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Estimating truncated hotel demand: A comparison of low computational cost forecasting methods

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ESTIMATING TRUNCATED HOTEL DEMAND: A COMPARISON OF LOW COMPUTATIONAL COST FORECASTING METHODS

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献给我的母亲李淑玲，父亲丁守仁。

我生命里美好一切愿与他们分享。

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ABSTRACT

Ding, Yue. M.S., Purdue University, May 2014. Estimating Truncated Hotel Demand: A Comparison of Low Computational Cost Forecasting Methods. Major Professor: Hugo Tang.

The aim of this thesis is to evaluate the effectiveness of six selected low computational cost hotel demand forecasting methods (SA, SMA, EMA, DEMA, BP and PU) in terms of restoring truncated demand data, and then identify a low-cost and easy to follow demand forecasting method that can be used by U.S. independent hotels.

Obtaining revenue gains by applying demand forecasting techniques have been proved by many studies in hospitality and other related industries. However, few studies have focused on low computational forecasting methods' comparison in hospitality field. For this reason, the author decided to test the performance of six selected demand forecasting techniques, with the aim of identifying an effective method for hotels operators constrained by financial resources and expertise.

This thesis first simulates leisure and business real demand booking curves under a pre-decided increasing rate in each of three leisure/business ratio scenarios (1:3, 1:1, and 3:1). In the second stage, true demands are truncated in three cases. They are 1) capacity truncation, 2) 50% truncation of total business demand, and 3) 25% truncation of total business demand. And then, six selected forecasting methods are applied to the truncated demand. Finally, the forecasting accuracy for each method is evaluated in both statistical and economical models.

The results of the experiment indicate that PU method outperform all the other selected methods and was proved to be the most effective forecasting method for U.S. independent hotels. Other new findings include that the data restoration accuracy ranged from a negative relationship with the business demand proportion of total bookings, and the higher the percentage the business bookings were truncated, the smaller the detruncation error occurs. The results also shows that the less the business booking was truncated; the more variable the forecasting error occurs. An interesting finding of this thesis is that in some specific circumstances, the results of statistical evaluation do not completely in accordance with economical evaluation results.

CHAPTER 1. INTRODUCTION

1.1 The Role of Demand Forecasting in Revenue Management

1.1.1 Definition of Revenue Management

Every product or service seller faces a certain number of elementary decision issues. For instance, a vendor selling hot dogs on the street in Washington, DC, has to decide on which day to have a sale, how much to ask for each hot dog, and when to drop (or raise) the price as the day rolls on. Businesses face even more complicated selling decisions, for example, how to segment customers by providing different conditions and terms of trade, how to profitably exploit customers' different buying behaviors or willingness to pay, and so on.

Revenue management (RM), or yield management, is concerned with such demand-management decisions and the methodology and systems required to make the decision (Talluri & Van Ryzin, 2005). The application of revenue management enables hot dog vendors and business companies to get the right methods to sell the right products to the right customers at the right time for the right price, thus maximizing revenue from their products or services (Cross, Higbie, & Cross, 2009).

1.1.2 Introduction of Demand Forecasting

Pricing, inventory, marketing, and channels are the four primary levers of revenue management (Phillips, 2005). Among them, inventory control is defined as the science-based art of controlling the amount of inventory (or stock) held within an organization to meet the demand placed upon that business economically (Dong, Kouvelis, & Tian, 2009). To control the amount of inventory, it is necessary to forecast the level of future demand, which makes demand forecasting an important element in revenue management decision making.

Demand forecasts are necessary because the basic operations process, moving from the suppliers' raw materials to finished goods to the consumers' hands, takes time, particularly in the current global economy. Most companies can no longer simply wait for demand to occur and then react to it with the right product in the right place at the right time because they need to sense demand information ahead of time and shape demand in anticipation of future customer behavior so that they can react immediately to customer orders. Demand forecasting is not only critical to driving out inefficiencies in the supply chain in the retail industry but also affects all facets of the company on an enterprise-wide basis for most service industries. Predicting future demand determines the quantities of raw materials, amount of finished goods inventory, number of products that need to be shipped, number of people to hire, number of plants to build, right down to the number of office supplies that should be purchased.

In most cases for the retail industry, manufacturers make to stock rather than make to order. They plan ahead and then deploy inventories of finished goods in distribution centers (DCs) to support demand at the source to more efficiently restock customers. This way, once a customer order materializes, it can be fulfilled immediately, as most customers are not willing to wait as long as it would take to actually make the product and ship it. Given the long lead times to acquire raw materials from multiple sources globally, it makes sense for companies to maintain finished goods inventories in designated markets at DCs in order to provide faster order cycle times. Even companies that claim to make to order, when in fact they are really packaging to order, need to rely on more accurate demand forecasts to order raw materials and common subassemblies. This is especially true in the electronics industry, and PC manufacturers in particular that take customer orders over the Internet. As a result, virtually all retail companies need to rely on a forecast of future demand, and the ability to accurately forecast demand provides a means for retail companies to improve supply chain efficiencies through a reduction in costs, not to mention improve their customer service.

In most service industries, customer demand forecasting is also an important step in many business revenue management settings. Suppose two types of consumers purchase a product. The first type values the product highly and thus is willing to pay much more than the other type. This first type also values superior product characteristics and will pay more for them. Any sensible businessperson would try to segment the two, offer the appropriate level of services, and charge accordingly. By estimating the quantity of the product or service that the customer will purchase using informal methods (i.e., educated guesses) and quantitative methods (i.e., the use of historical or current sales data from test markets), an enormous amount of data would be made available to decision makers. In addition, applying intelligent systems for balancing supply and demand and improving profits would not be a difficult task for revenue managers to achieve.

1.1.3 Demand Forecasting in the Hotel Industry

Hotel demand forecasting is defined as the activity of estimating the number of room nights or services that consumers will purchase (Frechtling, 2012). The most important problem in managing hotel revenue is forecasting customer demand by different market segments. For example, if customers all make reservations at the same time, the only task for the hotel revenue manager is to identify whether a customer was high value or not and then charge accordingly. However, passengers do not book at once. Usually, a chain hotel room's booking process is open up to a year ahead of time, and independent hotels' processes open up to half a year ahead of arrival day. Generally, a hotel's best rate can appear and disappear, on and off, at almost any time, and particularly at 90-, 60-, 30-, 14/15-, and 7-day periods before the arrival day. Thus, to follow this timeline, customers usually book rooms between 100 and 0 days ahead of their stay (Thyberg, 2008). In this case, a worrisome problem is created: If high-value customers arrive late and low-value customers arrive early, how do we ensure that enough rooms are saved for later-arriving customers without unnecessarily turning away low-value early arrivals? Decision makers have to determine how many hotel rooms (flight seats or rental cars) to allow low-fare customers to book when the possibility of future high-fare demand exists from forecasting.

However, in a hotel-specific case, demand is censored when bookings-in-hand reach booking limits, and no more requests will be taken unless a cancellation occurs. Therefore, when the true request is above the booking limit, only the observed maximum number of room restrictions will be carried out as true demand by hotels. With censored data, hotels are likely to underestimate the demand. Up to 3% of potential revenue may be lost if the forecast used by a revenue management system (RMS) has a negative bias (L. R. Weatherford, 1997).

Therefore, to solve customer demand forecasting issues, demand forecasting and detruncation methods are applied in the hotel industry. Detruncating, also called unconstraining or uncensoring, refers generically to the process of estimating the parameters of a distribution based on truncated or incomplete data (L. R. Weatherford, 1997).

1.2 Challenges for Independent Hotels in Applying RM

Independent hotels, as a special hotel classification, face special difficulties in applying revenue management in operations.

First, independent hotels are individual properties that not affiliated with a chain or a parent company or specific brand (*U.S. Hotel Operating Statistics Study·Report for the year 2011*, 2012). They typically have independent ownership and may have multiple investors. Different from chain hotels, independent hotels do not share in a widely recognized brand name, chain code, and various management resources, such as revenue management systems (Hutchison, 2011).

Second, in the past several decades, many studies and articles have promoted the use of demand forecasting and detruncation techniques in the hospitality industry (Queenan, Ferguson, Higbie, & Kapoor, 2007b; Larry R. Weatherford, 2013; Larry R. Weatherford & Pölt, 2002); however, not all methods are applicable for all types of hotels. The fact is, a number of forecasting and detruncation methods are based on complex statistical procedures and are often too difficult for independent hotel operators to understand and use. Unlike large chain hotels, independent hotels with fewer shared resources may not have sufficient fiscal expenditure plans to purchase commercial revenue management system, largely due to the price (Hutchison, 2011).

1.3 Why Independent Hotels

According to Smith Travel Research's 2012 report, the affiliation of a single hotel is classified into three types: corporate, franchise, or independent. A corporate hotel is a chain hotel owned/managed by the chain/parent company, while a franchise hotel is a chain hotel run by a third party where the chain receives some sort of franchise fee.

Different from corporate and franchise hotels, an independent hotel is not affiliated with a chain or a parent company or a specific brand.

In the last 50 years, the percentage of chains versus independents in the United States has changed dramatically. In the mid-1900s, the percentages in the U.S. were similar to the current percentages outside the U.S. (40% vs. 60%, or 30% to 70%). However, in 2012, the percentage changed to 70% vs. 30%. Figure 1.1 presents the current percentage of chain hotels versus independents in and outside the United States (*U.S. Hotel Operating Statistics Study·Report for the year 2011*, 2012).

Although chain hotels have gradually taken the leading position from independents and make up a larger proportion of the U.S. hotel market, independent hotels still occupy a certain proportion of the U.S. hospitality industry. Until 2012, there were nearly 22,000 independent hotels in the U.S., which consist of nearly 1.5 million rooms. There were nearly 92,000 independent hotels in the world with more than 6.7 million rooms. Table 1.1 shows the number of U.S. properties and hotel rooms in three hotel affiliations in 2012.

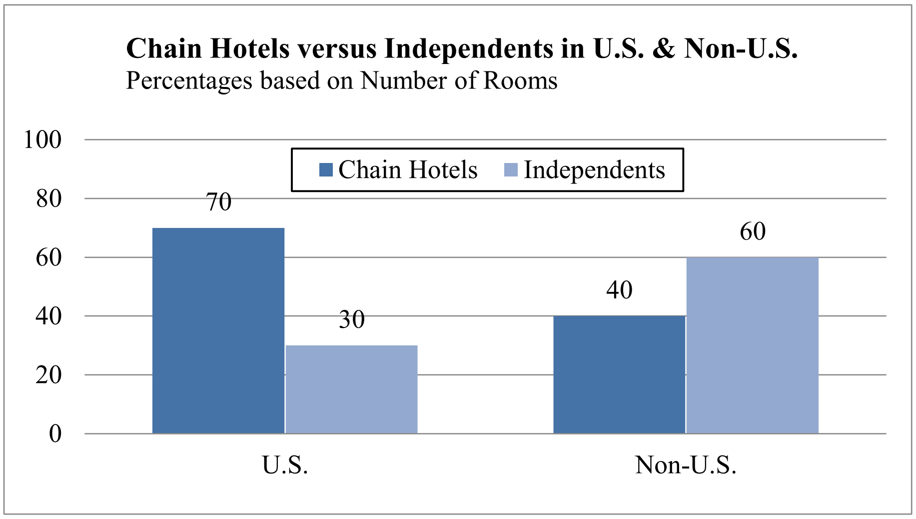


Figure 1.1 Chain hotels versus independents in U.S. and Non-U.S. (Non-U.S. percentage (40/60) is based on hotels in the STR database, much harder to find Non-U.S. independents, probably closer to 30/70 or 20/80 (*U.S. Hotel Operating Statistics Study·Report for the year 2011*, 2012))

Table 1.1 Number of properties and rooms in the U.S. of hotels in three hotel affiliations (*U.S. Hotel Operating Statistics Study·Report for the year 2011*, 2012)

Operation	**U.S. Properties**	**U.S. Rooms**
Chain- Corporate	4,541	896,550
Chain- Franchise	25,520	2,469,127
Independent	21,893	1,494,662

In addition, in the past 30 years, thanks to the fast growth of revenue management as a branch in operations research (OR), many demand detruncation methods have been designed specifically aimed at hotel and hotel-related industries. However, very few, if any, academic studies have explored the feasibility of demand forecasting or detruncation methods for independent hotels. Therefore, the gap regarding independent hotels in the literature needs to be filled, and industry practitioners' attention needs to be brought to which demand detruncation algorithm is the most effective for small non-chained hotels with different customer segment ratios.

1.4 Objectives of the Study

The goal of this study is to evaluate the performance of selected hotel demand forecasting and detruncation methods and then identify a low-cost, easy-to-follow detruncation method that can be used by hotel operators constrained by financial resources and expertise.

As discussed in the previous section, demand forecasting is a crucial step in the hotel revenue management process. In practice, however, the observable demand is not necessarily the true demand because true demand data are often truncated due to various constraints such as capacity limitation and booking restrictions. To overcome this problem, detruncation methods are used to extrapolate true demand from the observed demand (i.e., booking record). By comparing the performance of six selected forecasting methods (i.e., simple average [SA], simple moving average [SMA], exponential moving average [EMA], double exponential moving average [DEMA], booking profile [BP], and Pick-Up [PU]) with two robust statistical detruncation methods (i.e., expectation maximization [EM] and projection detruncation [PD]), this paper aims to 1) evaluate the effectiveness of simple hotel demand forecasting techniques in restoring the demand data and 2) analyze the eight methods' practical feasibilities and point out the advantages and disadvantages of selected forecasting and statistical detruncation approaches in different target market mix scenarios.

1.5 Benefit of the Study

Industry operators and academic researchers will benefit from the uniqueness of this study. The special contribution of the research can be summarized in two aspects.

The first contribution of this study lies in the study objectives. This research targets U.S. independent hotels and analyzes the effectiveness of the selected forecasting and statistical detruncation methods for these hotels in a revenue dimension and then tests whether our selected forecasting methods are sufficient in providing reasonable demand estimations for U.S. independent hotels. As explained in section 1.2.2, 1) independent hotels occupy a certain proportion of the hospitality industry; 2) some quick, inexpensive, simple, and short-term detruncation tools are necessary for independent hotels for actual demand estimation; and 3) only a handful of existing studies in hotel demand forecasting consider independent hotels, this specific hotel category.

Apart from the study objectives, another unique contribution of this study is that this research considers three customer segment ratios (i.e., the demand of leisure/business customer ratio equals 1:1, 1:3, and 3:1) when testing different detruncation techniques. In many hotels, most business travelers prefer to stay on weekdays while weekend stays are more popular for leisure travelers. Very little hospitality academic research has explored the implications of demand forecasting and detruncation methods for various customer segment ratios, let alone independent hotels. It is crucial for hotel practitioners to know if a difference exists in applying detruncation techniques to independent hotels for different guest constitution ratios.

1.6 Definition of Terms

- True demand

True demand, or real demand, for a hotel is defined as the total number of rooms demanded by customers. This includes booking (requests that are met) and rejections (requests that are not met) records.

- Truncated demand (data)

Demands are considered truncated (or constrained or censored) if the booking limit in a given type of room at a specified review point in the history of the service product is less than or equal to the number of bookings present at that time.

- Demand detruncation

Method by which hotels whose room bookings reached capacity are adjusted to gain a prediction of demand that has no capacity restriction.

- Detruncated (unconstrained) demand

Unconstrained demand is defined as the number of reservations that would be accepted if restrictions or capacity constraints were not in place.

CHAPTER 2. LITERATURE REVIEW

2.1 Revenue Management and Its Application in the Hospitality Industry

2.1.1 The Development of Revenue Management

Cleophas and Frank (2011) stated that the very basic example of revenue management is experienced firsthand at the farmer's market in the retailing industry 30–40 years ago. At that time, fruits, vegetables, and bread in the market were priced in accordance with the customer's arrival time. For example, early customers paid full price for fresh goods, but at the end of the day, vendors dropped the price for goods that are not fresh. However, Cross et al., (2009) demonstrated that revenue management was created by the airline industry. They illustrated that in the early 1980s, yield management began to be used in the airline industry as a crucial way to provide and control differentially priced, time-sensitive products in various market segments and therefore increase returns. At this point, the bulk of academic research on RM has been published on the airline industry (McGill & Van Ryzin, 1999).

Then, the technique of yield management was applied in the hospitality industry by Marriott International in the mid-1980s (Cross, et al., 2009). This technique made sense to the hotel industry because the airline and hotel industries share many of the same management issues, for example, perishable inventory, advance bookings, low-cost competition, and challenges in balancing supply and demand. After yield management was applied to the hotel industry, the name was changed to revenue management (Koestler, 2011).

Since then, revenue management has developed in a large part thanks to the collapse of international travel and the industry recession caused by the 9/11 terrorist attacks (Hawksworth, 2010). After experiencing nearly 3 years of a dark age triggered by 9/11, hospitality's revenue management started to shift from a tactics focus to a strategic focus (Cross, et al., 2009; Koestler, 2011). This role transition of revenue management has created broader responsibilities for hotel revenue managers. The front office manager no longer focuses only on inventory; revenue management must go beyond purely managing hotel room inventory to considering total revenue contributions, sales, marketing, and brand management (Hawksworth, 2010; Koestler, 2011). With the evolution of the hotel industry, the recruitment of more professional employees in this area led to more executive discipline in most international brand hotels (Cross, et al., 2009).

2.1.2 Revenue Management

- Original RM and modern RM

In one sense, revenue management is a very old idea, both in practice and theory. In 2005, Peter defined RM as the science and art of enhancing firm revenues while selling essentially the same amount of product. However, different from the original RM, modern revenue management is not demand management itself but rather how these decisions are made (Talluri & Ryzin, 2006).

