAE Forecast	MAPE Forecast
Atlanta	(0,0,0)(2,1,0)	2497.3424	555	15.09%	558	12.28%
Boston	(0,0,0)(2,1,0)	2445.9401	481	9.80%	576	10.35%
Chicago	(0,0,0)(2,1,0)	2473.4161	522	11.27%	429	8.69%
Denver	(0,0,0)(2,1,0)	2432.0963	455	9.51%	430	7.96%
Los Angeles	(0,0,0)(1,2,0)	2258.4106	271	7.96%	509	14.68%
Miami	(0,0,0)(0,1,1)	2339.2473	347	6.81%	283	5.17%
Nashville	(0,0,0)(2,1,0)	3267.9541	346	9.97%	560	13.95%
New York	(0,0,0)(2,1,0)	2269.6282	265	6.32%	344	7.47%
Phoenix	(0,0,0)(2,1,0)	2424.1000	451	11.64%	373	8.86%
Seattle	(0,0,0)(2,1,0)	2359.3837	382	11.50%	842	23.51%

Table 7

Results of Composite Forecasts

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
Simple Average										
MAE Training	378	410	348	374	185	254	273	194	297	261
MAPE Training	10.26%	8.68%	7.78%	7.72%	5.47%	5.01%	7.79%	4.72%	7.64%	7.85%
MAE Forecast	802	1150	733	745	400	318	674	525	377	718
MAPE Forecast	16.76%	19.38%	13.14%	13.06%	11.12%	5.71%	16.28%	11.53%	8.63%	17.92%
Fixed Optimized Weighting (Quadratic)										
SMA	0.1374	0.0000	0.0000	0.0000	0.0000	0.5999	0.1005	0.0000	0.0000	0.0000
SES	0.2792	0/4920	0.6906	0.5795	0.7360	0.1058	0.5029	0.6653	0.6996	0.6729
HWA	0.0000	0.0423	0.0186	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
HWM	0.2906	0.0067	0.0000	0.0000	0.0000	0.0000	0.0617	0.0001	0.0000	0.0000
SARINA	0.2928	0.4591	0.2908	0.4205	0.2640	0.2942	0.3349	0.2980	0.3004	0.3271
Accuracy										
MAE Training	358	359	306	331	159	224	240	161	260	205
MAPE Training	9.87%	7.45%	6.75%	6.84%	4.71%	4.39%	6.81%	3.89%	6.62%	6.04%
MAE Forecast	795	1413	1098	1037	652	481	904	639	487	1162
MAPE Forecast	16.57%	23.77%	19.49%	18.36%	18.19%	8.55%	21.79%	13.81%	10.62%	29.69%

Conclusions and Discussion

The application of five different forecasting methods to these data sets produced results that differ slightly from earlier studies. Table 8 below recaps the results of these individual methods. SES produced the best level of accuracy for the traing set as measured by mean absolute error and mean absolute percentage error in each of the 10 different markets. This is not surprising given the higher correlation of recent periods and the fact that the smoothing coefficients are selected to maximize the accuracy of the known training set. When this method is used to forecast the results were not accurate for these time series data.

The additive Holt-Winters method was found to be the most accurate in forecasting in seven of the 10 markets, even though it was not the most accurate in the training set. This result should be further studied. In three of the markets, the SARIMA method produced the highest level of accuracy.

Table 8

Results of the Individual Forecasting Methods

	Atlanta	Boston	Chicago	Denver	Los Angeles	Miami	Nashville	New York	Phoenix	Seattle
SMA Accuracy										
MAE Training	449	454	400	433	180	271	275	213	338	280
MAPE Training	11.0%	9.5%	8.4%	8.9%	5.2%	5.3%	7.4%	5.1%	8.2%	7.7%
MAE Forecast	2,084	2,629	1,678	1,778	657	602	1,439	912	637	1,386
MAPE Forecast	43.6%	44.2%	29.6%	31.6%	18.2%	10.6%	35.1%	19.5%	13.9%	34.6%
SES Accuracy										
MAE Training	421	433	386	419	172	269	267	202	317	269
MAPE Training	10.9%	9.0%	8.3%	8.5%	4.9%	5.2%	7.3%	4.8%	7.7%	7.3%
MAE Forecast	1,236	2,394	1,447	1,582	664	369	1,170	803	623	1,317
MAPE Forecast	25.8%	39.9%	25.4%	28.0%	18.4%	6.6%	28.2%	17.3%	13.9%	32.7%
H-W Additive Accuracy										
MAE Training	493	564	498	553	398	450	389	513	458	
MAPE Training	12.8%	11.9%	10.7%	11.4%	11.2%	12.3%	9.3%	13.1%	13.0%	
MAE Forecase	399	494	382	541	275	318	307	395	345	
MAPE Forecast	9.3%	9.3%	7.5%	10.1%	8.2%	5.9%	7.3%	10.0%	9.3%	
H-W Multiplicative Accuracy										
MAE Training	475	609	608	553	281	361	403	379	463	420
MAPE Training	12.7%	13.4%	13.8%	11.7%	8.3%	7.1%	11.7%	9.2%	11.8%	12.2%
MAE Forecast	506	680	723	628	299	339	480	498	507	485
MAPE Forecast	12.2%	14.0%	15.3%	12.4%	9.0%	6.3%	13.4%	11.6%	12.9%	14.4%
SARIMA Accuracy										
MAE Training	555	481	522	455	271	347	346	265	451	382
MAPE Training	15.09%	9.80%	11.27%	9.51%	7.96%	6.81%	9.97%	6.32%	11.64%	11.50%
MAE Forecast	558	576	429	430	507	283	560	344	373	842
MAPE Forecast	12.28%	10.35%	8.69%	7.96%	14.68%	5.17%	13.95%	7.47%	8.86%	23.51%