The conceptual change from original RM to modern RM was driven by two complementary forces (Talluri & Ryzin, 2006). The first one is scientific advancement in economics, statistics, and operation research, which makes it possible to model demand and economic conditions, quantify the uncertainties faced by decision makers, estimate and forecast market response, and compute optimal solutions to complex decision problems. The second complementary force is the improvement in information technology, which provides the capability to automate transactions, capture and store vast amounts of data, quickly execute complex algorithms, and then implement and manage highly detailed demand-management decisions. Above all, modern revenue management has been defined by Talluri and Van Ryzin (2006) as the process of managing demand decisions with science and technology implemented with disciplined processes and systems, and overseen by human analysts. RM can also be viewed as a sort of "industrialization" of the entire demand-management process.

- Characteristics of organization for RM implementation

In general, any time a service business has the characteristics of 1) constrained supply 2) high fixed costs, 3) variable demands, 4) versioning opportunities, 5) perishable inventory, 6) the ability to manage differential pricing, and 7) the ability to communicate efforts, the business can use revenue optimization strategies and tactics in RM operations (Hayes & Miller, 2011).

Taking the hotel industry as an example and assessing an organization's ability to implement revenue management strategies, using the seven characteristics provided in the previous paragraph, the organization assessment is shown in Table 2.1.

Table 2.1 Organization Assessment of the Hotel Industry

Characteristics	**Organization Assessment**
1. Constrained supply	Yes. Further demand requests will be denied by the hotel's booking system when its booking limit is reached; meanwhile, the hotel's historical data represents only censored demand at the restricted record.
2. High fixed costs	Yes. The incremental cost of accommodation for each customer is the major cost. If customers purchase food, beverages, or banquet services from the hotel, each incremental guest likely contributes additional revenue that exceeds his or her incremental costs.
3. Variable demand	Yes. In most cases, business customer demand is predictably highest on weekdays, and leisure customer demand is highest on weekends and selected holidays.
4. Versioning opportunities	Yes. Traditional versioning includes providing standard rooms. However, different room sizes, features, and amenities all provide grounds for creative product versioning for hotels.
5. Perishable inventory	Yes. Hotel room nights as the inventory cannot be carried over from one day to the next.

6. Ability to manage differential pricing	Hotel revenue managers routinely implement differential pricing strategies. They charge different prices to different buyers for the same product or slightly different versions of the same product.
7. Ability to communicate efforts	Beyond traditional price advertising, this could be limited and thus restricted. The typical customer may visit the hotel's web site or hear of it through other customers; however, call-in or walk-in customers are very common. External communications may be limited to electronic communication with customers who have previously stayed in the hotel or who have been exposed to the hotel's advertising. As a result, well-designed external and internal communication programs are essential for an effective differential pricing program.

2.1.3 Revenue Management Industry Application

Revenue management is traditionally applied primarily in the airline, hotel, and car rental industries, while other service industries, such as restaurants, golf, and retail, which share some common characteristics with traditional industries, can improve their revenues and profit from an appropriate application of revenue management as well (Hayes & Miller, 2011). However, most current studies still focus on traditional areas, and those on non-traditional industries are in the beginning stage (Talluri & Ryzin, 2006). The implementation of revenue management will be discussed in the next few paragraphs.

- Hotel industry

Hotels serve a wide range of customers, including individual guests as well as groups. The classic segmentation of individual customers is between business and leisure guests (Queenan, Ferguson, Higbie, & Kapoor, 2007a; Talluri & Ryzin, 2006). Those traveling for business purposes have strong time preferences. They thus tend to value schedule convenience and booking/cancellation flexibility and are considered relatively price-insensitive, because, in most cases, their travel expenses are paid by their employers or charged to clients. Leisure travelers, however, tend to be more sensitive to price because they are paying from their own pockets (Talluri & Ryzin, 2006). However, because these customers are traveling for discretionary purposes, they tend to have more flexibility in their travel dates and can modify their schedule to find a good deal. They are also willing, and even prefer sometimes, to pre-commit to travel many days ahead of departure. The two segments also differ in travel-time preferences, with business travelers preferring to leave on weekdays and return by the weekend, and leisure travelers preferring to depart at the end of the week and stay over a weekend. Leisure travel peaks around major holidays, while business travel drops at these points in time.

Other than customer types, the diversity in sales channels, types, and operations of hotels means RM practices in the industry also vary considerably. Hotels are categorized as business, extended-stay, resorts, or a mix of business and leisure and by size (large, small) and location (airport, urban, central business district or CBD, highway, beach). Hotels may be managed by independent owners, as part of a chain that is managed directly by employees of a single corporation, or as part of a franchise. Some hotel companies manage only individual properties, while large hotel chains sometimes manage a property without taking ownership. In a typical large hotel, approximately 60% to 80% of the bookings are made directly with the hotel, either locally, through the Internet, or through a centralized call center. The remaining bookings come from Global Distribution Systems (GDSs). The Hotel Electric Distribution Network Association (HEDNA) reported that GDSs delivered more than 43 million bookings for hotels, with a value in excess of $12.5 billion in 1999.

Due to the more fragmented nature of the industry, hotel RM practices tend to exhibit greater variation than airline RM practices. Revenue management has been widely applied in the booking process, property management systems (PMSs), and capacity controls area in hotels (Badinelli, 2000). Cross (1997) reported that revenue management helped Marriott Hotels gain $100 million of additional annual revenue. Elliott (2003) presented how revenue management can contribute substantially to cost savings and revenue maximization while helping maintain quality.

- Airline industry

The airline industry was the earliest and largest user of revenue management. As mentioned in chapter 1, RM has its origins in the rise of capacity-controlled discount fares after the U.S. airline industry was deregulated. Before deregulation, the only service options offered by commercial airlines were first-class and coach-class service. Fares on a route were identical for all carriers and set by the Civil Aeronautics Board (or by the International Air Transport Association) on international flights based on standard cost. The period after deregulation in the United States was characterized by successive innovations in creating discounted products. Today, most airlines offer discounts based on a relatively stable set of restrictions, such as advance purchase or round-trip travel requirements, etc.

In addition to different restrictions, different prices can be set at different levels of itinerary, data of travel, fare product, and point of sale. Because airline products are itineraries on a network of flights, an itinerary can also consist of flights involving several airlines (or interlining). Even if all flights are on a single airline, pricing an itinerary is complicated by the fact that there are often many different ways to do so since an itinerary many involve multiple connection possibilities. Thus, an airline with 500 flights a day may offer hundreds of thousands of possible itineraries for sale.

Obtaining revenue gains by applying RM techniques in the airline industry has been proved by many studies in the past. Chairman and CEO of AMR Corporation (American Airlines holding company), R.L. Crandall estimated in 1992 that revenue management had generated $1.4 billion in incremental revenue in 1990–1992. The President of Sabre Decision Technologies (a provider of business solutions to clients worldwide in the travel, transportation, and other industries), Tom Cook, asserted in 1998 that the yield management system at American Airlines created almost $1 billion in annual incremental revenue.

- Car rental industry

RM applications in the car rental industry have similarities to airline and hotel RM. However, there are differences worth noting. One significant feature of car rental RM is the nature of capacity. Capacity is much more flexible than in either airline or hotel RM. For example, a car rental company may operate more than one location in a city or a geographic area. Inventory at the locations can be pooled, allowing greater flexibility in adjusting capacity to meet demand. Even if there is only one location in a given area, capacity can usually be increased or decreased by inter-pool moves, by moving cars from nearby cities, and by controlling the sale of older vehicles and turn-backs to manufacturers. Available capacity is also affected by customers who rent at one location and drop off at another. This means the capacity itself is often uncertain. Thus, suggestions that researchers give to car rental industry in applying revenue management techniques are adjust prices frequently according to demand, serve high-valued fleet utilization with priority, and accept or reject booking requests based on length-of-rental controls.

- Golf industry

Revenue management applies well to golf course management as the RM strategy relies on controlling the duration of service use and basing pricing mainly on consumer demand for golf (Kimes, 2000; Kimes & Chase, 1998). In 2009, Lila and Yihua analyzed golf course tee-time reservation practice, and presented a unique linear model that can be used to assign the demand to the available tee times, and thus, maximize their use and the total revenue (Rasekh & Li, 2011). Kimes and Wirtz (2003) also studied the perceived fairness of six revenue management practices in the golf industry. The researchers stated that fences can be physical or non-physical, and fences ensure that if customers are willing to pay a higher fee or price they will.

- Casino industry

In terms of the casino industry, RM is applicable in two areas: renting out the casino's hotel rooms and managing capacity and pricing in the gaming area. According to Pinchuk (2006), the average daily gambling revenue from the different gamer types can range from $20 to $20,000, so it is understandable that the revenue from rooms is not the highest priority for a casino. Indeed, many casinos give rooms away free to their top, "high-roller" customers. The RM problem in casinos, therefore, is one of controlling availability based on a combination of room revenues and the amount a customer is expected to spend on the casino's gambling floor. RM systems are designed to assess customer value through a gaming value function. The software recognizes and ranks repeat guests by their gambling history. Guests are ranked in tiers. High-rollers are identified and receive the lowest room rates, while first-time guests and non-gamblers get the rack room rate (Pascal, Kelly, Glusker, Nicely, & Burns, 2001).

- Restaurant industry

Unlike the widespread application of revenue management method in traditional industries, the number and depth of studies on revenue management in the restaurant industry have been comparatively slim. Kimes (1999; 1998) and Kimes et al. (1999) were among the first to directly address the issue of restaurant revenue management. They stated that the crucial element in a strategy for boosting restaurant revenues is how to relate prices to the length of time guests spend at the table, and they built a strategic framework for applying RM to restaurants to increase demand, and thus revenue, by effective duration management and demand-based pricing. Similarly, Sill et al. (1999) proposed the use of capacity-management science (CMS) as a systematic method of assessing a restaurant's capacity potential and process efficiency. In 1992, Vakharia et al. (1992) developed models and heuristics to find the best trade-off between wages and hour preferences to minimize the cost of employees while maintaining employee satisfaction. Quain et al. (1998) and Muller (1999) addressed managerial factors that may improve restaurant efficiency, such as realizing profit centers, dispersing demand, decreasing operating hours, and decreasing service time by making the restaurant operational procedures as efficient as possible.

- Retail industry

Revenue management in retailing is a relatively new but growing practice. Apparel and grocery retailers have to deal with highly perishable and seasonable products. High-tech retailers (PCs, consumer electronics) have similar problems, as their inventory loses value rapidly due to technological obsolescence. These characteristics mean that tactical demand management is important economically for retailers. In 2001, Coulter stated that revenue management is appropriate in the “seasonal” retailing industry in which capacity (inventory) is not necessarily “perishable” but the value of the capacity may decline significantly after the selling season. He investigated using discount pricing to maximize the revenue gained from selling a “seasonal” product. Aviv and Pazgal (2005) performed a quantitative analysis on applying dynamic pricing to sell fashion-like goods for “seasonal” retailers. Attention has focused on pricing strategy, market share preservation, and customer loyalty when implementing RM methods for grocery retail outlets in studies by Hawtin (2003) and Lippman (2003).

2.2 Demand Forecasting

2.2.1 The Development of Demand Forecasting

Business forecasting during the early years was largely based on the exponential smoothing forecasting methods developed by an industry practitioner, Robert G. (Bob) Brown, in the late 1950s (Chase Jr, 2013). These exponential smoothing methods still live on today and are often regarded as the under-the-hood statistical forecasting engines powering many software packages. In the last two decades, forecasting methods have evolved since then to include a wide variety of statistical time series methods, and the focus started changing toward demand-driven forecasting.

More sophisticated and effective techniques for estimating demand were created in the 1990s. This decade was a period of increased consumerism, and a business forecasters' job became much more difficult, especially in the United States. During this period, the dramatic growth in the entities that must be forecast by multinational organizations made demand forecasting methods and systems larger in scale. Business planning became more complex in terms of having to deal with the many products being sold, many with short life cycles, the number of countries into which the products are sold, as well as the number of channels sold through. In addition, technology has been evolving to keep up with this dramatic growth in scale. By necessity, marketing and sales organizations developed more sophisticated and effective ways to simulate demand for the products the organizations were promoting. Industry forecasters started to experiment with and use methods that no longer assumed that demand just magically happened and could be estimated only from understanding what happened in the past. Now, demand forecasting has become a critical function that influences companies worldwide across all industries, including airline, hospitality, heavy manufacturing, consumer packaged goods, retail, pharmaceutical, automotive, electronics, telecommunications, financial, and others.

2.2.2 The Role of Demand Forecasting in Revenue Management

Forecasting is defined as the use of systematic procedures (e.g., judgment, a "rule of thumb," or mathematical technique) and historical data to predict how demand will be realized in the future. Demand forecast is the single most crucial piece of data revenue managers will review and evaluate when seeking to maximize room revenue (Larry R. Weatherford & Kimes, 2003). In the hospitality industry, an accurate demand forecast can help hotel revenue managers to evaluate whether the room demand is robust (or frail) enough to dictate significant changes in the pricing strategies, which is designed to assist hotels in terms of decision making, planning, and then achieving their market goals (Larry R. Weatherford & Kimes, 2003).

Obtaining revenue gains by applying RM techniques have been proved by many studies in hospitality and other related industries (Klophaus & Pölt, 2007; S. Lee, Garrow, Higbie, Keskinocak, & Koushik, 2011; Thompson & Killam, 2008; Larry R. Weatherford & Pölt, 2002). Revenue gain occurred at Ford Motor Co. From 1995 to 1999, revenue rose 25%, and pretax profits soared 250%, from $3 billion to $7.5 billion. Of that $4.5 billion growth, Ford's Lloyd Hansen, controller for global marketing and sales, estimated in 2000 that about $3 billion came from a series of revenue management initiatives (Olive, 2005). For an airline company, the impact of underestimating demand by 12.5% can hurt revenue by 1–3% on high-demand flights (Larry R. Weatherford & Pölt, 2002). Pölt (2000) estimated that a 20% improvement in forecasting error translates into a 1% increase in revenue generated from the revenue management system. In terms of hotel food and beverage outlets, forecast accuracy improved by more than 11% on average when occupancy data are used (Thompson & Killam, 2008).

Forecasting is particularly important in hotel revenue management because of the direct influence demand forecasts have on the booking limits that determine hotel profits (Guo, Xiao, & Li, 2012). Many researchers have stated that accurate demand forecast for each market segment is a significant step in a successful revenue management process for hotels (A. O. Lee, 1990). For instance, Lee (1990) estimated that a small improvement of 10% in forecasting accuracy contributed to a 0.5–3% increase in expected revenue in a hotel. If no active and accurate forecasting program is in place, hotel revenue managers consistently make misinformed decisions and continually lead their hotels in directions that are detrimental to the property and customers, causing unexpected consequences for hotel organizations (Hayes & Miller, 2011). Table 2.2 provides the uses of demand forecasts and the consequences of poor forecasting in the hotel industry (Hayes & Miller, 2011).

Table 2.2 Uses of demand forecast and corresponding consequences of poor forecasting (Hayes & Miller, 2011)

Uses of demand forecasts	**Consequences of poor forecasting**
Setting marketing goals	Over-or under-budgeting for marketing
Exploring potential markets	Marketing to the wrong segments, ignoring the right ones
Simulating impacts on demand	Incorrect marketing mix, e.g., setting prices too high
Determining operational requirements	Excess labor, or customer unhappiness with limited service
Examining the feasibility of a major investment in plant or equipment	Wasted financial resources, difficult in financing interest payments

Predicting economic, social, and environmental consequences	Environmental and social/cultural degradation; inflation or unemployment
Assessing potential impact of regulatory policies	Business losses, unemployment, price inflation
Projecting public revenue	Budget deficits
Planning for adequate capacity and infrastructure	Traffic congestion, delays, and accidents

2.3 Independent Hotels

In the United States, independent hotels constitute a certain proportion of the hospitality industry. According to Rick Swig (2000), independent hotels have lost ground in market coverage to the brand sector. Although the percentage of U.S. independent hotel rooms versus total supply slipped from 38.9% in 1990 to 30.3% in 1999 due to significant growth in the economy and mid-scale chain sectors, the actual inventory has barely decreased. Today, approximately 1.5 million independent hotel guest rooms are available daily versus 1.25 million average daily rooms in 1990 (*U.S. Hotel Operating Statistics Study·Report for the year 2011*, 2012).

Tables 2.3 through 2.5 are drill-down tables of U.S. independent hotels. Table 2.3 provides the number of properties in each independent hotel class, while Tables 2.4 and 2.5 drill down independent hotels in the U.S. by location and room size, respectively. To sum up: there is a high percentage of independent hotels in economy scale, small town location, and in 50 rooms or less size group.

Table 2.3 Independent Hotels in the U.S.: Drill Down by Price Level

Class (Price Level)	**Properties**
Economy	**13,901**
Midscale	2,781
Upper Midscale	1,834
Upscale	1,589
Upper Upscale	1,259
Luxury	780

Table 2.4 Independent Hotels in the U.S.: Drill Down by Location

Location	**Properties**
Urban	2,190
Suburban	5,083
Airport	404
Resort	2,525
Interstate	2,290
Small Town	**9,652**

Table 2.5 Independent Hotels in the U.S.: Drill Down by Room Size

Number of Rooms	**Properties**
25 or fewer	**6,158**
26–50	**8,090**
51–75	3,021
76–100	1,622
101–125	988
126–150	625
151–175	375
176–200	297
201–250	320
251–300	171
301–400	200
401–800	176
More than 800	101

Table 2.6 and Figure 2.1 provide the average Occupancy, ADR, Property, and Rooms Size for the seven hotel scales (i.e., Luxury Chains, Upper Upscale, Upscale Chains, Upper Midscale, Midscale Chains, Economy Chains, and Independents). The average ADR for Independents ranks between Upscale Chains and Upper Midscale Chains, while the number of properties and rooms of Independents ranks the top among all the hotel scales.

Table 2.6 Occupancy, ADR, number of Properties and Rooms in each hotel scale (*U.S. Hotel Operating Statistics Study·Report for the year 2011*, 2012)

U.S. Scales				
Scale	Occupancy	ADR	Properties	Rooms
Luxury Chains	66.5%	$243.62	378	124,185
Upper Upscale	67.4%	$142.54	1,494	547,641
Upscale Chains	66.8%	$107.81	3,652	565,703
Upper Midscale	58.4%	$91.42	7,674	766,494
Midscale Chains	51.7%	$73.68	6,374	563,582
Economy Chains	51.6%	$49.31	10,271	781,825
Independents	**54.7%**	**$95.83**	**20,919**	**1,438,525**

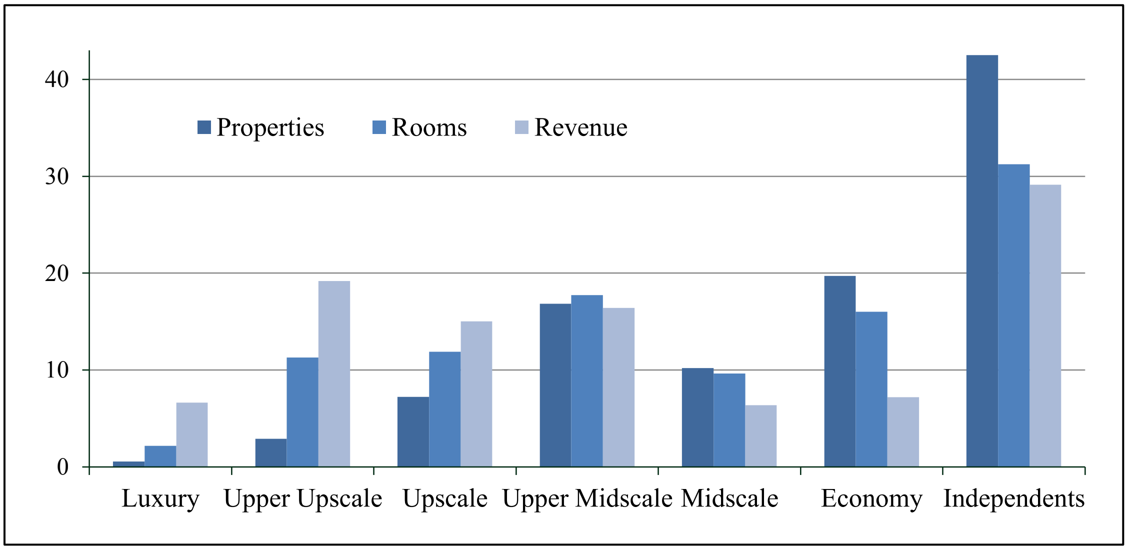


Figure 2.1 Scale Overview: Percent of Properties, Rooms, and Revenue by Scale, Counts as of July 2012 (Copyright 2012 Smith Travel Research)

2.4 Censored Data Forecasting

Censored data detruncation is a major step in the demand forecasting procedure of the revenue management system, especially when a hotel is always fully booked (Larry R. Weatherford, 2013). Further demand requests will be denied by the hotel booking system when its booking limit is reached. Hotels' historical data represent only censored demand at the restricted record. Since hotels have records only of actual bookings, hotels must estimate the true demands that would have been received without any constraint on the products. The forecasting accuracy can be improved by 2–12% if hotels use appropriate detruncation methods (Wickham, 1995).

In general, a hotel has five real demand forecasting options when the hotel's true demands are truncated. The options are 1) observe directly, 2) ignore the censored data, 3) discard the censored data and use uncensored data only, 4) impute, and 5) statistically detruncate (Guo, et al., 2012). These five detruncation method categories will be described in the following paragraphs.

The first three categories originated in the early years of revenue management. They are the simplest methods for estimating detruncation demand from censored data (Pölt, 2000):

1) **Observe directly**. This refers to direct observation and record of potential demand. Historical records that must be observed include requests that are met and not met. This method, however, is not an ideal demand detruncation option for most industries because it is susceptible to observer bias and can lead to erroneous demand forecasting results. Thus, many issues should be considered when using it. For example, only a small part of booking is controlled directly by the company.

2) **Ignore the censored data**. This means ignore censorship and accomplish estimates as though the censoring never happened. When this method is used, unexpected consequences such as underestimated or overestimated future demand can easily happen.

3) **Discard the censored data and use uncensored data only**. This can be viewed as a complete data method of dealing with incomplete data. It performs well only when the data are censored completely at random, and the missing data are fairly minimal. However, if there are some correlations between censored data and variables in the study, discarding them is potentially harmful.

These approaches yield biased estimates of future demand, and none provides acceptable results. The other two detruncation categories were generated after demand forecasting issues were intensively studied in the airline industry (Pölt, 2000).

4) **Time-Series forecasting.** Time-Series forecasting methods are based on well-specified classes of models that describe the underlying time series of data. Although these models have relatively simple mathematical structures, the model classes are rich enough to represent a wide range of data characteristics (Talluri & Ryzin, 2006). Techniques that based on simple time series theory include average and smoothing methods. Among them, DES, which usually been used in the hotel industry, is based on simple time-series theory (Talluri & Ryzin, 2006).

5) **Deterministic detruncation.** An algorithm is said to be deterministic if at any point of execution there is, at most, one possible way to proceed, i.e., if the next consecutive is uniquely determined (Ueberhuber, 1997). Formally, deterministic detruncation methods will always produce a particular value as output for any given input. Among the selected deterministic detruncation techniques, BP and PU are two of the most frequently use in practice (Zeni, 2001).

6) **Statistically detruncate**. As the name implies, this kind of detruncation is usually built on a foundation of complicated statistics theories. For example, the projection detruncation approach is based on the maximum likelihood theory; Gibbs Sampling is part of a broader set of methods called Markov-chain Monte Carlo (MCMC)

methods, they have found application in price-based RM. In this study, we chose the two top robust statistical detruncation methods, PD and EM, as the benchmark for comparison (L. R. Weatherford, 2000; Larry R. Weatherford & Pölt, 2002; Zeni, 2001; Zeni & Lawrence, 2004).

2.5 Comparison of Forecasting Methods

Several studies were reviewed to see how comparisons of the different categories of forecasting methods had been previously addressed. No study provided a clear guide regarding whether our selected forecasting or the statistical detruncation technique leads to more accurate forecasting.

Zeni (2001) and Weatherford and Pölt (2002) compared six forecasting and detruncation techniques, three naïve average methods, one deterministic detruncation method (i.e. BP) and two statistical detruncation methods (i.e. PD and EM) by simulating data in the environment of a single carrier in the airline industry. In terms of revenue impact, the results showed that the two statistical techniques were stronger than the other selected approaches with a 2.9% revenue improvement in business markets and an 11.6% improvement in leisure markets with strong demand. In addition, within the two statistical detruncation methods, EM was more robust than PD, peculiarly when 10% of the data were uncensored.

However, 11 years later, different results showed in Weatherford's (2013) research. This study focused on examining the statistical detruncation methods (EM and PD), as well as two deterministic detruncation techniques (PU and BP) in the airline industry. By using the sophisticated passenger origin-destination simulator (PODS) simulator and considering the impact of spill, upgrades, and recapture, the author concluded that in some situations, airline companies should switch from simple detruncation techniques and in other cases should not. A 2–25% revenue difference would be generated between switching and not switching.

Similarly, Queenan et al. (2007a) compared double exponential smoothing (Holt's method) with EM and found that Holt's approach has the edge only when all the demand sets were censored. Otherwise, EM was more robust.

In accordance with the review of the literature, Weatherford and Kimes (2001) used real-world data in the hotel industry to study the accuracy of various forecasting methods and found that PU methods and SES produced the most accurate results.

2.6 Review of Selected Forecasting Methods

From what has been discussed above, first, for deterministic detruncation method, based on Zeni's (2001) conclusion that BP and PU are two of the frequently used deterministic detruncation methods in practice, we selected BP and PU in our study. In addition, following Weatherford and Kimes's (2001) statement that PU and Simple Exponential Moving Average are the most accurate methods, smoothing methods are included in this study. SMA, EMA, and DEMA are all smoothing methods with different levels of power for weak data noise. Thus, we selected these three smoothing methods in the comparison and found the best smoothing method in demand detruncation. In addition, we chose SA as a non-smoothing method. In terms of statistical detruncation methods, we selected the two most robust performers (EM and PD) for comparison (Lawrence R. Weatherford, et al., 2001; Larry R. Weatherford & Pölt, 2002; Zeni, 2001; Zeni & Lawrence, 2004).

To sum up, we selected SA, SMA, EMA, DEMA, BP, and PU as the selected methods for comparison in this study. We included two robust statistical detruncation approaches for comparison: EM and PD. The eight methods are listed in Table 2.7.

Table 2.7 Summary of Selected Methods

Model #	**Classification**	**Method**
1	Time-Series	Simple Average (SA)
2	Time-Series	Simple Moving Average (SMA)
3	Time-Series	Exponential Moving Average (EMA)
4	Time-Series	Double Exponential Moving Average (DEMA)
5	Deterministic Forecasting	Booking Profile (BP)
6	Deterministic Forecasting	Pick-Up (PU)
7	Statistical Detruncation	Expectation-Maximization (EM)
8	Statistical Detruncation	Projection Detruncation (PD)

2.6.1 Simple Average

Averaging methods generate forecasts based on an average of past observations. Simple average is one of the simplest kinds of averaging methods. It uses the mean of all the relevant historical observations as the forecast for the next period (Hanke, Reitsch, & Wichern, 1998).

First, a decision is made to use the first t data point as the initialization part (i.e., the not constrained part) and the rest as a test part (i.e., the constrained period). Next, the following equation is used to average the initialization part of the data and to forecast the next period:

$$\hat{Y}_{t+1} = \frac{1}{t}\sum_{i=1}^{t} Y_i \ , \qquad (2.1)$$

When a new observation becomes available, the forecast for the next period, $\hat{Y}_{t+2}$, is the average or the mean computed using Equation 2.5.

When forecasting a large number of series simultaneously, only the most recent forecast and the most recent observation need to be stored as time moves forward, as shown in the following equation:

$$\hat{Y}_{t+2} = \frac{t\hat{Y}_{t+1} + Y_{t+1}}{t+1} \ , \qquad (2.2)$$

This method is an appropriate technique when the forces generating the series to be forecast have stabilized, and the environment in which the series exists is generally unchanging.

2.6.2 Simple Moving Average

A moving average of order k is the mean value of k consecutive observations. This method is appropriate to use by analysts who are more concerned with recent observations. Equation 2.3 gives the simple moving average model. A moving average of order k is computed by

$$\hat{Y}_{t+1} = \frac{(y_t + y_{t-1} + y_{t-2} + \cdots + y_{t-k+1})}{k} \quad , \qquad (2.3)$$

Where

$\hat{Y}_{t+1}$ = forecast value for the next period,

Y_t = actual value at period t,

k = number of terms in the moving average.

2.6.3 Exponential moving average

Exponential moving average is a procedure for continually revising a forecast in light of more recent experience. Different from the method of moving averages, this technique method not only considers the most recent observations but also provides an exponentially weighted moving average of all previously observed values. The model is often appropriate for data with no predictable upward or downward trend. The formulae are presented in Equations 2.4 and 2.5:

$$\hat{Y}_0 = Y_0 \quad , \qquad (2.4)$$

$$\hat{Y}_t = \alpha Y_{t-1} + (1-\alpha)\hat{Y}_{t-1}, (t > 0, 0 < \alpha < 1) \quad , \qquad (2.5)$$

Where

$\widehat{Y}_t$ = forecast value for the current period,

$\widehat{Y}_{t-1}$ = forecast value for the previous period,

Y_{t-1} = actual value at previous period t,

α = moving factor (exponential weight).

2.6.4 Double Exponential Moving Average

The DEMA was created by Patrick Mulloy and first published in 1994. Similar to the exponential moving average, the DEMA applies more weight to the most recent data in an attempt to smooth out noise while remaining highly reactive to changes in the data. The calculation steps are provided in the following equations.

1) The first two steps are the same as in Equations 2.4 and 2.5 in the exponential moving average.

2) The formula for the third step is presented in Equation 2.6:

$$\widehat{D}_t = 2 * \hat{Y}_t - \hat{Y}_t\ (\hat{Y}_t)\ , \qquad (2.6)$$

Where

$\widehat{Y}_t$ = forecast value for the exponential moving average curve,

$\widehat{D}_t$ = forecast value for the current period.

2.6.5 Booking Profile

Wickham (1995) developed a deterministic method called booking profile detruncation. By acquiring the average booking curves for flights with booking closures from those that have never been closed, the author estimates true demand with either additive or multiplicative techniques.

The algorithm for the detruncation process is the following:

First, identify the arrivals (n) in each market that are not constrained over the entire booking profile for the arrival.

Second, for these n arrivals, calculate the average bookings at each interval to produce a single representative detruncation booking profile, given by:

$$\hat{Y}_t = \frac{1}{n}\sum_{k=1}^{n} Y_{t_{notdetruncated}} \;, \qquad (2.7)$$

Third, calculate the percentage of the bookings at day t relative to the bookings in the previous period:

$$\prod_{t,t-7} = \frac{\hat{Y}_t}{\hat{Y}_{t-7}} \;, \quad (2.8)$$

Fourth, for an arrival, in a given market, with a booking profile constrained at day $t - 7$, calculate the unconstrained bookings at day $t - 7$:

$$Y_{t-7_{unconstrained}} = \frac{Y_t}{\prod t,t-7} \;, \qquad (2.9)$$

Finally, repeat the previous step for the bookings on days $x < t - 7$, even if they are not constrained, as all data subsequent to the constrained booking at day $t - 7$ are considered corrupted.

Where

$\hat{Y}_t$ = estimated value at period t,

Y_t = actual value at period t.

In this thesis, a cumulative data set is used instead of incremental data sets to prevent the situation that zero exists in the divisor in a division operation. To illustrate this method's detruncation process, as shown in Table 2.8, assume we have non-truncated demand information from 6 to 0 days before arrival. To forecast the true demand from 2 to 0 days before arrival for another truncated demand data set, using the booking profile method, first we calculate the corresponding percentage of the bookings at day 2 relative to the bookings at day 3 $\Pi_{2,3} = 11/8$ of the non-truncated demand. The detruncation booking for day 2 of truncated demand becomes $\hat{Y}_2 = Y_3 \times \Pi_{2,3} = 13 \times \left(\frac{11}{8}\right) \approx 18$. The real demand for day 1 and day 0 is calculated the same way.

Table 2.8 Booking Profile Detruncation

Days before arrival	**6**	**5**	**4**	**3**	**2**	**1**	**0**
Non-truncated demand	2	5	6	8	11	12	15
Truncated demand	3	7	9	13	13	13	13
Detruncated demand	3	7	9	13	18	20	25

2.6.6 Pick-Up

The pickup detruncation method was developed by Skwarek (1996). He wanted to obtain the total true demand by adding the simple average of pickup from the closure on unclosed flights to bookings already received.

In contrast to the projection technique, pickup detruncation assumes that the absolute increase in bookings from the closure interval to the arrival interval on the historical data base observation is the best indicator of the average increase in bookings between the time periods on unclosed bookings.

Formally, as shown in Equation 2.10, the k-day ahead forecast of customers to come is given by

$$\hat{Y}(t+k) = \sum_{i=0}^{k} \hat{Y}_{[i]}(t+k) \ , \qquad (2.10)$$

Where

k = the number of days ahead of arrival,

$\hat{Y}_{[i]}(\cdot)$ = the incremental bookings forecast i days before the time of service.

To explain the Pick-Up detruncation process, consider the following example of a booking truncated at day 2 before arrival. The data set in Table 2.9 is incremental demands. First, we calculate the average absolute increase from day 3 to day 2 of the non-truncated demand data = (3+2)/2=2.5. Thus, the detruncated demand of day 2 equals 2.5. Calculating the same way, the real incremental demand of day 1 and day 0 is 2.5 and 2, respectively.

Table 2.9 Pick-Up Detruncation

Days before arrival	**6**	**5**	**4**	**3**	**2**	**1**	**0**
Non-truncated demand1	2	3	1	2	3	1	3
Non-truncated demand2	2	2	3	1	2	4	1
Truncated demand	3	4	2	4	0	0	0
Detruncated demand	3	4	2	4	2.5	2.5	2

2.6.7 Expectation Maximization

After Salch looked at EM in the airline context and applied the algorithm to unconstrained censored data, this method became the most widely used method for correcting for constrained data in quantity-bases RM (Talluri & Ryzin, 2006). The EM was given by Dempster et al. (1997) in their pioneering paper. The method has been successfully used in circumstances where there are censored observations, missing data, and truncated distributions (McKercher & Tony, 2012).

The EM method uses the complete-data likelihood function in an iterative algorithm with an alternating E-step and M-step (thus the name). The E-step replaces the censored data with estimates of the uncensored values using the current estimates of the mean and the standard deviation. The M-step then maximizes the complete-data log-likelihood function based on these updated data to obtain new estimates of the mean and the standard deviation.

2.6.8 Projection Detruncation

The PD method is similar to the EM algorithm, because the PD calculation process also includes an E (expectation) step and an M (maximization) step. However, the conditional median replaces the conditional mean in the expected value calculation part. Compared with EM, there is an additional parameter that affects the aggressiveness of the detruncation (Zeni, 2001). It has been used in the PODS simulations for quantity-based RM, and its origin is credited to Hopperstad in 1995 (Talluri & Ryzin, 2006).