Given that each of these markets exhibited differing demand patterns for occupied rooms over the time period of the study, these results are not surprising. The results do indicate that there may be no "one-size-fits-all" best forecasting method, and this should be a focus of further studies.

The fixed weighting method of combining forecasts resulted in the most accurate composite forecasts of the training set as the weights were optimized to arrive at this result. However, this method resulted in the most accurate forecast in only one market. The results of the simple average combination method produced the most accurate composite forecast in the remaining markets, and in most cases by a fairly wide margin.

This study examined the accuracy of five different time series forecasting methods that were the most accurate in prior academic studies of tourist arrivals and revenue per available room (RevPar). Further, this study examined the results of two methods of combining forecasts that were also tested in earlier studies of tourist arrivals and revenue per available room. None of these methods offer acceptable levels of accuracy for practitioners. The mean absolute error in each of the methods is so wide as to be useless. There are many reasons for this, including the time horizons this study was using and the general dynamic nature of the demand for occupied rooms in different markets and the attributes of the individual time series data. The time series sample in this study exhibited changing trends, levels, and rates of change over the period studied. This presents significant challenges for most time series forecasting methodologies, which imply that historical patterns, once identified and measured, can be effectively projected into the future.

The results of this study have produced empirical evidence of the relatively low accuracy of the various individual forecasting and combining methods used in prior studies of other tourism related time series data when applied to occupied rooms data**.** This study was conducted to provide researchers and practitioners with initial empirical evidence of the results of the various forecasting methods that have resulted in the best accuracy in other tourism related studies. Given the importance of accurate forecasting of occupancy to the lodging industry, other methods of creating more accurate forecasts need to be studied in the future.

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CHAPTER 4. THE APPLICATION OF EXPERT JUDGEMENT TO STATISTICALLY BASED FORECASTS OF OCCUPANCY IN THE HOTEL INDUSTRY

Introduction

In 2016, the direct contribution of the travel and tourism industry in the United States was $503.7 billion dollars and directly supported more than 5.486 million jobs (World Travel and Tourism Council, 2017). As a subset of the tourism industry, the lodging industry generated over $189 billion in 2015 revenue (Statista, 2017). The ability to accurately forecast arrivals to a tourist destination is important to minimize the financial and environmental costs of excess capacity or the opportunity costs of unfulfilled demand (Chu, 2011). Similarly, 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 lodging facility. The production and consumption of the service experience are simultaneous and may not be inventoried, and the opportunity perishes every night (Zeithaml, Parasuraman, & Berry, 1985). Revenue management is most effective in transactions which involve variable demand and relatively fixed, highly perishable inventories (Cetin, Demirciftci, & Bilgihan, 2016).

Over time periods of between 3 and 30 days from arrival, a forecast of occupancy is needed to appropriately schedule staff in both the rooms and other departments of a lodging facility and as a basis for the purchases of supplies. Profitability and guest service in lodging are optimized when these resources are carefully matched with the number of occupied rooms (Johns & Lee-Ross, 1996).

Over time periods of 30 to 365 days from the date of arrival, the forecast of occupied rooms informs pricing decisions to maximize average rate and segment availability (Zakhary, Atiya, Sishiny, & Gayar, 2009). In forecasts beyond 365 days, forecasts of occupancy and average rate are used primarily to inform investment decisions (Newell & Seabrook, 2006).

While statistical forecasting methods may lead to a reliable demand forecast in some industries by extrapolating regular patterns in a time series, demand in a market is subject to many non-recurring events and unpredictable changes which interrupt historical patterns (Cheikhrouhou, Marmier, Ayaidi, & Weiser, 2011). This is particularly true in the hotel industry where travel decisions are highly discretionary. Revenue and other hotel managers have partial knowledge of future events, and it is typical that this knowledge is used to adjust the statistically generated forecast to improve forecast accuracy.

To date, the literature within the hospitality domain has focused primarily on tourist arrival forecasts for specific destinations. These studies have concluded that while certain forecasting methods may yield more accurate forecasts than the models being used by managers today, there is no one "best" model. Recent research has examined several types of time series forecasts of revenue per available room night (RevPar) at the market or hotel level and concluded that the simpler methods might perform better (Zheng, Bloom, Wang, & Schrier, 2012). Although there have been improvements in forecasting systems in the hotel industry, human judgement is still an important factor (Chiang, Chen, and Xu, 2006). There has been little research into the perspectives of revenue management professionals (Kimes, 2011).