CHAPTER 3. METHODOLOGY

To evaluate the effectiveness of demand forecasting techniques in terms of restoring truncated demand data, and thus test how these methods affect hotel revenue, we compared six selected forecasting algorithms with two robust data detruncation methods. In Table 3.1, the eight models are summarized.

Table 3.1 Summary of Selected Models

Model #	**Classification**	**Method**
1	Time-Series	Simple Average (SA)
2	Time-Series	Simple Moving Average (SMA)
3	Time-Series	Exponential Moving Average (EMA)
4	Time-Series	Double Exponential Moving Average (DEMA)
5	Deterministic Detruncation	Booking Profile (BP)
6	Deterministic Detruncation	Pick-Up (PU)
7	Statistical Detruncation	Expectation-Maximization (EM)
8	Statistical Detruncation	Projection Detruncation (PD)

The premise behind the procedure for this study involves simulating a short-term forecasting environment and reviewing the performance of the selected forecasting methods in this environment. Therefore, the fundamental component of this study is the methods to the same simulated data set. The forecasting environment involved three total leisure/business customer demand ratio (L/B ratio) scenarios: 1:3, 1:1, and 3:1. All selected methods were applied to the simulated data set under each scenario. The structure of the revenue management models for testing the forecasting and detruncation methods under each scenario is provided in Figure 3.1. The revenue management models were applied to our simulated data set.

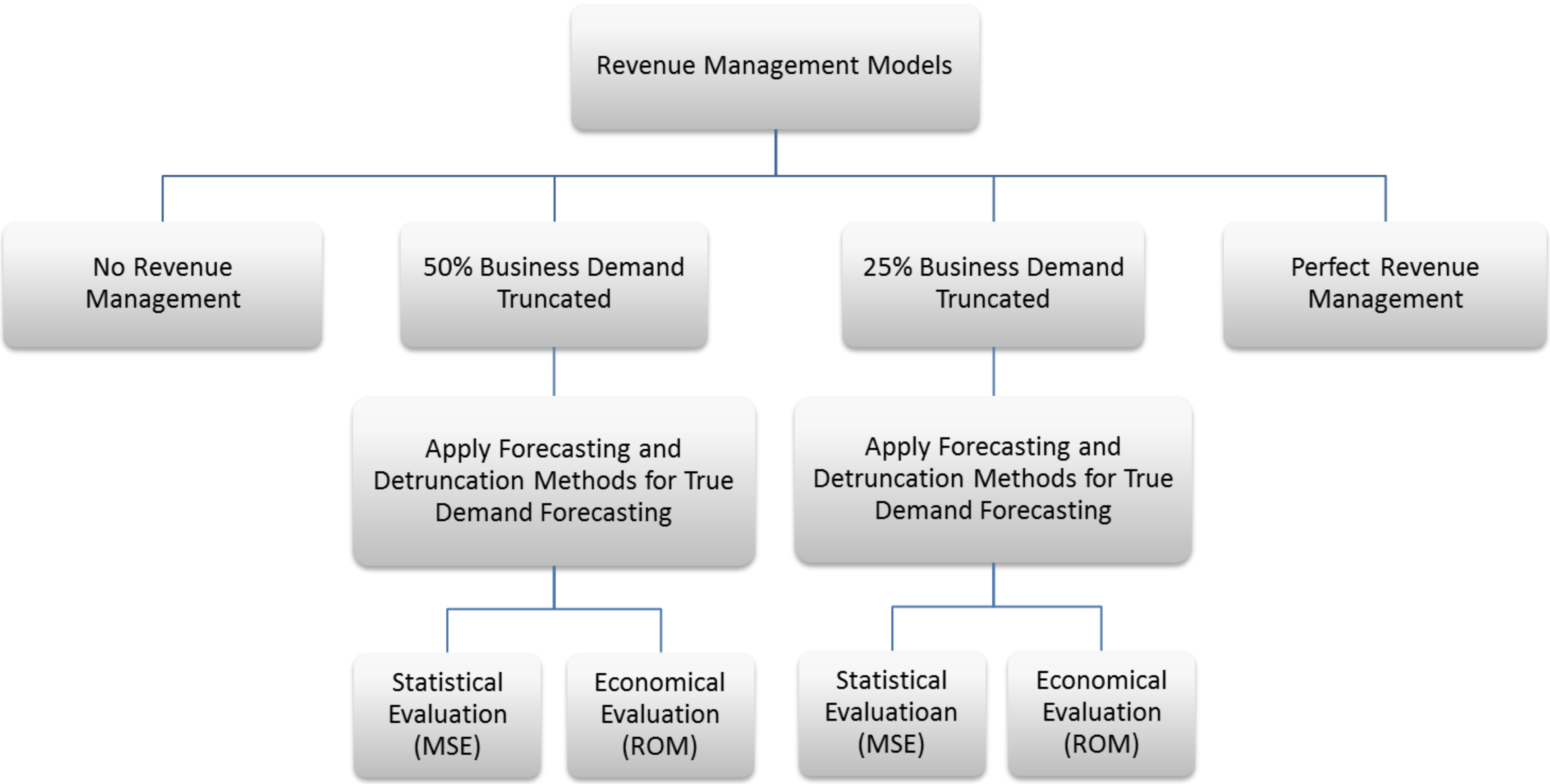


Figure 3.1 Summary of Revenue Management Models for Each L/B Ratio Scenario

3.1 Real Demand Simulation

To compare the performance of our selected forecasting and detruncation methods, first, under each, we simulated leisure and business real demand booking curves under a pre-decided increasing rate. The simulation method has been selected in this study because 1) it is the most widely used method for real demand generating in past studies; and 2) hotel real demand is hard to observe from historical booking data while hotel booking curve shape is not hard to summarize. In each booking curve, we simulated the data set for a 61-day period (from 60 days before arrival to the arrival date). The arrivals are created based on a Poisson distribution. Afterward, a total true demand curve is generated by summing up the leisure and business demands. By applying the Monte Carlo Randomized Method (Hammersley & Handscomb, 1964), this simulation step is run 100 times to generate 100 random real demand samplings.

By observing the real booking curves' shapes for the four given customer segment arrivals illustrated in Queenan et al.'s (2007a) study, the booking curve for fare class 1 in Figure 3.2 is the sample for the leisure segment in this research, and the reservation shape for fare class 3 is the sample for the deciding business segment. Figure 3.2 provides cumulative hotel/casino reservations for four separate fare classes in Queenan et al.'s (2007a) article.

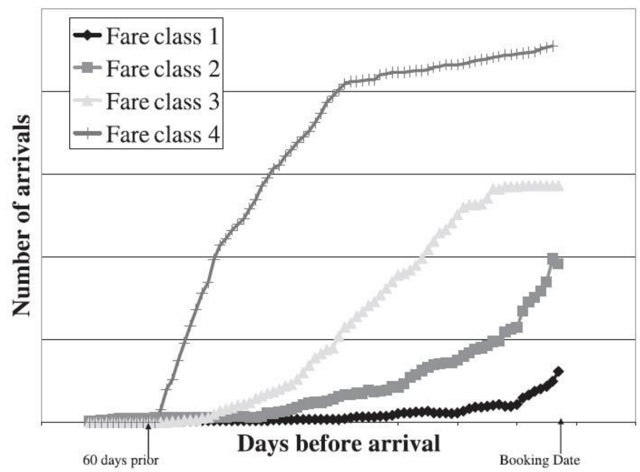


Figure 3.2 Cumulative Hotel/Casino Reservations for Four Fare Classes (Queenan et al., 2007)

To create the actual demand curves, we assumed that the arrivals on a given day are randomly drawn from a Poisson distribution. This assumption has been widely illustrated in the hotel- and airline-related literature and matches closely with actual hotel industry data (Badinelli, 2000; Bitran & Gilbert, 1996; Bitran & Mondschein, 1995; Liu, Smith, Orkin, & Carey, 2002; Queenan, et al., 2007a; Rothstein, 1974).

As shown in Table 1.1 in Chapter 1, more than 85% of U.S. independent hotels are in the size range of 100 or fewer rooms. However, hotels with a limited number of rooms (i.e., Bed & Breakfasts) do not benefit from revenue management because they have very specific target markets and may not be able to further segment the already narrowly-defined market. Independent hotels that attract diverse market segments benefit most from revenue management. These hotels usually have more rooms than those targeting a specific market (i.e., Bed & Breakfasts; (Hayes & Miller, 2011)). Therefore, we initiate the hotel capacity at 100.

The amount of total real demand is set at 160 (60% more than capacity) for two reasons:1) To take into account the diversity of the simulated data set, the total true demand must be a number that when the leisure/business ratio equals 3:1, business demand is smaller than the capacity (i.e., 100), and when the leisure/business ratio equals 1:3, business demand is larger than the capacity. 2) With the precondition of a diversity simulation, this number (i.e., 160) is initiated as a matter of convenience. When total demand equals 160, the leisure and business demand is a whole number in all L/B ratio scenarios.

We assume the demand for each market segment is independent, and there are no cancellations or no-shows. For the leisure demand curve, we maintain constant demand increases in declining rates, from high to low, over 60–51, 50–31, and 31–0 days before the arrival time periods. For the business demand curve, we increase the arrival in rising rates on 60–51, 50–31, 30–11, and 10–0 days before the arrival time periods. The aim for the rate settings is to make sure that the simulated leisure booking curves are concave and the business ones are convex and guarantee their shapes are as close as the samples in Queenan et al.'s (2007a) booking curve plot. Figures 3.3 through 3.5 provide the simulated cumulative demand plot for the three scenarios. The numbers in the plot are the averages of the 100 runs.

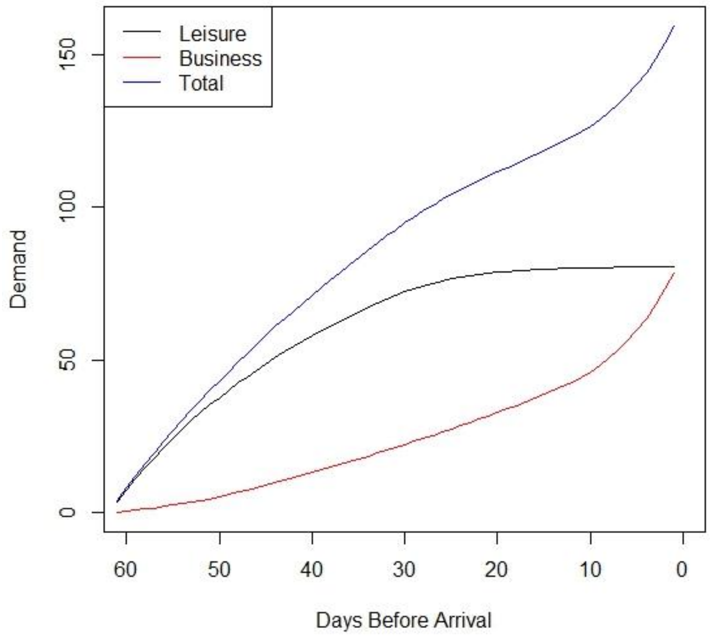


Figure 3.3 Simulated Real Cumulative Demand Curve (L/B Ratio=1:1)

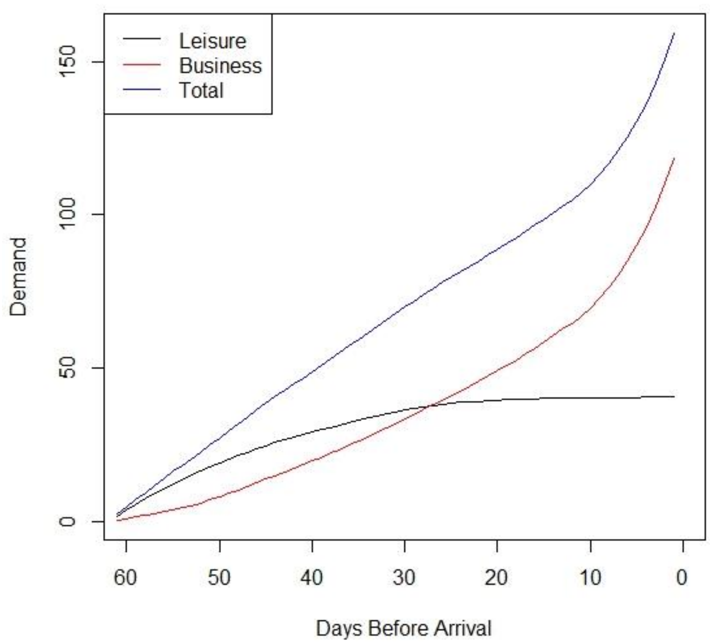


Figure 3.4 Simulated Real Cumulative Demand Curve (L/B Ratio=1:3)

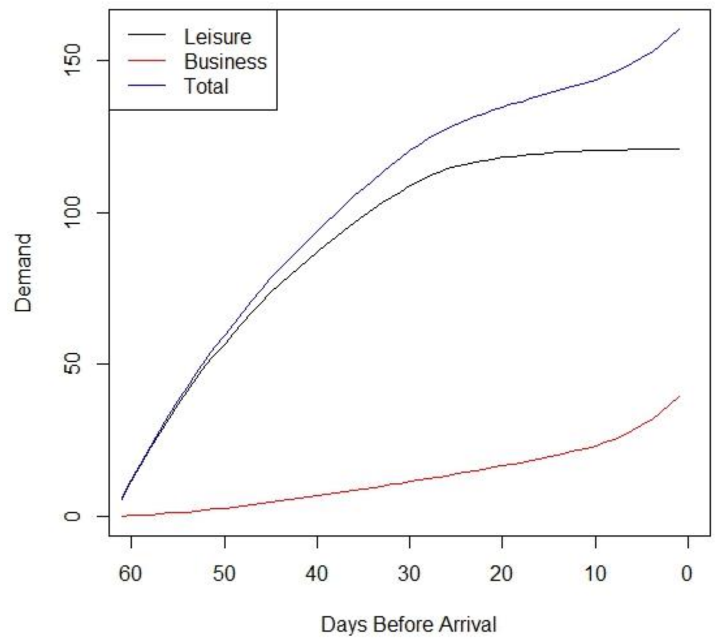


Figure 3.5 Simulated Real Cumulative Demand Curve (L/B Ratio=3:1)

3.2 Demand Truncation

Based on the revenue management models in Figure 3.1, true demand will be truncated in three cases: 1) capacity truncation (for No RM and Perfect RM Models), 2) 50% truncation of total business demand, and 3) 25% truncation of total business demand. Case 1, using hotel capacity (i.e., 100) for the limitation setting, is a naïve situation. Meanwhile, the aim of doing cases 2 and 3, truncating total business demand in two different proportions, is to evaluate each forecasting method's performance under different data truncation percentages. Since in overbooking environments, the number of hotel business (full-price) customers can bring more profit for independent hotels than leisure customers (discount price), hotel revenue managers care more about how to protect the number of business bookings than leisure bookings. Therefore, booking limits were set only for the business demand curves in this study.

3.2.1 Case 1: Capacity Truncation

For capacity truncation, we first set the hotel capacity at 100 and then calculate the first date that total demand arrives at 100. After that date, we close the leisure and business booking classes. Figures 3.6 through 3.8 present the capacity truncation plot over all three leisure/business demand ratios.