The purpose of this study to understand how the sample of revenue management experts uses judgment to modify statistically based forecasts of hotel occupancy. This is an area that offers some opportunities for impactful, practical application and future studies. Sanders and Manrodt (2006) found from a large survey of 240 U.S. corporations, 60%

indicated they routinely adjusted the forecasts based on their judgment. It is clear that adjustments made to forecasts by expert judgement with contextual knowledge of future events are a mandatory component of forecasting (Lawrence, Goodwin, O'Connor, & Onkal, 2006). Thus, understanding the proper use of expert judgment is more than ever an important activity for researchers and practitioners.

Review of Literature

Forecasting in general.

Accurate forecasts are essential to successful to organizational planning (Fildes & Goodwin, 2007). While statistical forecasting methods may lead to a reliable demand forecast in some industries by extrapolating regular patterns in a time series, demand in a market is subject to many non-recurring events and unpredictable changes which interrupt historical patterns (Cheikhrouhou et al., 2011).

Academic research has focused heavily on improving statistical methods of forecasting (Fildes, Goodwin, & Lawrence, 2006) and the use of judgmental approaches to adjust these forecasts (Lawrence et al., 2006).

Time series forecasting

Time series based forecasting is defined as the extrapolation of patterns from historical data to obtain an approximation of the future demand over a time horizon (Cheikhrouhou et al., 2011). Time series forecasting assumes that the patterns identified in a time series repeat themselves in the future and then when extrapolated may be used for the development of forecasting models.

Time series models have been used in both research and practice as the inputs into the model are based on historical observations; data collection and model construction are comparatively inexpensive (Song & Li, 2008). There are many different mathematical and statistical methods (Makridakis, Wheelwright, & Hyndman, 1998) used in time series forecasting. Studies, including the M-Competitions, concluded that the accuracy of various methods of time series forecasting varies based on the time horizon being forecast. (Makridakis & Hibon, 2000; Makridakis et al., 1998).

Forecasting in hospitality and tourism

The ability to accurately forecast arrivals to a tourist destination is important to minimize the financial and environmental costs of excess capacity or the opportunity costs of unfulfilled demand (Chu, 2011). The time series models studied in the academic literature about hospitality and tourism include autoregressive integrated moving average (ARIMA) model, autoregressive distributed lag model (ADLM), error correction model (ECM), vector autoregressive (VAR) model (Wong, Song, Witt, & Wu, 2007), Box-Jenkins Procedure (ARIMA models), and smoothing methods such as simple moving average, single exponential smoothing, and Holt-Winters (Zheng, Bloom, Wang, & Schrier, 2012).

To date, the literature which is specific to hospitality and tourism has focused primarily on tourist arrival forecasts for specific destinations using time series models, econometric models, and methods of forecast combination. Time series models examine historical trends and seasonal patterns and predict the future based on the trends and patterns recognized in the model. Various studies of arrivals into Hong Kong (Chan, Witt, Lee, & Song, 2010; Cho, 2003; Song & Lin, 2011) used different time series forecast and forecast combination methods and reported mixed results in improving accuracy. Econometric models attempt to predict the impact of outside factors such as guests' income, exchange rates, and competitors' prices on demand (Song & Li, 2007).

A review of recent literature suggests it is very challenging to identify a "best" forecasting method (Song & Li, 2008).

Forecasting in hotels

Accurate forecasting of occupancy in the hotel industry is essential. The position of revenue manager or general manager is typically responsible for creating these forecasts. While there has been significant research into revenue management as a discipline in the hotel industry (Guilet & Mohammed, 2015), there has been little research published on forecasting occupancy in hotels specifically.

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).

The basic concept of revenue management is to maximize revenues through demand-based variable pricing (Choi & Matilla, 2004) based on a forecast of demand for each future date (Emeksiz, Gursoy, & Icoz, 2006). Revenue management is most effective in transactions which involve variable demand and relatively fixed, highly perishable inventories (Cetin et al., 2016). 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 lodging facility. The production and consumption of the service experience are simultaneous and may not be inventoried, and the opportunity perishes every night (Zeithaml et al., 1985).

Hotel management uses forecasts of occupancy to price, to schedule staff, to purchase supplies and to manage cash flow (Johns & Lee-Ross, 1996). The contribution of revenue management techniques on profits has been acknowledged and proven beneficial in a range of industries (Cross, Higbie, & Cross, 2009) and specifically the hospitality industry (Deighton & Shoemaker, 2001).

Over time periods of between 3 and 30 days from arrival, a forecast of occupancy is needed to appropriately schedule staff in both the rooms and other departments of a lodging facility and as a basis for the purchases of supplies. Profitability and guest service in lodging are optimized when these resources are carefully matched with the number of occupied rooms (Johns & Lee-Ross, 1996). Over time periods of 30 to 365 days from the date of arrival, the forecast of occupied rooms informs pricing decisions to maximize average rate and segment availability (Zakhary et al., 2009). In forecasts beyond 365 days, forecasts of occupancy and average rate are used primarily to inform investment decisions (Newell & Seabrook, 2006).