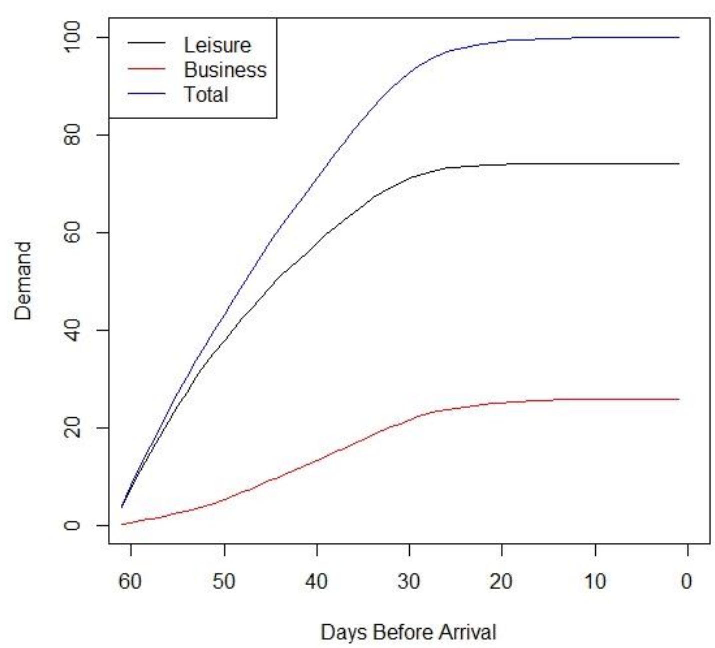


Figure 3.6 Observed Cumulative Demand Curve (L/B Ratio=1:1)

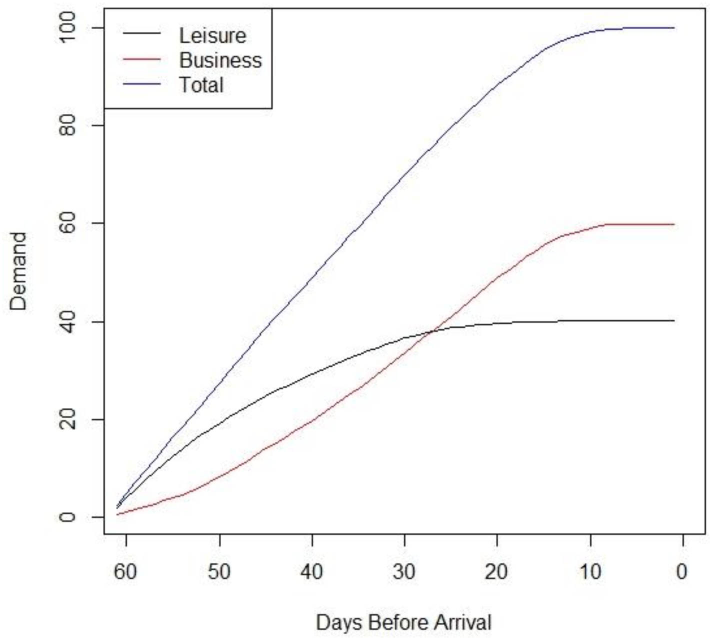


Figure 3.7 Observed Cumulative Demand Curve (L/B Ratio=1:3)

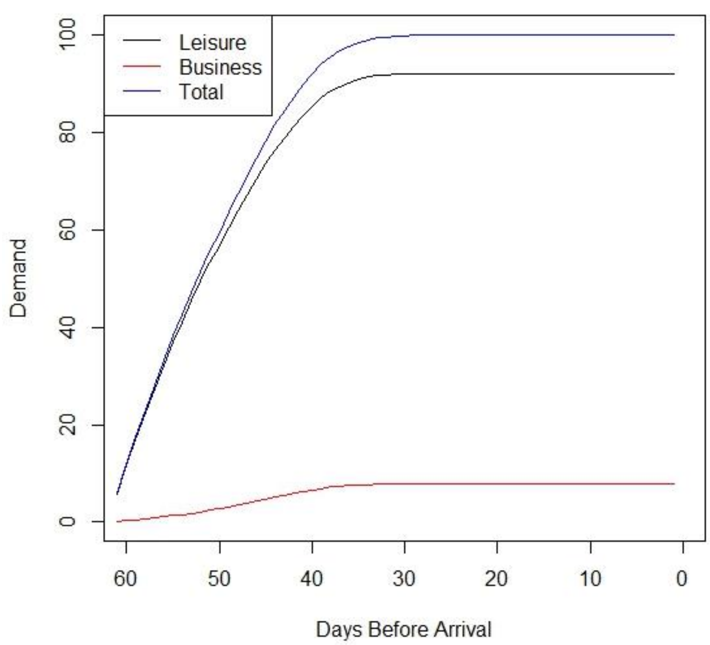


Figure 3.8 Observed Cumulative Demand Curve (L/B Ratio=3:1)

3.2.2 Case 2: 50% Business Demand Truncated

In this case, we calculate the first date while demand in business class arrives at 50% of the real total demand (for example, if the total real business demand is 100, we calculate the first date that business arrivals arrive at 50). After that day, we stop receiving bookings in business class, but reservations in the leisure market are still open. Bookings in the leisure market will close when the total demand reaches the hotel capacity (i.e., 100). Plots of case 2 for each leisure/business class ratio are shown in Figures 3.9 through 3.11.

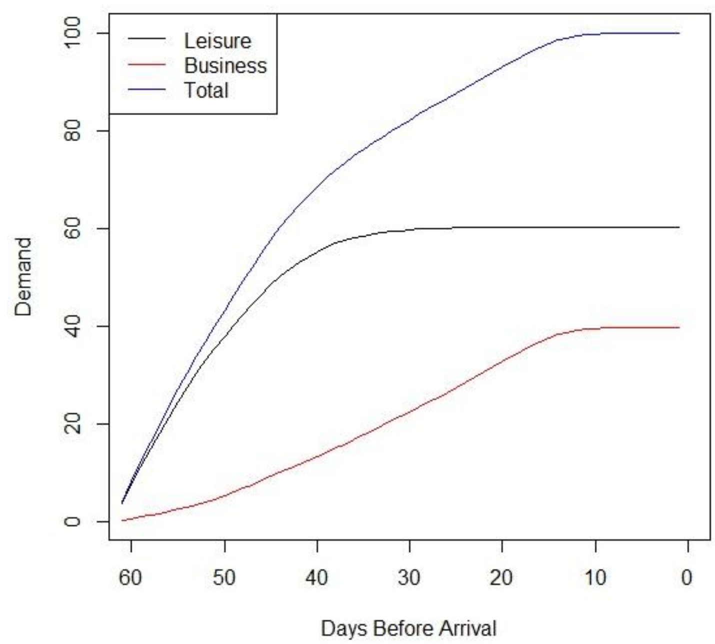


Figure 3.9 Observed Cumulative Demand Curve (L/B Ratio=1:1)

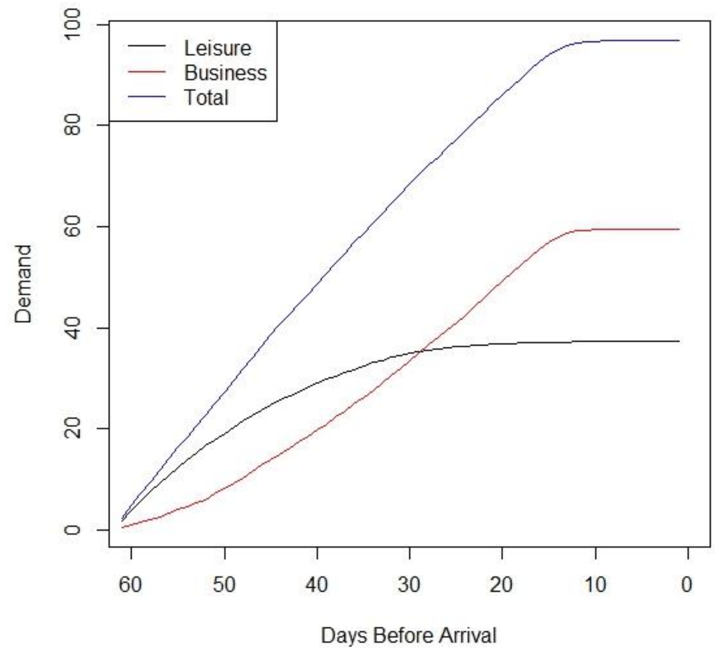


Figure 3.10 Observed Cumulative Demand Curve (L/B Ratio=1:3)

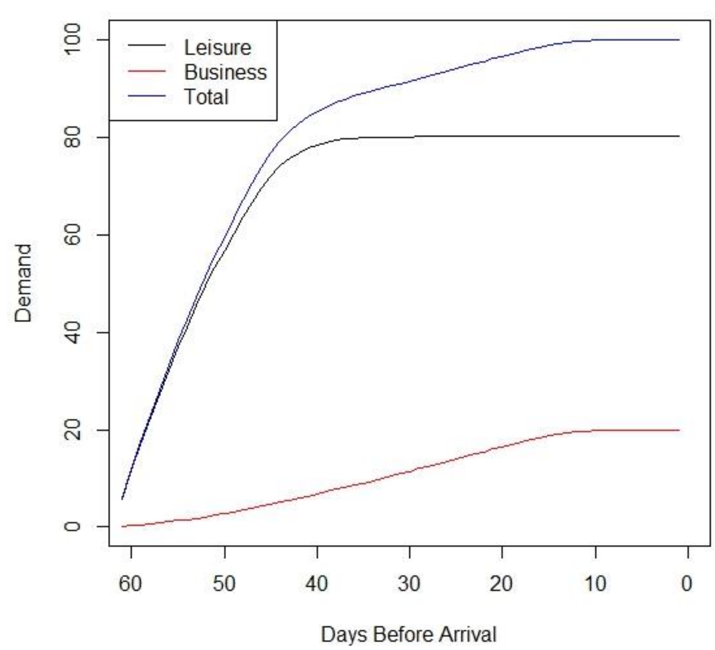


Figure 3.11 Observed Cumulative Demand Curve (L/B Ratio=3:1)

3.2.3 Case 3: 25% Business Demand Truncated

In Case 3, similar to Case 2, bookings received in business class will be stopped when the total business demand reaches 75% of our simulated total real business demand. At the same time, the leisure market will not open until the total bookings reach the hotel's capacity. Plots in Figures 3.12 through 3.14 provide specific booking curves in this case under the three ratios.

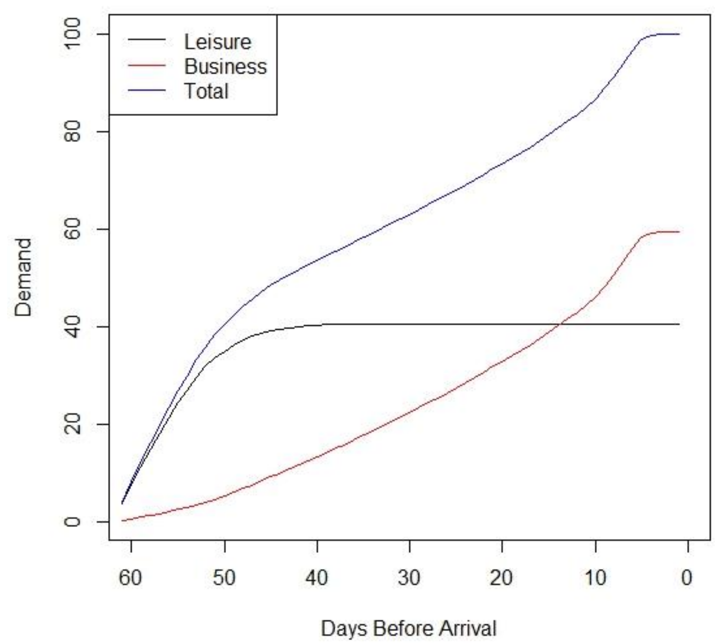


Figure 3.12 Observed Cumulative Demand Curve (L/B Ratio=1:1)

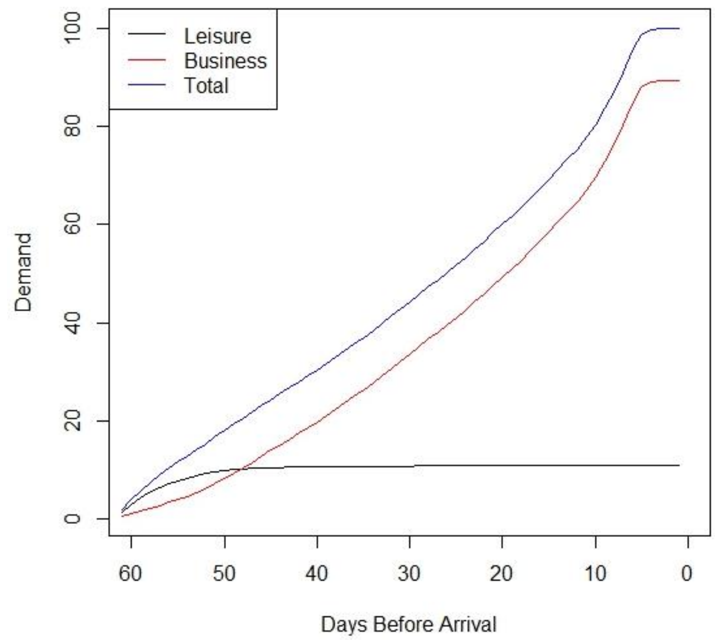


Figure 3.13 Observed Cumulative Demand Curve (L/B Ratio=1:3)

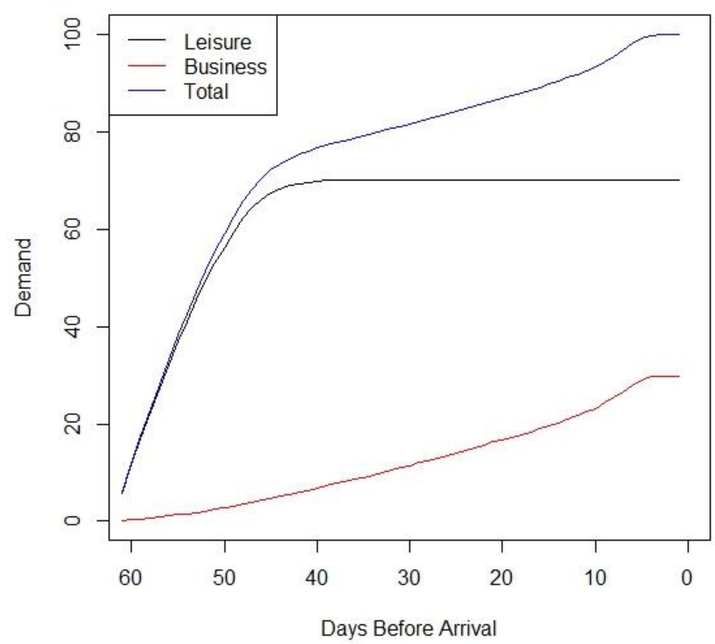


Figure 3.14 Observed Cumulative Demand Curve (L/B Ratio=3:1)

3.3 Demand Forecasting

This is the step to apply the forecasting and detruncation methods to the truncated demand created in the previous steps. The goal is to restore truncated demand to the true demand. We call the demand derived from the forecasting and detruncation methods detruncated demand. This is the forecasted demand in most revenue management systems. In this step, only business curves are detruncated to compare forecasting and detruncation methods.

Except for the BP method, in each scenario, all the other forecasting and detruncation methods (SA, SMA, EMA, DEMA, PU, EM, and PD) are applied for incremental truncated business demand data. In terms of BP, because this method sets observed incremental booking as the denominator in the formula, zeros exist in our truncated incremental business demand. Thus, the divisor in a division operation could be zero. This could limit the detruncated value of business demand to be defined eventually. Therefore, to avoid this situation, we use cumulative truncated business booking values in forecasting with the BP method.

In addition, for the BP, PU, EM, and PD methods, detruncation demand must be calculated from the bookings of the unclosed demand curves. Thus, we simulate the non-truncated business booking curves, and assume these curves follow the same increasing rate with real business demand. The number of total reservations for these curves is initiated as their correspondent business booking limit in each scenario.

3.4 Statistical Evaluation

This is the step to evaluate forecasting accuracy for each forecasting and detruncation method statistically. We use statistical error tests to see which forecasting method produces the best result. In this study, errors are defined as the differences between the real and detruncated business booking curves for each scenario. Data used in the error calculations are incremental business bookings. Errors are calculated only between intervals from the day true demand begins to be truncated until the arrival day.

Detruncated booking data for closed intervals are derived from the bookings of the non-truncated booking intervals; therefore, the business demand from non-truncated booking intervals is known information. There is no need to compare the mean square error of detruncated business bookings versus the actual booking demand distribution within these intervals.

To measure the forecasting performance of each method, several metrics have been used in previous academic studies (Wickham, 1995), where D and $\widehat{\mathrm{D}}$ are the real and detruncated incremental demand, respectively, generated from n observations:

- **The Mean Absolute Deviation (MAD)** indicates the average of the absolute values of the detruncated errors. This is the simplest statistical measure of forecast errors, defined mathematically as:

$$\text{MAE} = \frac{1}{n}\sum_{k=1}^{n} abs(\widehat{D} - D) \ , \quad (3.1)$$

The mean absolute deviation is particularly useful when the cost of the forecasting errors is proportional to the absolute size of the error.

- **The Mean Percent Error (MPE)** is simply the average of the percentage deviations. The MPE is defined mathematically as:

$$\text{MPE} = \frac{1}{n}\sum_{k=1}^{n}\frac{(\hat{D}-D)}{D}\times 100 \quad , \qquad (3.2)$$

- **The Mean Absolute Percent Error (MAPE)** is the average of the absolute values of the percentage errors. The mathematical formula for computing the MAPE is:

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n} abs\left[\frac{\hat{D}-D}{D}\right]\times 100 \quad , \qquad (3.3)$$

One advantage of this measure is that it is dimensionless. However, a particular drawback is that the MAPE is not defined when the real number of bookings is equal to zero, which is also true for the MPE.

- **The Root Mean Square Error (RMSE)** is the square root of the squared forecasting errors, defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(\hat{D}-D)^2} \quad , \qquad (3.4)$$

Where n is the number of observations generated for the particular model. This measure weighs large forecast errors much more heavily than smaller errors to the extent that it is considered biased against large errors. Nevertheless, this measure is valuable because of the independence issue.

- **The Mean Square Error (MSE)** measures the average of the squares of the forecasting errors. The mathematical formula for computing the MSE is:

$$\text{MSE} = \frac{1}{n}\sum_{k=1}^{n}(\widehat{D} - D)^2 \quad , \qquad (3.5)$$

MSE has been chosen for testing errors in this study because it avoids most drawbacks of the previous error measurement metrics. In addition, it is one of the most widely used loss functions in statistics to qualify the difference between values implied by an estimator and the true values of the quantity being estimated (Lehmann & Casella, 1998). The standard deviation (SD) of every MSE is also calculated to evaluate how much variation from the average MSE exists.

3.5 Economic Evaluation

The aim of this step is to economically compare the performance of each technique. Revenues are generated under three RM models: No RM, Perfect RM, and RM under Demand Detruncation. 1) The No RM model calculates the revenue a hotel would receive if it simply accepts the reservation whenever it arrives (calculated under the capacity truncation cases). 2) The Perfect RM model computes the revenue the hotel could have received if it knew the true demand ahead of time. 3) The RM with Demand Detruncation presents the revenue the hotel would have generated if it had applied detruncation methods to get a sense of the true demand and reserved rooms for the full-rate market. In this study, revenues are calculated under 50% and 25% business demand truncation levels.

In this step, revenue calculations for all the three models must obey the capacity limitation of 100 rooms. In the RM with Demand Detruncation model, business bookings are identified first with the detruncation demand, and then the remaining capacity is given to leisure customers. Any business bookings beyond the capacity will be counted as 100, and the corresponding leisure demand will become zero.