Recent research has examined several types of time series forecasts of revenue per available room night (RevPar) using aggregated weekly U.S. lodging industry data and concluded that the simpler methods might perform better (Zheng, Bloom, Wang, & Schrier, 2012).

Seven different forecasting models were examined by Weatherford and Kimes (2003). The methods included simple exponential smoothing, moving average, liner regression, logarithmic linear regression, additive and multiplicative, and Holt's double exponential smoothing. These models had varying degrees of forecasting accuracy, much dependent on the time horizon being forecast. Weatherford, 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.

Additional studies have included daily occupancy, ADR, and RevPar in a sample of hotels in Milan (Baggio & Sainaghi, 2011); a single hotel in Ankara, Turkey (Yüksel, 2007) and a sample of international tourist hotels in Taiwan (Chen & Yeh, 2012). The forecast accuracy of the approaches in these studies are mixed. 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.

Expert judgement.

Statistical forecasting methods can detect systematic patterns rapidly in large sets of data and can filter out noise, but they can be unreliable when data are scarce or have little relevance for future events. On the other hand, judgmental forecasters can anticipate the effects of special events, but they are subject to a range of cognitive and motivational biases (Lawrence et al., 2006). When historical time series patterns are disrupted by foreseeable special or non-reoccurring events as is the case in the hotel demand environment, judgmental modifications of statistical forecasts may improve accuracy by allowing the estimated effects of these events to be incorporated into the forecast (Goodwin, 2000). Sanders and Manrodt (2006) found from a large survey of 240 U.S. corporations, 60% indicated they routinely adjusted the forecasts based on their judgment.

In their meta study, Goodwin and Wright (1993) concluded that most research suggests that judges in possession of continuously available contextual information that has predictive validity can outperform statistical time series methods either by adjusting these forecasts of making forecasts independently. A second meta study in judgmental forecasting concluded that there is now an acceptance of the role of judgements and a desire to learn how to blend judgements with statistical methods to estimate the most accurate forecasts. (Lawrence et al., 2006).

A third meta study covering 25 years of published research found that forecasts adjusted by judgmental input have been found to be more accurate than those unaided judgements and proposed a method of judgmental bootstrapping as a model of regressing expert forecasts against the information the expert used (Armstrong, 2006).

Much of the research has been conducted into rules-based forecasting (RBF), which uses judgmental coding to select and weight extrapolation techniques (Adya, Collopy, Armstrong, & Kennedy, 2001). Studies have also focused on the use of panel and Delphi approaches to expert judgements (Archer, 1980).

Of course, the use of expert judgement has challenges. Polanyi (1958) distinguished between explicit and tacit knowledge. Explicit knowledge is open and codifiable. Tacit knowledge refers to all intellectual capital or physical capabilities and skills than an individual cannot fully articulate, represent, or codify. Tacit knowledge is thus difficult to measure and represent but is described as a critical asset for an individual, group, and organizational performance (Styhre, 2004). The use of tacit knowledge is common in the forecast of occupancy.

Eroglu and Croxton (2010) examined the impact of judgmental bias in the adjustment process and found that the forecasters personal and motivational orientation have significant effect. Sanders and Ritzman (2001) proposed that forecasters should consider six principles in deciding when and how to use judgement in adjusting statistical forecasts: (a) adjust statistical forecasts if there is important domain knowledge, (b) adjust statistical forecasts in situations with a high degree of uncertainty, (c) adjust statistical forecasts when there are known changes in the environment, (d) structure the judgmental adjustment process, (e) document all judgmental adjustments made and periodically relate to forecasting accuracy, and (f) consider mechanically integrating judgmental and statistical forecasts over adjusting.

Expert judgement in hotel revenue management forecasts

Forecasting systems used in hotels are not able to predict or recognize non-recurring events from historical data and rely on inputs based on the revenue managers' knowledge to improve the accuracy of forecasts (Radjopadhye, Mounir, Wang, Baker, & Eister, 2001). Although there have been improvements in forecasting systems in the hotel industry, human judgement is still an important factor (Chiang et al., 2006). There has been little research into the perspectives of Revenue Management professionals (Kimes, 2011).

Radjopadhye et al. (2001) reviewed the problems of forecasting unconstrained room demand and the challenges with various traditional forecasting methods and concluded that incorporating expert knowledge into a forecast is one of the most important objectives of improving forecast accuracy. Revenue and other hotel managers have partial knowledge of future events, and it is typical that this knowledge is used to adjust the statistically generated forecast to improve forecast accuracy.

As with the broader research into the application of expert judgement, Schwartz and Cohen (2008) pointed out the subjectivity of forecasting occupancy using a simulation methodology in a survey of revenue management professionals and found that experience and gender both affect the level of forecast uncertainty.

Method

Purpose.

The need for qualitative studies to enhance revenue management has been urged by Guillet and Mohammed (2015). The revenue manager has the primary responsibility for forecasts of future occupancy for a hotel. Once complete, these forecasts are provided to the various operating department managers of the hotel. The forecasts of occupancy from 3 to 30 days from arrival are used for labor scheduling and the purchase of supplies. To the extent they are used, most automated forecasting systems in the hotel industry rely on historical data to produce a time series forecast. The ability to modify a time series forecast based on historical data with tacit knowledge of future market demand is key to improving forecast accuracy (Goodwin, 2000). The purpose of this qualitative study was to explore the sources of demand information used by revenue managers in the United States to inform their expert subjective judgment in adjusting the historical time series forecasts and to describe the methods these managers may use to modify statistical forecasts based on historical data with this market demand information. This will build upon work done by Schwartz and Cohen (2004); Song, Gao, and Lin (2013); and Sanders and Ritzman (2001), among others.

Sample.

A convenience sample of hotel and corporate revenue management support sites in the United States was being selected, based on researcher access to the to these units and their availability and willingness to participate in one-on-one interviews. Consistent with Fredericks (2005), a convenience sample was developed from the researcher's contacts and enhanced by snowball sampling to obtain the remainder of the sampling base. This approach is appropriate when the research is exploratory in nature (Zikmund, 2003), subjects are hard to reach, or when there is the potential for confidential information to be discussed (Fredericks, 2005).

The researcher interviewed 10 revenue managers for this study. Four of these were working on a revenue management team, which supported groups of franchised hotels for a major global brand. These managers worked directly with the multiple hotels they supported in their assigned geographies. The remaining six revenue managers worked at the property they supported. Two of these managers also supported one or more properties in their geographic area in addition to their property.

Table 9:

Descriptive statistics of the interview sample:

Participant	A	B	C	D	E	F	G	H	I
Years in the hotel industry	10	30	26	18	20	6	42	22	3
Years in revenue managment	5	22	16	13	8	4	20	15	3
Years in present position	3	14	1.5	4	1.5	2	3	.5	1.5

Marriott International, Hilton Worldwide, Starwood Hotels and Resorts Worldwide, Intercontinental Hotels Group, and Wyndham Hotels and Resorts were represented in the sample. The revenue managers interviewed oversaw the revenue management function in the limited and select service, full service, and luxury quality tiers.

Interview design.

As this study is exploratory in nature, a semi-structured interview was conducted one on one with the study participant sample (Zickmund, 2003). The semi-structured interview process allows the interviewees to express their ideas and opinions in their words. The use of a semi-structured interview will allow insight into other important concerns of these managers as they emerge.

A one-on one interview of survey design, as described by Creswell (2012) and Esterberg (2001), was used to answer the research questions. The questions of interest for this study were:

1. What sources of market demand information do the participants use to inform their subjective opinion and adjust an occupancy forecast based on historical information? There are various sources of contextual future market demand information available to revenue managers. These include channel velocity information, future group business booked, special events in the market and convention center future booking activity. In all cases, this information is continuously available. Most researchers suggest that expert judges in possession of continuously contextual information which has predictive validity can improve the accuracy of time series forecasts (Goodwin & Fildes, 1999).
2. Which of these sources do the participants find most helpful in improving forecast accuracy, and why? Research on the accuracy and judgement has suggested that expert judges are subject to cognitive biases and inconsistency (Goodwin & Wright, 1994). As much of the contextual future demand information is available in most markets in the United States, this question is designed to test for both cognitive bias and inconsistency.
3. What market demand information would the participants like to have, but do not have, that would be helpful in improving forecast accuracy? The ability of forecasters to make effective use of contextual information is based on the

predictive power, regularity, and frequency of information (Goodwin & Fildes, 1999). This question is designed to investigate whether there is a consistent argument for additional demand data that is not currently available.

The researcher asked each interviewee these structured questions and then asked unstructured follow on questions based on participant response. The average length of the 10 interviews was 48 minutes. The researcher conducted the interviews over a 4-month period, from December of 2015 through March of 2016. Each interview was conducted at the participant's business location. Before the start of each interview, the participant was given an informed consent document, which had been previously approved by the Institutional Research Board at Iowa State University, and given the opportunity to read and sign it.

Each interview was digitally recorded and transcribed verbatim using the Rev Audio Transcription Service (Rev, 2016). Following a review of the transcription, all digital audio files were deleted, and all personally identifying information about the interview participant and the companies they worked for was removed from the transcription notes. Also, the transcripts were further anonymized by redacting references to proprietary systems or processes which could identify the company for which the interviewee worked (Corti, Day, & Blackhouse, 2000).

The transcripts were manually coded separately by the principal researcher and a second researcher to improve inter-coder reliability.

Results

Sources of information.

Each revenue manager used different sources of future demand information to inform the forecasts they were charged with producing. The variability was wide. For example, Participant G: "We look at segmentation data, obviously internal and external. We get some segmentation data from Travel Click. The information that comes from there we compare with ours. Some of the other things that we'll use is Smith Travel Data. Year over year forecasting, if we're forecasting the year, in the beginning, we'll take Smith Travel, we'll take PKF, PWC ... All of those metrics that they're saying are going to grow at a certain rate in the industry and then we'll appropriate proper numbers per metro market." This was a the most analytical of the approaches in the study. Participant J: "I would say 75% of it is just their own memory and knowledge, but some of the hotels do have the convention calendar, and I ask them to give me those key dates that I need to know about, because they have a better indication of when they can see on paper how many room nights come into the market, how that's actually going to impact us." Both of these revenue managers worked in the same office for the same brand and were providing revenue managent support to multiple hotels.