Since traditional industry overbooking statistics, such as over-sales and spoilage, are influenced by external factors (Smith, Leimkuhler, & Darrow, 1992), the revenue effectiveness of each method is measured with the overbooking revenue opportunity model (OROM). The OROM was originally developed by American Airlines (Phillips, 2005). This model measures the revenue impact of overbooking by comparing the actual net revenue, which equals total revenue minus any over-sale costs, to the maximum net revenue that could have been achieved with perfect overbooking controls. This method is referred to as measuring the revenue opportunity (Smith, et al., 1992).

To be specific, if the hotel is full, the revenue achieved under any actual revenue management control will generally lie between two extremes: better than the No RM program but never better than Perfect RM. Thus, the difference between the revenue achieved from Perfect RM and the revenue achieved from No RM is called the total revenue opportunity. The revenue obtained from applying revenue control minus revenue obtained from No RM is called the realized revenue opportunity. Then the revenue opportunity metric (ROM) is the revenue actually achieved from that hotel room/night minus the revenue that would have been achieved under No RM expressed as a percentage of the total revenue opportunity (Phillips, 2005). For example, in this study, the ROM of the 50% truncation scenario is:

$$\text{ROM} = \frac{Revenue\ under\ 50\%\ truncation - Revenue\ under\ No\ RM}{Revenue\ under\ Perfect\ RM - Revenue\ under\ No\ RM}\ .$$

According to the room rate we observed online among different independent hotels, the price ratio of the business and leisure market is created to be 2:1. Theoretically speaking, the higher the value of the ROM, the better the method's revenue effectiveness will be.

CHAPTER 4. RESULTS

As shown in Table 3.1 in Chapter 3, eight demand forecasting and detruncation methods were examined in this study, where models 1–6 use selected forecasting methods, while the data in models 7 and 8 are detruncated by statistical detruncation methods. We discuss the results, presented in the order of the forecasting methods, beginning with selected forecasting methods and then the statistical detruncation methods. Comparisons of three leisure/business demand ratios are presented. Method effectiveness differences between 50% and 25% of the total business demand truncation levels are summarized as well. Finally, the revenue impacts are discussed.

4.1 Statistical Evaluation of Selected Models

To facilitate the presentation of results, a summary of the set of selected methods is given in Table 4.1. Methods 1 through 6 are selected forecasting methods to be compared, while methods 7 and 8 are the two statistical detruncation methods.

Table 4.1 summarizes the statistical error testing outcomes for the chosen methods over all three scenarios. Errors are presented with the MSE and the SD.

Table 4.1 Mean Square Error (MSE) and Standard Deviation (SD) for Each Scenario

Mean Square Error (MSE) and Standard Deviation (SD) for Each Scenario

$\underline{\quad}$ Smallest number in the column
$\boxed{}$ Largest number in the column

Total leisure/Business demand ratio	**1/1**				**1/3**				**3/1**			
Percentage of total business demand been truncated	**50**		**25**		**50**		**25**		**50**		**25**	
	MSE	**SD**	**MSE**	**SD**	**MSE**	**SD**	**MSE**	**SD**	**MSE**	**SD**	**MSE**	**SD**
Simple Average (SA)	9.39	4.31	$\boxed{21.67}$	10.42	19.04	7.15	34.63	15.26	2.91	1.62	2.65	1.95
Simple Moving Average (SMA)	9.26	4.26	16.61	10.16	18.73	7.03	34.46	15.26	2.88	1.60	4.63	2.93
Exponential Moving Average (EMA)	9.51	4.32	16.79	10.17	19.29	7.17	34.88	15.30	2.94	1.63	4.68	2.94
Double Exponential Moving Average (DEMA)	11.24	4.3	13.59	9.12	23.36	7.19	27.67	12.84	3.36	1.6	3.9	2.57
Pick-Up (PU)	$\underline{5.42}$	2.95	$\underline{5.60}$	4.97	$\underline{9.72}$	4.55	$\underline{9.05}$	6.34	$\underline{2.10}$	1.30	$\underline{2.49}$	2.19
Booking Profile (BP)	$\boxed{12.14}$	4.89	19.07	8.62	$\boxed{25.1}$	8.36	$\boxed{40.31}$	14.15	$\boxed{3.74}$	1.85	5.45	3.22
Expectation Maximization (EM)	11.13	4.85	18.00	10.00	22.11	8.23	36.47	15.02	2.36	2.57	5.63	3.35
Projection Detruncation (PD)	11.45	4.93	18.94	10.35	22.89	8.35	38.55	15.55	2.40	2.60	$\boxed{5.83}$	3.41

4.1.1 Comparison among Leisure/Business Demand Ratios

The proportion of the business demand attributed to total bookings gradually diminished as the leisure/business ratios increased from 1:3 to1:1 to 3:1. The MSE correlations for each method with the different L/B ratios are shown in Table 4.1. Overall, the error for each forecasting and detruncation method decreased from L/B ratio 1:3 to 1:1 and then to 3:1. In L/B ratio 1:3, the MSE for all methods falls clearly in the range [9.05, 40.31]; while in L/B ratio 1:1, this range decreases to [5.42, 21.67]. When the L/B ratio becomes 3:1, the MSE values drop again to [2.1, 5.83]. We can conclude that the data restoration accuracy ranged from a negative relationship with the business demand proportion.

4.1.2 Comparison between Demand Truncation Levels

Observing Table 4.1 longitudinally, for all three total leisure/business demand ratio categories, the values of the MSEs for most methods decreased when the 50% of the total business demand was truncated compared to the values for the 25% truncation. This outcome indicates that the more the business bookings are truncated, the smaller the error becomes, thus the closer the detruncated demands to true demands. However, PU and SA forecasting methods showed opposite results under L/B ratio 1:3 and 3:1 respectively. In ratio 1:3, when 50% of the total business demand is truncated, the MSE of PU was 9.72 with a standard deviation of 4.55, while under the 25% truncation level, the MSE surprisingly decreased to 9.05 with a standard deviation of 6.34. At the same time, in ratio 3:1, when truncation level decrease from 50% to 25%, the MSE for SA drop from 2.92 to 2.65.

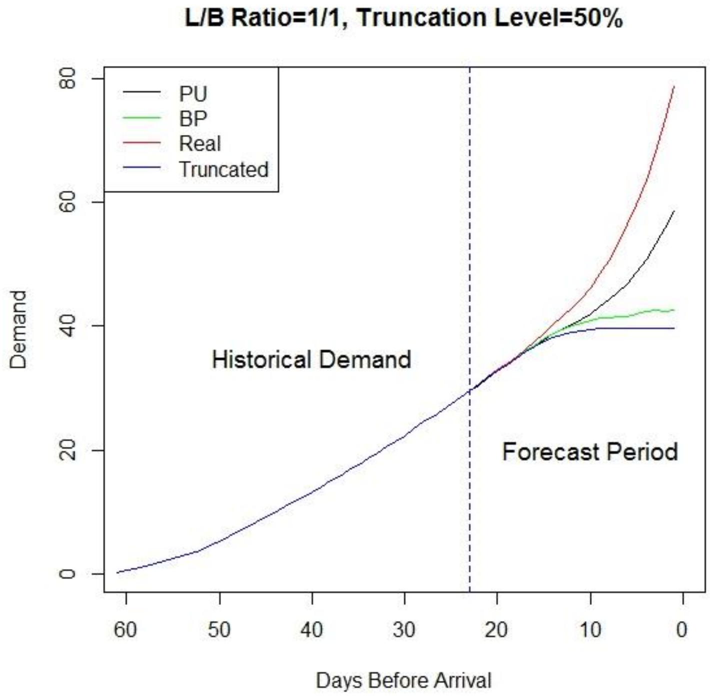
Aside from the MSE values, the errors' standard deviations also showed an increase changing trend from the 50% to 25% business truncating percentage over all three L/B ratios. This can be interpreted as the less the business bookings are truncated, the more variable the error becomes.

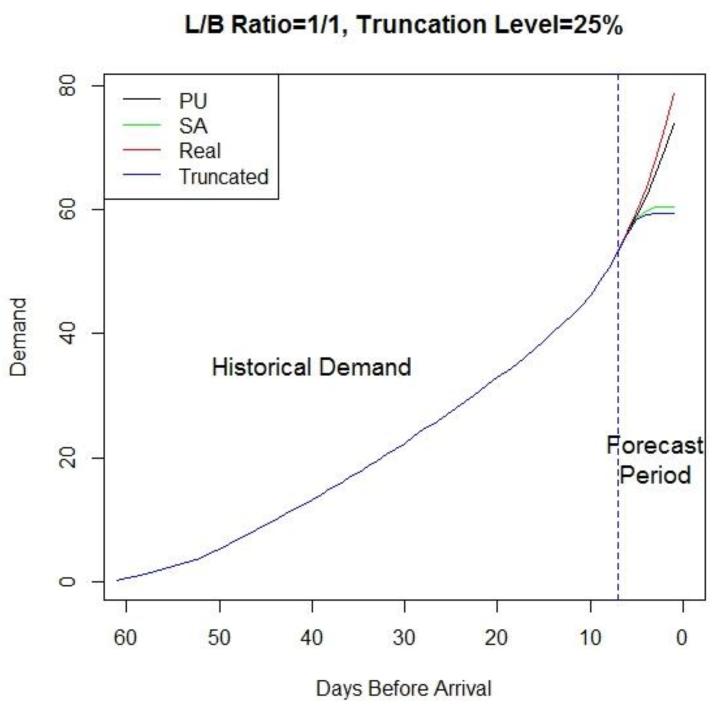
Another interesting result is that in each L/B ratio scenario, for both business truncation levels, PU was the best performer among all the selected methods with the smallest MSE. However, the least accurate method kept changing in 50% and 25% truncation level categories. In 50% truncation category, BP was the weakest over three L/B ratio scenarios with MSE values of 12.14, 25.10, and 3.74. While in 25% truncation category, for ratio 1:3, BP remained at the bottom. For ratio 1:1 and 3:1, SA and PD replaced BP and become the least accurate methods. Surprisingly, in category that ratio equals 3:1 percentage equals 25, BP was not even the second worst choice. Its performance even surpassed EM, and was the third worst method.

4.1.3 Comparison between Selected Methods

Figure 4.1 presents the strongest and weakest statistical performers in each L/B ratio and truncation level scenario based on the MSE values provided in Table 4.1. Plots displayed in the coordinate system are cumulative bookings. In each plot, the black, green, red, and blue lines represent the strongest method's detruncation bookings, the weakest method's detruncation bookings, real bookings and truncated bookings, respectively. Business bookings we compared in this study were incremental rather than cumulative. Errors were calculated only in intervals from the day true demand began to be truncated until the arrival day. The reasons we show cumulative plots instead of incremental plots here are 1) cumulative plots ensure easy observation for readers and 2) they are inconsistent with the cumulative plots we inserted in the previous chapter. The detruncation plots of other methods are in the appendix.

As shown in Table 4.1 and Figure 4.1, PU, with the smallest MSE and SD values, was the strongest performer among all selected forecasting and detruncation methods. Surprisingly, following PU, the MSE values for the EM and PD methods did not rank second and third smallest compared with the other methods. Thus, we can conclude that statistical detruncation methods (i.e., EM and PD) do not always outperform other selected forecasting methods (SA, SMA, EMA, DEMA, and BP) over all L/B ratio scenarios and business truncation percentage cases. However, the rankings of these two statistical detruncation methods remained the same over all scenarios. That is to say, EM and PD performed with great consistency in this study.


L/B Ratio=1/1, Truncation Level=50%
PU
BP
Real
Truncated
Historical Demand
Forecast Period
Demand
Days Before Arrival
0
20
40
60
80
60
50
40
30
20
10
0


L/B Ratio=1/1, Truncation Level=25%
PU
SA
Real
Truncated
Historical Demand
Forecast
Period
Demand
Days Before Arrival
0
20
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80
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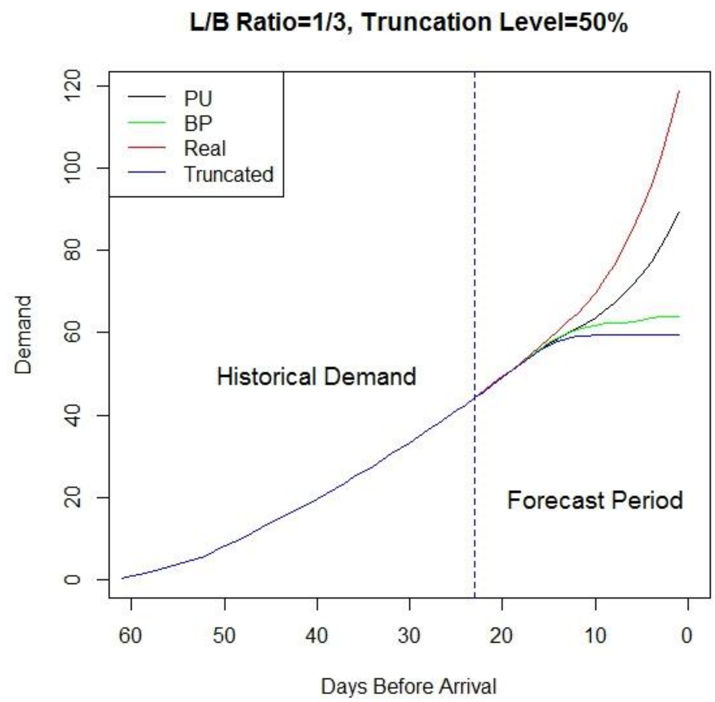
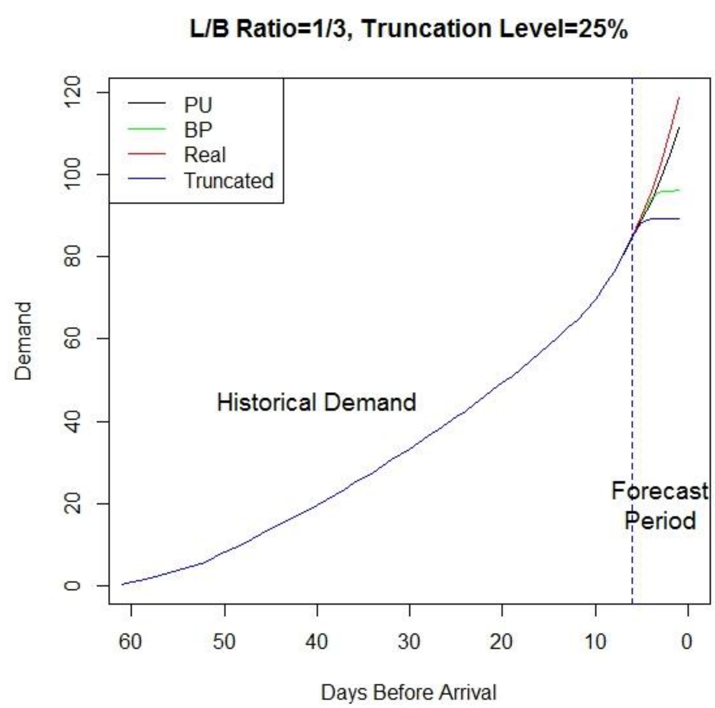


L/B Ratio=1/3, Truncation Level=50%
PU
BP
Real
Truncated
Historical Demand
Forecast Period
Demand
Days Before Arrival



L/B Ratio=1/3, Truncation Level=25%
PU
BP
Real
Truncated
Historical Demand
Forecast Period
Demand
Days Before Arrival

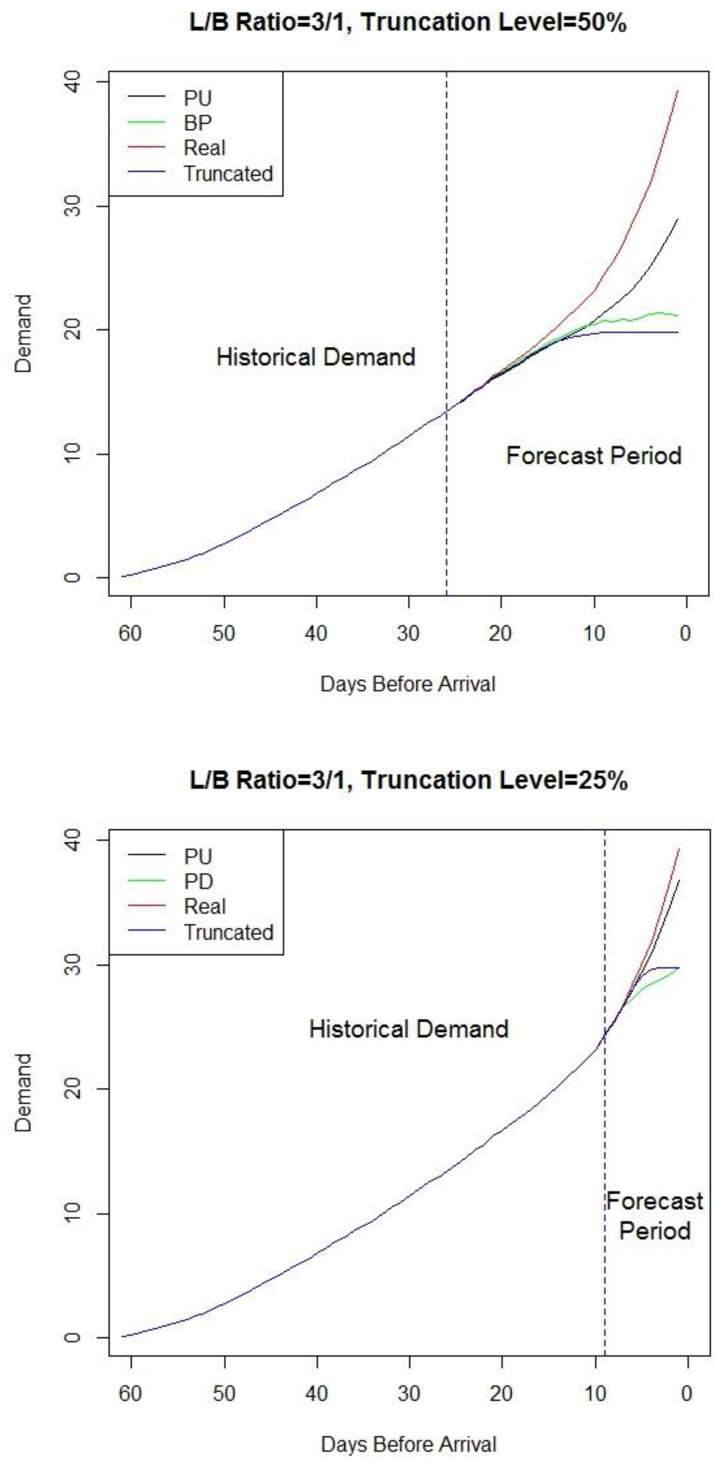


Figure 4.1 Strongest and Weakest Statistical Performer in Each Scenario

4.1.3.1 Selected forecasting method

Among the selected forecasting methods, PU outperformed all methods over the L/B ratio scenarios data set because the error remained under 10 for all levels on business demand truncation. PU and BP are forecasting methods that restore truncated values from unclosed booking data. The MSE difference between these two methods is substantial. BP underperformed on this test because it used the proportion in each interval of non-truncated curves to estimate data, while PU uses the absolute increase. Thus, one advantage of PU method is that it fully uses all available reservation information. Moreover, as partial bookings are recent bookings, using these data can make the estimation more responsive to shifts in demand. Even though the method looks simple and heuristic, PU can be better used in quantity-based revenue management.