There were several common sources of information, including the following: a) convention calendars and attendee estimates from local and regional convention and visitors bureaus; b) professional sporting and entertainment events from local and regional sporting and entertainment venues; c) group booking and booking pace projections from the hotel or area sales staff; and d) notes from prior historical period prepared by local hotel staff. This local market knowledge was used by the revenue managers to adjust the time series based forecasts, which were produced by the Brand (Franchisor) Revenue Management forecasting systems.

Most of the revenue managers also used a group of third party reports which provide transient booking pace by major channel into their market and their hotel's relative market share of that channel activity. The most frequently cited report was a proprietary report known as Demand360 (TravelClick, 2016), to which all the brands represented in the study subscribed. Booking pace variations were used to adjust forecasts of transient demand. This capability has become more important in the recent year as more and more brands and individual hotels participate in reporting making the data increasingly representative of the entire reported market.

Weatherford, Kimes, and Scott (2001) ested the accuracy of aggregated and disaggregated forecasting methods for two large hotels over a two year period and found that the disaggregated forecasts outperformed the various aggregated methods.

Each revenue manager used the contextual demand information differently to adjust their forecasts of occupancy and rate. Participant C provided this response: “Every week we do revenue strategy calls. During those calls, we talk about what's going on in the market. For instance, if there is a snow storm or a hurricane, or what have you, we use that information as well. It doesn't affect too many things too often, but for instance when Hurricane Sandy hit, that had a very big impact on all of the forecasts the following year because of the cancellations, etc, and when the Boston marathon bombing happened, that had an effect on the forecast the following 2 years. We keep track of it, again on our weekly calls, we keep track of it, just on a simple Excel spreadsheet.”

Interestingly, even in situations where two or more revenue managers were working for the same company, there was no standardized method of applying this market knowledge. Each manager used different methods, and there was little if any statistical or process consistency. Based on the sample, the adjustments to the forecasts were largely intuitive.

Each revenue manager felt that it was very important to forecast by segment due to the significant variations in historical patterns, which occurred in certain segments. Much of this was based on specific markets, and there was no consistent focus or weighting of segment importance between markets.

Each of the major global brand companies represented in this sample were continually improving their statistical forecasting technology. One of the brand companies was in the process of rolling out a much more sophisticated system which incorporated external demand information into the forecast engine.

Discussion

This study revealed some important opportunities for industry consideration and further study. Each of the brands represented continues to spend significant time and resources on improving their automated demand forecasting systems as the importance of demand forecasting is widely recognized. Each of the brands also relies on the individual revenue and property managers to adjust these forecasts based upon their local market, however this little training or consistency in how this process should occur. This results in a sub-optimal situation in which the knowledge, skills, and abilities in the application of expert judgement vary widely. There appears to be no consistent process, training, or knowledge transfer capabilities in place for this human element. Thus, the organizations are unable to capture the institutional knowledge of each individual and replicate it. Each organization is highly reliant on the individual capabilities of each revenue manager, and these capabilities vary widely based on this small sample.

This presents an opportunity for forecast accuracy improvement across each of the major brands represented in the sample. Much of the literature has demonstrated that rule-based forecasting results in more accurate forecasts, particularly when there is good domain knowledge and that knowledge has a significant impact (Armstrong, 2006). Standardizing practices that result in greater accuracy and creating a more robust structure to be followed across brands could prove to be quite beneficial.

An increased focus on leveraging best practices and developing more standardized processes should result in increased forecast accuracy, which in turn would lead to greater pricing opportunity during future high demand periods, greater profitability from better matching demand and staffing, and greater hotel valuations as a result of increased profitability. Even a relatively small but consistent increase in forecast accuracy would be beneficial to each hotel, each brand, and the industry as a whole.

There is opportunity for a wide range of future study in this area. A focus on developing a framework for the application of external demand information would be an area with immediate applicability for industry practitioners and should be pursued. Studies of the correlation of external demand such as search engine volume and channel velocity on demand are underway now with several published. This is a very promising area of improving future demand accuracy and should be continued.

CHAPTER 5. GENERAL CONCLUSIONS

General Discussion

This dissertertation presented two studies related to forecasting occupancy in hotels. In comparison to other studies of hospitality and tourism forecasting, the forecasting of occupancy has not been fully explored. The studies conducted as a part of this dissertation benefit the industry by highlighting the quantitiave findings on the accuracy of time-series forecasts of hotel occupancy and on the common sources of tacit information used by practicing revenue managers to adjust the time series forecasts to account for known changes in demand from historical patterns in future periods and the process by which this is done. Application of the findings and future research may ultimately help the hotel industry to improve forecasting accuracy for both pricing decisions and the management of variable costs.

This two questions explored were:

1. Does one method of forecasting future occupancy outperform others?
2. Are there common sources of contextual information about future demand in a market used to adjust the time series based forecast baseline and what is the process by which the forecasts are adjusted?

Each of the two studies stands alone on an individual basis and contribute to the extant literature on forecasting in the hotel industry. Overall, these two studies advance the body of knowledge in the hotel industry by discussing and applying quantitive methods of forecasting and further by exploring the sources of tacit market information used by revenue managers to apply their expert judgement to a forecast to improve forecast accuracy.

The first paper, entitled "Effective methods of forecasting occupied rooms," presented a quantitative study that examined the accuracy of five different time series forecasting methods which have been demonstrated as the most accurate in prior academic studies of tourist arrivals and revenue per available room (RevPar). The results of this study have produced empirical evidence of the relatively low accuracy of the various individual forecasting and combining methods used in prior studies of other tourism related time series data when applied to occupied rooms data**.** This study was conducted to provide researchers and practitioners with initial empirical evidence of the results of the various forecasting methods that have resulted in the best accuracy in other tourism related studies.

The second paper, entitled "The application of expert judgement to statistically based forecasts in the U.S. hotel industry," revealed some important opportunities for industry consideration and further study. Each of the brands represented continues to spend significant time and resources on improving their automated demand forecasting systems as the importance of demand forecasting is widely recognized. Each of the brands also relies on the individual revenue and property managers to adjust these forecasts based upon their local market; however, this little training or consistency in how this process should occur.

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Recommendations for Future Research

Given the highly competitive nature of the hotel industry in the United States and the transparency of publicly available room rates and the number of distribution channels available for the sale of rooms, the discipline of revenue management has become increasingly important. Forecast accuracy is of critical importance, but for various reasons at various time horizons. Forecasts of 30 to 550 days before arrival help establish appropriate rates based on future demand and the relative positioning of competitors' rates. Forecasts of between 3 and 30 days are important to the ability of operation managers to properly purchase and schedule to the variable demand.

Given the unpredictability of demand, it is unlikely that one "best model" will emerge; however, this research does point to certain methods of time series forecasting being more accurate than others. Further research into the effectiveness of time series models on different time horizons would be beneficial. The data for competitive sets is easily available and generously shared, and so a quantitative focus is relatively straightforward.

The technology supporting revenue management and forecasting systems has grown rapidly in sophistication, from very early Excel models developed independently by each property to the integrated systems today that use historical data and known future bookings to forecast, and rate shopping engines to continually monitor and update rates in response to changes competitors make. It is likely that many of the functions that are manual in nature today will become increasingly automated in the future. That said, there will always be a need for revenue managers to utilize their tacit knowledge of future demand to modify these automated forecasts. This study revealed that across several major brands and in a single unit, area, and centralized regional teams—each revenue manager approaches this process differently, but tend to use similar sources of external data.

Future research may study the most practical application of best practices from other industries related to structured approaches to modifying forecasts. To the extent application of expert judgement may be standardized and benchmarked it may result in increasing forecast accuracy. It is also possible that as these processes are standardized, they may be further automated. For example, the channel booking velocity data produced by the TravelClick Demand 360 products could be integrated into the forecasting systems, removing the need for human intervention in considering that particular series of data.

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APPENDIX A: INFORMED CONSENT DOCUMENT

Title of Study: Expert Judgement inputs for Hotel Occupancy Forecasting

Investigator(s):

Rex Warren,	Principal Investigator
Mailing Address:	185 Providence Street, A430
	West Warwick, RI 02893
Email Address:	rex.warren@jwu.edu
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Tianshu Zheng, Ph.D	Dissertation Committee Chair
Mailing Address	9W MacKay
	Ames, Iowa 50011
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This form describes a research project. It has information to help you decide whether or not you wish to participate. Research studies include only people who choose to take part—your participation is completely voluntary. Please discuss any questions you have about the study or about this form with the project staff before deciding to participate.

Introduction

The purpose of this study is to learn how revenue management experts in the hotel industry use their knowledge of future market demand to modify statistical forecasts that are based on historical demand to improve forecast accuracy.

You are being invited to participate in this study because you are an expert in the field of hotel revenue management and are primarily responsible for or involved with the generation of occupancy forecasts for the hotel or hotel(s) you oversee.

Description of Procedures

If you agree to participate, you will be asked to participate in a semi-structured interview in which the Primary Investigator will ask you the following questions:

Demographic:

1. How long have you worked in the hotel industry?
2. How long have you worked in the field of Revenue Management?
3. How long have you been in your present position?

Interview Questions

1. What sources of market demand information do you use to adjust an occupancy forecast based on historical information?
2. Which of these sources do you find most helpful in improving forecast accuracy, and why?
3. How do you modify statistically based forecasts based on this information?

4. What market demand information would you like to have, but do not have that would be helpful in improving forecast accuracy?

The interview should last for 30 minutes to 45 minutes. The interview will take place at a time and location convenient to you either in person or via telephone. A digital audio recording of the interview will be made, and destroyed immediately upon transcription. No personally identifiable information will be recorded nor associated with the interview notes.