In terms of the simple average method, it outperformed most of other selected forecasting method with the 50% business demand truncation cases, but did not do a good job when the business truncation level was 25%. Since SA uses the means of all known observed data to estimate true demand, SA is an appropriate method when the forces generating the truncated demand to be restored have a stabilized and unchanging environment. In our study, the business demand curve’s increasing rate rose progressively at first but suddenly was truncated to zero when it got to the given limitation. Therefore, the less business demand truncated, the more erratic the known data could be, and then the less accurate the SA method becomes.

Compared with the simple average method, the moving average forecasting methods are more concerned with recent booking observations. A constant number of data points can be specified at the outset and the mean computed for the most recent observations. The new mean is calculated through adding the newest value and dropping the oldest when each new booking becomes available. The first two moving averages in this study, SMA and EMA, outperformed most of the other techniques SMA seemed a litter stronger than EMA, but not much more, whereas DEMA's performances kept changing in 25% and 50% truncation levels. It was evident that DEMA worked way better in 25% truncation categories than in 50%'s. One possibility is that booking truncation made the later part of our known incremental observation go to zero. Thus, the average bookings the methods computed from the latest part of observations went to zero as well.

4.1.3.2 Statistical detruncation method

Comparisons in previous studies showed EM outperformed PD (Weatherford & Pölt, 2002; Zeni, 2001). We confirmed this result. Except for accuracy issues, PD has two more drawbacks compared with EM. First, PD takes more iteration to cover than EM when restoring the missing value. Second, when using PD for data detruncation, users need to create a weighting parameter as an opportunity for varying results.

4.2 Revenue Impact Analysis

The ROM result for each method is presented in Table 4.2. Most methods' revenue performances show consistencies with the detruncation effectiveness within the same ratio and truncation category. Although, technically speaking, the revenue percentage impact for each method does not need to cohere with its detruncation effectiveness because the deciding factor of revenue impact is the absolute increase of business detruncation demand curve from the day it begin to be truncated until the arrival day, the decisive factor of the MSE value is the distance from the detruncation curve to the real demand curve in each day within truncation intervals. It is possible for a method that has strong detruncation effectiveness and weak revenue impact at the same time.

PU, with the largest percentage of revenue impact, was the top performer among the methods. Especially in the 1:3 L/B ratio, the 25% percentage level, the ROM for PU was 1, which means the revenue effectiveness was close to the revenue achieved under the Perfect RM scenario. The most likely explanation is that in ratio 1:3, our simulated real business demand exceeded room capacity (i.e. 100), plus there is only 25% of real business demand has been truncated, our forecasted total business demand using PU method is still above the capacity. These are also the reasons why ROMs of the other methods in this scenario (ratio=1:3, percentage=25%) are close to 1. EM and PD did not show much difference between the economic evaluation and the statistical evaluation. The most interesting discovery is, between 25% and 50% truncation levels, ROM for each method does not cohere with its MSE result. Although, as we demonstrated in 4.1.2, the more the business bookings are truncated, the smaller the error becomes, thus the closer the detruncated demands to true demands, ROMs in 25% truncation level are larger. That is to say all our selected forecasting methods could generate more revenue in 25% business truncation levels, even though they subject to greater statistical errors than in 50% truncation levels.

Table 4.2 Revenue Opportunity Metric for Each Scenario

Revenue Opportunity Metric (ROM) for Each Scenario

__ Smallest number in the column
☐ Largest number in the column

Total leisure/Business demand ratio	**1/1**		**1/3**		**3/1**	
Percentage of total business demand been truncated	**50**	**25**	**50**	**25**	**50**	**25**
Simple Average (SA)	0.448	$\underline{0.650}$	0.378	0.895	0.545	0.911
Simple Moving Average (SMA)	0.455	0.703	0.391	0.897	0.550	0.755
Exponential Moving Average (EMA)	0.442	0.701	0.365	0.892	0.538	0.753
Double Exponential Moving Average (DEMA)	0.366	0.742	0.215	0.976	0.471	0.790
Pick Up (PU)	$\boxed{0.629}$	$\boxed{0.893}$	$\boxed{0.763}$	$\boxed{1.000}$	$\boxed{0.689}$	$\boxed{0.918}$
Booking Profile (BP)	$\underline{0.320}$	0.693	$\underline{0.112}$	$\underline{0.877}$	$\underline{0.441}$	0.759
Expectation Maximization (EM)	0.356	0.705	0.223	0.899	0.412	0.749
Projection Detruncation (PD)	0.341	0.696	0.191	0.880	0.407	$\underline{0.741}$

4.3 Steps to Follow for Pick-Up Method Calculation

In this study, Pick-Up detruncation method was proved to be the strongest performer among all the selected low computational forecasting techniques. Specific steps for estimating total real hotel demand through this method will be presented as follows:

- Step one: collet historical booking data

In this step, hotel operators need to collect two set of historical data—non-truncated and truncated historical demands. Suppose for the data in figure 4.1, we want to forecast the real total bookings for 16-January assuming cumulative bookings for this date met the reservation limitations when we have two days remaining, and bookings for arrival date 8-January, 11-January and 14 January have not been constrained by hotel booking limits. The non-truncated historical bookings we need to collet are demand from 6 to 0 days before arrival for January-8, 11 and 14 (data marked in pink). The truncated reservation historical demands are 6-1 days ahead of arrival for 16-January (data marked in blue).

Table 4.3 Incremental bookings for four arrival days of a hotel. 14-Janury is the current date with full historical bookings. 16-Janury has partial booking information

Days Before Arrival							Arrival
6	**5**	**4**	**3**	**2**	**1**	**0**	**Date**
2	3	1	2	3	1	3	**8-Jan**
2	2	3	1	2	4	1	**11-Jan**
0	1	2	4	3	2	1	**14-Jan**
4	3	4	2	3			**16-Jan**

- Step two: find the average absolute increase for non-truncated data set

Pick-Up detruncation assumes that the absolute increase in bookings from the non-truncated interval to the arrival interval on the historical data base observation is the best indicator of the average increase in bookings between the time periods on truncated bookings. To get the average absolute increase of non-truncated demands from day 2 to day 1, add each incremental demand in day 1 and then divide by the number of arrival days. This is the average absolute increase from day 2 to day 1. In our example, average absolute increase for non-truncated data set equals $\frac{1+4+2}{3} = 2.33$. Thus, our estimate 1 day before arrival bookings for arrival date 16-January is 2.33. Similarly, we can compute the 0 day ahead of arrival bookings for 16-January. It equals $\frac{3+1+1}{3} = 1.67$.

- Step three: the estimate real total demand is the sum of incremental demand we get.

This number will tell you how many reservations in total the hotel would have for arrival date 16-January. To get this number, we need to sum up all the incremental booking from 6 to 0 days before arrival for 16-January. So the forecast of demand to come for 16-January equals $4 + 3 + 4 + 2 + 3 + 2.33 + 1.67 = 20$.

CHAPTER 5. CONCLUSION

By integrating demand data testing in three leisure/business demand ratios and two business demand truncation levels, and designing the experiment based on U.S. independent hotels, the presented research provided a new perspective on implications for hotel demand forecasting and detruncation methods. The objectives of this study were 1) to evaluate the performance of the selected hotel demand forecasting and detruncation methods and (2) to identify a low-cost, easy-to-follow forecasting method that can be used by independent hotels and other hotel operators constrained by financial resources and expertise.

To examine the effectiveness of selected forecasting and statistical detruncation techniques in terms of restoring truncated demand data for U.S. independent hotels, and thus evaluate how those methods impact hotel revenues, six selected forecasting methods (SA, SMA, EMA, DEMA, BP, and PU) were compared with two strong statistical detruncation methods (EM and PD). Data production and analysis were operated in the R statistical programming system. Data forecasting environments were created with three total leisure/business demand ratio (i.e., 1:1, 1:3, and 3:1) scenarios. Under each scenario, actual booking curves for leisure and business market were simulated under a pre-decided increasing rate. Truncated booking curves were created under the given situations. Eight selected forecasting and detruncation methods were applied to truncated business demand curves to generate detruncated demand. Statistical errors were tested for differences between real and detruncation bookings. The detruncation effectiveness of each method was analyzed, and the revenue impact was discussed.

Based on the analysis, several new findings regarding the effectiveness of the selected methods among different leisure/business demand scenarios and business demand truncation percentage levels were identified. The results indicate that, for all methods, 1) PU was the strongest performer with the smallest detruncation error and most positive revenue impact; 2) the data restoration accuracy ranged from a negative relationship with the business demand proportion of total bookings; 3) the higher the percentage the business bookings were truncated, the smaller the detruncation error; and 4) the less the business booking was truncated, the more variable the error. For statistical detruncation methods, 5) EM and PD performed with great consistency; however, they are not the best choice in our model. 6) We confirmed the result from previous studies that PD underperformed EM (Weatherford & Pölt, 2002; Zeni, 2001). Finally, for selected forecasting models, 7) PU was identified as a low-cost, easy-to-follow forecasting method for U.S. independent hotels as well as hotel revenue managers limited by financial resources and expertise.

5.1 Discussion

The study examined the effectiveness of selected forecasting and statistical detruncation methods from the perspective of U.S. independent hotels. The results show that different methods produce various outcomes for different leisure/business demand ratios and under different percentages of total business demand truncation levels.

The most important result is that PU outperformed the other methods and was the most effective method with the smallest errors. PU is also recommended as the low-cost and easy-to-follow forecasting technique to U.S. independent hotels that are well in agreement with the simulated demand situations in this study. First, the PU method uses all available booking information. Second, PU's use of recent bookings makes the forecasting more responsive to shifts in demand.

Interestingly, the result suggests that the two robust statistical detruncation methods, EM and PD, we included in the testing were not the best performers among all the techniques. Possible reasons might be the extra non-truncated demand curve we simulated created a deviation from the true demand, and EM and PD did not detect the deviation. However, since their rankings in terms of the value of errors remain consistent for the scenarios, these methods are the most stable ones in this research.

5.2 Implications

5.2.1 Theoretical Implications

First, the current study is among the first to explore the effectiveness and revenue impact of forecasting methods for U.S. independent hotels. Not only the data simulations step of this research was designed based on features of independent hotels. The forecasting methods selected were simple operating techniques. To sum up, the findings of the current study contribute to the literature on hotel demand forecasting and detruncation by identifying the most effective forecasting method for U.S. independent hotels.

Second, this thesis integrates hotel demand forecasting methods into different leisure/business demand ratios and various business demand truncation percentage levels. Although previous studies have focused on issues between demand detruncation methods' effectiveness with booking curve shapes and the percentage of data set truncated (Queenan et al., 2007), few studies have explored the relationship between demand truncating performance with customer segment ratios and the truncation levels of a specific segment market. The findings of this thesis contribute to the literature by providing a new perspective on the correlation to these issues.

Finally, particularly worth noting is that the study compared the performances between statistical detruncation methods with our selected forecasting method is in the field of airline industry (Weatherford, 2013). To that end, the current study added to the existing literature on forecasting and detruncation method comparisons in the hotel industry.

5.2.2 Practical Implications

The present research provides several important practical implications for selecting demand forecasting methods for U.S. independent hotels. First, the results indicate that the PU method was the top performer with the smallest detruncation errors and the most positive revenue impact. For independent hotels with financial and expertise limitations, more attention should be paid to the PU method when estimating real business demand. Second, the findings of this study also provide suggestions for hotel reservation managers and revenue managers. Hotel revenue managers should recognize that each method's data restoration accuracy stemmed from a negative relationship with the business demand proportion of the total bookings. By acknowledging this accuracy tendency, revenue managers at independent hotels with a large proportion of business customers must pay more attention to selecting a detruncation method and applying the appropriate adjusting parameters to the detruncated demand if necessary. Reservation agents should pay more attention to the leisure/business customer ratios and inform the revenue management department when the ratio exceeds a specific number.

Third, the results show a negative correlation between detruncation error variations with the percentage level of business booking truncation. This finding has practical implications for revenue managers when calculating detruncation errors. The managers should be aware that the same error value for two different business booking truncation level curves does not mean the same accuracy of specific detruncation methods.

Last but not least, this study demonstrated that in some specific circumstances, the statistical evaluation does not completely in accordance with economical evaluation. By acknowledge with this inconsistency, revenue managers at independent hotels who value revenue more than forecasting accuracy should put efforts on economical evaluation first, statistical evaluation second.

5.3 Limitations

Although this study contributes to the literature in the area of hotel demand estimation methods in several important ways, the study has limitations. The major limitation is the method used to generate hotel true demand. In this study, we simulated real demand by observing a real demand booking curve illustrated in another article rather than obtaining true demand data from a real hotel. Even though our simulated data present an ideal forecasting environment for conducting the study, some unique features of our simulated curve might limit the generalizability of this study to other hotels that have different demand forecasting environments.

In addition, a possible limitation of this study results from the method of truncating business demand. This study used static ways for booking limitation settings. For some big chain hotels, advanced statistical systems could make revenue managers control their booking limitations dynamically along as more new data become available. Therefore, setting the booking limit dynamically could have provided researchers with insightful opinions.

5.4 Directions for Future Research

There are other interesting avenues for future research on this topic. First, due to the limited generalizability of this study, future studies can simulate real demand under other forecasting environments or collect actual booking curves in real hotels and compare the differences of the effect of the detruncation methods. Second, due to the other limitation of the current research regarding the method for truncating business demand, future studies can focus on using dynamic booking controls for hotel demand detruncation. Finally, more forecasting detruncation methods can be used in the study for comparison; thus, more patterns of differences among those methods can be concluded.