Risks or Discomforts

While participating in this study you should experience no risk or discomfort.

Benefits

If you decide to participate in this study, there will be no direct benefit to you. It is hoped that the information gained in this study will benefit the industry by reporting commonly used information sources used by expert revenue management. You will be provided a copy of the findings of the study upon completion.

Costs and Compensation

You will not have any costs from participating in this study. You will not be compensated for participating in this study.

Participant Rights

Participating in this study is completely voluntary. You may choose not to take part in the study or to stop participating at any time, for any reason, without penalty or negative consequences. You can skip any questions that you do not wish to answer.

If you have any questions *about the rights of research subjects or research-related injury*, please contact the IRB Administrator, (515) 294-4566, IRB@iastate.edu, or Director, (515) 294-3115, Office for Responsible Research, Iowa State University, Ames, Iowa 50011.

Confidentiality

Records identifying participants will be kept confidential to the extent permitted by applicable laws and regulations and will not be made publicly available. However, federal government regulatory agencies, auditing departments of Iowa State University, and the Institutional Review Board (a committee that reviews and approves human subject research studies) may inspect and/or copy study records for quality assurance and data analysis. These records may contain private information.

To ensure confidentiality to the extent permitted by law, the following measures will be taken:

1. Each interview participant will be asked to select a first name pseudonym from a list. Only the pseudonym will be used in all documented information, notes, and audio recordings.
2. Only the interviewer will have access to information which links the coded participant to any personally identifiable information, and this key will be stored in a secure location separate from all other research documentation until transcription of

the audio file is completed. At that point, both the identifying key and the audio file will be destroyed.

Questions

You are encouraged to ask questions at any time during this study. For further information ***about the study,*** contact Rex Warren, at Rex.warren@jwu.edu

Consent and Authorization Provisions

Your signature indicates that you voluntarily agree to participate in this study, that the study has been explained to you, that you have been given the time to read the document, and that your questions have been satisfactorily answered. You will receive a copy of the written informed consent prior to your participation in the study.

Participant's Name (printed) ____

____ ________________________

Participant's Signature Date

APPENDIX B: IRB APPROVAL

IOWA STATE UNIVERSITY
OF SCIENCE AND TECHNOLOGY

Institutional Review Board
Office for Responsible Research
Vice President for Research
1138 Pearson Hall
Ames, Iowa 50011-2207
515 294-4566
FAX 515 294-4267

Date: 2/12/2016

To: Rex Warren
185 Providence St. A430
West Wawick, RI 02893

CC: Dr. Tianshu Zheng
9W MacKay Hall

From: Office for Responsible Research

Title: Expert Judgement inputs for Hotel Revenue Management

IRB ID: 16-038

Study Review Date: 2/12/2016

The project referenced above has been declared exempt from the requirements of the human subject protections regulations as described in 45 CFR 46.101(b) because it meets the following federal requirements for exemption:

- (2) Research involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey or interview procedures with adults or observation of public behavior where
  - Information obtained is recorded in such a manner that human subjects cannot be identified directly or through identifiers linked to the subjects; or
  - Any disclosure of the human subjects' responses outside the research could not reasonably place the subject at risk of criminal or civil liability or be damaging to their financial standing, employability, or reputation.

The determination of exemption means that:

- **You do not need to submit an application for annual continuing review.**

- **You must carry out the research as described in the IRB application.** Review by IRB staff is required prior to implementing modifications that may change the exempt status of the research. In general, review is required for any modifications to the research procedures (e.g., method of data collection, nature or scope of information to be collected, changes in confidentiality measures, etc.), modifications that result in the inclusion of participants from vulnerable populations, and/or any change that may increase the risk or discomfort to participants. Changes to key personnel must also be approved. The purpose of review is to determine if the project still meets the federal criteria for exemption.

  Non-exempt research is subject to many regulatory requirements that must be addressed prior to implementation of the study. Conducting non-exempt research without IRB review and approval may constitute non-compliance with federal regulations and/or academic misconduct according to ISU policy.

  Detailed information about requirements for submission of modifications can be found on the Exempt Study Modification Form. A Personnel Change Form may be submitted when the only modification involves changes in study staff. If it is determined that exemption is no longer warranted, then an Application for Approval of Research Involving Humans Form will need to be submitted and approved before proceeding with data collection.

Please note that you must submit all research involving human participants for review. **Only the IRB or designees may make the determination of exemption**, even if you conduct a study in the future that is exactly like this study.

Please be aware that **approval from other entities may also be needed.** For example, access to data from private records (e.g. student, medical, or employment records, etc.) that are protected by FERPA, HIPAA, or other confidentiality policies requires permission from the holders of those records. Similarly, for research conducted in institutions other than ISU (e.g., schools, other colleges or universities, medical facilities, companies, etc.), investigators must obtain permission from the institution(s) as required by their policies. **An IRB determination of exemption in no way implies or guarantees that permission from these other entities will be granted.**

Please don't hesitate to contact us if you have questions or concerns at 515-294-4566 or IRB@iastate.edu.