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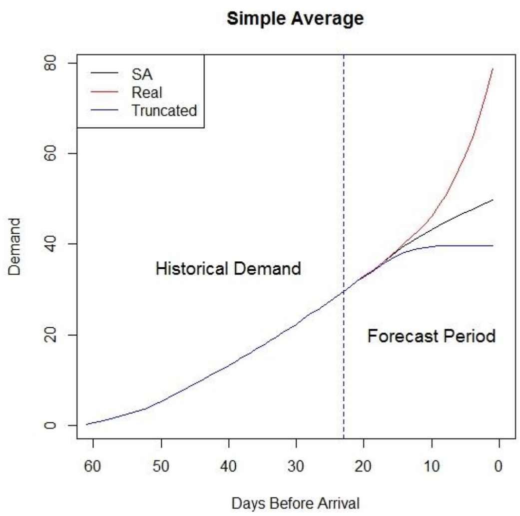
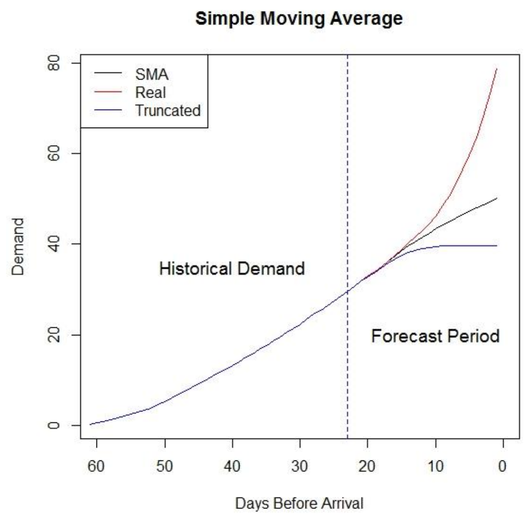
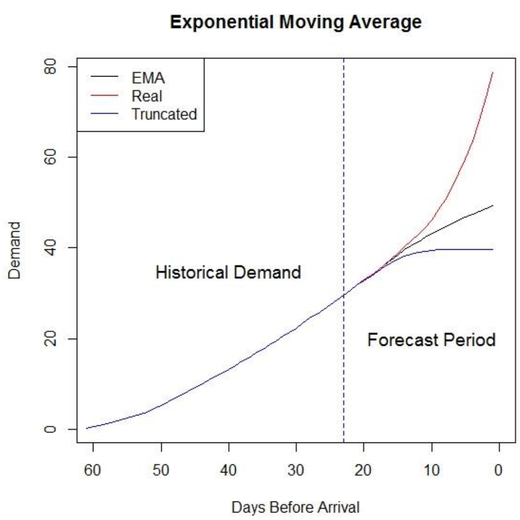
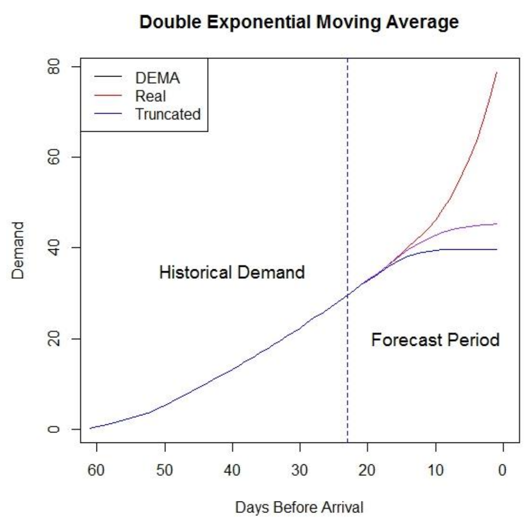
APPENDICES

Appendix A Detruncation Plots









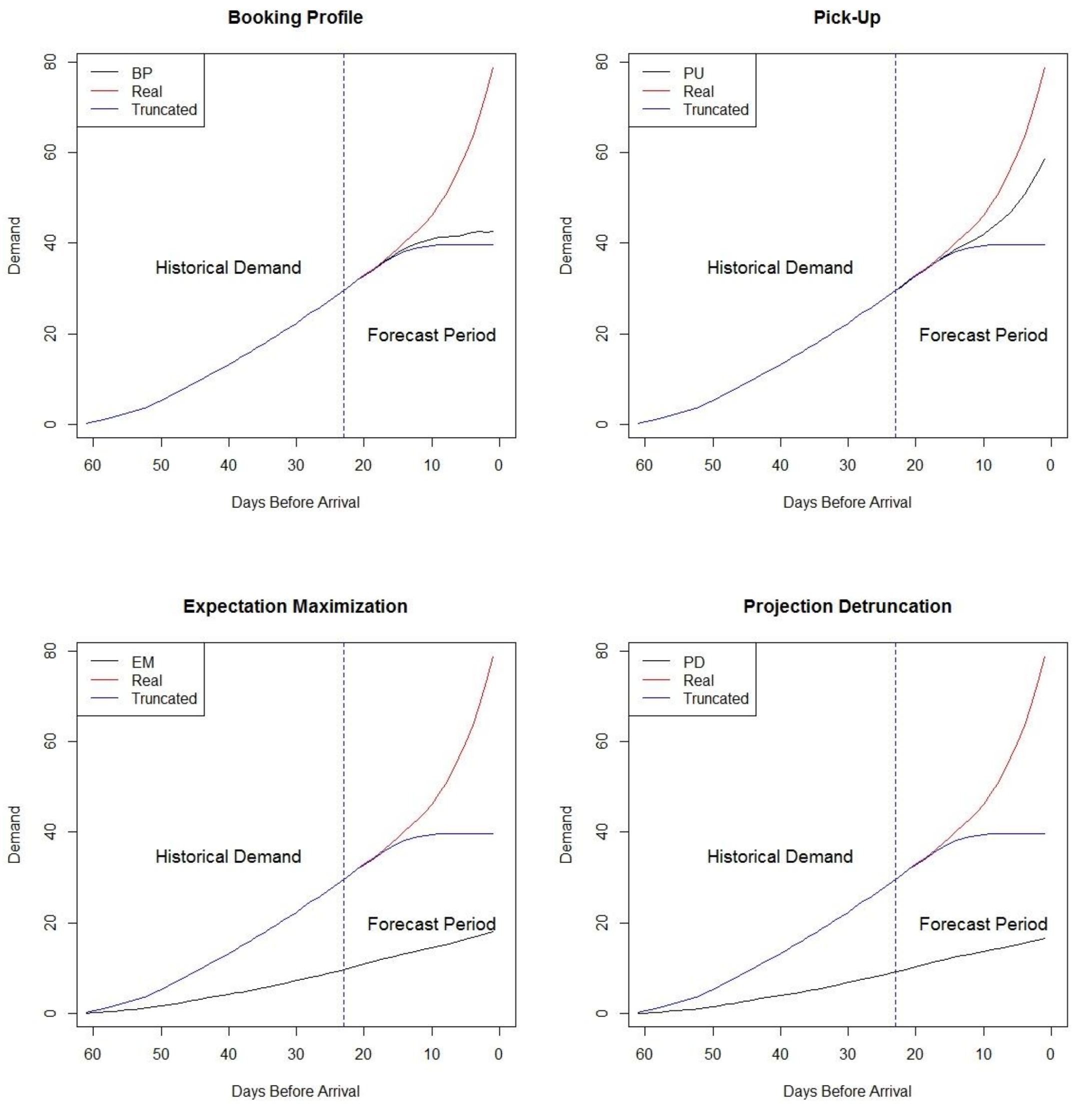


Figure A.1 Detruncation Plot (L/B Ratio=1:1, Truncation Percentage Level=50%)

Appendix B Calculation Code in R

```
set.seed(333) #####  Leisure/Business Customer Ratio=1:1  ####

####### BEGIN: Model Constant Parameters ######
M <- 100 # number of replicates (of simulated data)
N <- 61 # number of days before arrival (for each simulated data)

## Parameters for ***LEASURE*** data ##
# Phase 1: from day 0 to 10
L_LEN_1 <- 11 # number of days in phase 1
L_alpha_1 <- 1.386294 # initial value of demand for phase 1 (in log scale)
L_rate_1 <- -0.0449 # rate of demand increase

# Phase 2: from day 11 to 30
L_LEN_2 <- 20 # number of days in phase 2
L_alpha_2 <- 0.8923943 # initial value of demand for phase 2 (in log scale)
L_rate_2 <- -0.03575 # rate of demand increase (phase 2: from day 11 to 30)

# Phase 3: from day 31 to 60
L_LEN_3 <- 30 # number of days in phase 3
L_alpha_3 <- 0.1773944 # initial value of demand for phase 3 (in log scale)
L_rate_3 <- -0.14 # rate of demand increase (phase 3:from day 31 to 60)

## Parameters for ***BUSINESS*** data ##
# Phase 1: from day 0 to 10
B_LEN_1 <- 11 # number of days in phase 1
B_alpha_1 <- -0.3573992 # initial value of demand for phase 1 (in log scale)
B_rate_1 <- -0.2528 # rate of demand increase

# Phase 2: from day 11 to 30
B_LEN_2 <- 20 # number of days in phase 2
B_alpha_2 <- 0.005290978 # initial value of demand for phase 2 (in log scale)
B_rate_2 <- -0.0811 # rate of demand increase (phase 2: from day 11 to 30)

# Phase 3: from day 31 to 50
B_LEN_3 <- 20 # number of days in phase 3
B_alpha_3 <- 0.4757595# initial value of demand for phase 3 (in log scale)
B_rate_3 <- -0.1052 # rate of demand increase

# Phase 4: from day 51 to 60
B_LEN_4 <- 10 # number of days in phase 3
B_alpha_4 <- 1.791759 # initial value of demand for phase 3 (in log scale)
```

```
B_rate_4 <- -0.1316 # rate of demand increase

## Parameters for ***NON-CONSTRAINED BUSINESS*** data ##
# 1:1 50% #

# Phase 1: from day 0 to 10
NB_LEN_1 <- 11 # number of days in phase 1
NB_alpha_1 <- -1.050547 # initial value of demand for phase 1 (in log scale)
NB_rate_1 <- -0.2528 # rate of demand increase

# Phase 2: from day 11 to 30
NB_LEN_2 <- 20 # number of days in phase 2
NB_alpha_2 <- -0.6878564 # initial value of demand for phase 2 (in log scale)
NB_rate_2 <- -0.0811 # rate of demand increase (phase 2: from day 11 to 30)

# Phase 3: from day 31 to 50
NB_LEN_3 <- 20 # number of days in phase 3
NB_alpha_3 <- -0.2173878# initial value of demand for phase 3 (in log scale)
NB_rate_3 <- -0.1052 # rate of demand increase

# Phase 4: from day 51 to 60
NB_LEN_4 <- 10 # number of days in phase 3
NB_alpha_4 <- 1.098612 # initial value of demand for phase 3 (in log scale)
NB_rate_4 <- -0.1316 # rate of demand increase


########## END: Model Constant Parameters ###########

########## BEGIN: Initialize Model Variables ##########
Leasure_Simulated = c() # simulated data for leasure customers
Business_Simulated = c() # simulated data for business customers
########## END: Initialize Model Variables ############

########## BEGIN: DATA Simulation ###########
### Simulate for **LEASURE_DEMAND** Data ###
L_1 <- matrix(rpois(M*L_LEN_1, exp(L_alpha_1 + L_rate_1*seq(0,L_LEN_1-1))),
nrow=M, ncol=L_LEN_1, byrow=T) # simulated data for phase 1
L_2 <- matrix(rpois(M*L_LEN_2, exp(L_alpha_2 + L_rate_2*seq(0,L_LEN_2-1))),
nrow=M, ncol=L_LEN_2, byrow=T) # simulated data for phase 2
L_3 <- matrix(rpois(M*L_LEN_3, exp(L_alpha_3 + L_rate_3*seq(0,L_LEN_3-1))),
nrow=M, ncol=L_LEN_3, byrow=T) # simulated data for phase 3
L <- cbind(L_1,L_2,L_3)

### Simulate for **BUSINESS_DEMAND** Data ###
```

```
B_1 <- matrix(rpois(M*B_LEN_1, exp(B_alpha_1 + B_rate_1*sqrt(seq(B_LEN_1-
1,0)))), nrow=M, ncol=B_LEN_1, byrow=T) # simulated data for phase 1
B_2 <- matrix(rpois(M*B_LEN_2, exp(B_alpha_2 + B_rate_2*sqrt(seq(B_LEN_2-
1,0)))), nrow=M, ncol=B_LEN_2, byrow=T) # simulated data for phase 2
B_3 <- matrix(rpois(M*B_LEN_3, exp(B_alpha_3 + B_rate_3*sqrt(seq(B_LEN_3-
1,0)))), nrow=M, ncol=B_LEN_3, byrow=T) # simulated data for phase 3
B_4 <- matrix(rpois(M*B_LEN_4, exp(B_alpha_4 + B_rate_4*seq(B_LEN_4-1,0))),
nrow=M, ncol=B_LEN_4, byrow=T) # simulated data for phase 4
B <- cbind(B_1,B_2,B_3,B_4)

### Simulate for **NON-CONSTRAINED BUSINESS_DEMAND** Data ###
NB_1 <- matrix(rpois(M*NB_LEN_1, exp(NB_alpha_1 +
NB_rate_1*sqrt(seq(NB_LEN_1-1,0)))), nrow=M, ncol=NB_LEN_1, byrow=T) #
simulated data for phase 1
NB_2 <- matrix(rpois(M*NB_LEN_2, exp(NB_alpha_2 +
NB_rate_2*sqrt(seq(NB_LEN_2-1,0)))), nrow=M, ncol=NB_LEN_2, byrow=T) #
simulated data for phase 2
NB_3 <- matrix(rpois(M*NB_LEN_3, exp(NB_alpha_3 +
NB_rate_3*sqrt(seq(NB_LEN_3-1,0)))), nrow=M, ncol=NB_LEN_3, byrow=T) #
simulated data for phase 3
NB_4 <- matrix(rpois(M*NB_LEN_4, exp(NB_alpha_4 + NB_rate_4*seq(NB_LEN_4-
1,0))), nrow=M, ncol=NB_LEN_4, byrow=T) # simulated data for phase 4
NB <- cbind(NB_1,NB_2,NB_3,NB_4)
############# END: DATA Simulation #############

############ BEGIN: MODEL Simulation ##########
T <- L+B # cap demand
cumL <- t(apply(L, 1, cumsum)) # cumulative sums of L (leasure data set)
cumB <- t(apply(B, 1, cumsum)) # cumulative sums of B (buisness data set)
cumNB <- t(apply(NB, 1, cumsum)) # cumulative sums of NB (NON-CONSTRAINED
buisness data set)
cumT <- cumL + cumB # cumulative cap sums

## Generate metrix for days before arrival ##
day <- matrix(rep(seq(from=1,to=61),100),nrow=100,byrow=T)# days before arriaval
(two demension matrix)

X11() # Open a new window
# Plot Real CUMULATIVE demand curve for leisure, business and cap customers
plot(rev(colMeans(day)),colMeans(cumL),xlim=c(60,0),ylim=c(min(colMeans(cumB)),
max(colMeans(cumT))),type='l',xlab='Days Before Arrival',ylab='Demand')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(cumT),type='l',col='blue')
legend("topleft", legend=c("Leisure","Business","Total"),
       lty=c(1,1,1),
```

```
    col = c("black","red","blue"))

##### BEGIN: CONSTRAIN 50 PERCENT OF TOTAL BUSINESS DEMAND #####
oldL <- L
oldB <- B
oldT <- T
cumOldL <- cumL
cumOldB <- cumB
cumOldT <- cumT

S50B <- matrix(rep(0,6100),nrow=100)
dim(S50B)
rho <- 0.5 #PERCENTATE OF BUSINESS DEMAND NEED TO BE CONSTRAINED

for (i in 1:100)

{
        for (j in 1:61)
          {
                if (cumB[i,j] <= ceiling(cumB[i,61]*rho))
                        S50B[i,j] <- cumB[i,j]
                else
                        S50B[i,j] <- ceiling(cumB[i,61]*rho)
          }
}

S50L <- matrix(rep(0,6100),nrow=100)
cap <- 100
for (i in 1:100)

{
        for (j in 1:61)
          {
                if (cumL[i,j] <= (cap-S50B[i,61]))
                        S50L[i,j] <- cumL[i,j]
                else
                        S50L[i,j] <- (cap-S50B[i,61])
          }
}

S50T <- matrix(rep(0,6100),nrow=100)

S50T <- S50B+S50L

X11() # Open a new window
```

```
# Plot 50 PERCENT BUSINESS DEMAND TRUNCATED CUMULATIVE demand
curve for leisure, business and cap customers
plot(rev(colMeans(day)),colMeans(S50L),xlim=c(60,0),ylim=c(min(colMeans(S50B)),m
ax(colMeans(S50T))),type='l',xlab='Days Before Arrival',ylab='Demand')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50T),type='l',col='blue')
legend("topleft", legend=c("Leisure","Business","Total"),
      lty=c(1,1,1),
      col = c("black","red","blue"))

##### END: CONSTRAIN 50 PERCENT OF TOTAL BUSINESS DEMAND #####

##  BEGIN: GENERATE INCREMENTAL CAPACITY TRUNCATED DEMAND ##

LF <- matrix(nrow=100, ncol=61)
BF <- matrix(nrow=100, ncol=61)
TF <- matrix(nrow=100, ncol=61)

for (i in 1:100)
{

          for (j in 1:61)
          {
          if (j==1)
            {
                    LF[i,1] <- S50L[i,1]
                    BF[i,1] <- S50B[i,1]
                    TF[i,1] <- S50T[i,1]

            }
          else
            {
                    LF[i,j] <- S50L[i,j]-S50L[i,(j-1)]
                    BF[i,j] <- S50B[i,j]-S50B[i,(j-1)]
                    TF[i,j] <- S50T[i,j]-S50T[i,(j-1)]
            }
          }

}


### END: GENERATE INCREMENTAL CAPACITY TRUNCATED DEMAND ###


#### BEGIN: APPLY DETRUNCATION METHOD TO TRUNCATED DATA ####
```

```
# 1. SA - Simple average #

#n <-7
rd1.sa_index <- rep(0,100)
rd1.sa_mse <- rep(0,100)
rd1.sa <- matrix(nrow=100,ncol=61)
rd1.sa_0 <- matrix(nrow=100,ncol=61)

for (i in 1:100)
{
        rd1.sa_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1] # find out the fist
day biz begin to be truncated
        rd1.sa[i,] <- BF[i,] # predicted demand
        rd1.sa_0[i,] <- BF[i,] # Copy observed business demand to metrix rd1.sa_0
        rd1.sa[i,1:rd1.sa_index[i]] <- rd1.sa_0[i,1:rd1.sa_index[i]]
        rd1.sa[i,rd1.sa_index[i]+1] <- mean(rd1.sa_0[i,1:rd1.sa_index[i]])

        for (a in rd1.sa_index[i]:59)
         {
         rd1.sa[i,a+2] <- (rd1.sa[i,a+1]*a+ rd1.sa_0[i,a+1])/(a+1)
         }
        rd1.sa_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.sa[i,])[rd1.sa_index[i]:61]),"F"))^2/(61-rd1.sa_index[i]+1)

}

cum_rd1.sa <- rd1.sa

for (i in 1:100)
{
                for (j in 2:61)
                {
                cum_rd1.sa[i,j] <- cum_rd1.sa[i,j-1]+rd1.sa[i,j]
                }

}

# MSE Calculation
rd1.sa_error <- sum(rd1.sa_mse)/100 # average MSE
rd1.sa_error
sd(rd1.sa_mse) # standard deviation

# Cumulative plot
```

```
plot(rev(colMeans(day)),colMeans(cum_rd1.sa),xlim=c(60,0),ylim=c(min(colMeans(cu
mB)),max(colMeans(cumB))),type='l',xlab='Days Before Arrival',ylab='Demand')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
    lty=c(1,1,1),
    col = c("black","red","blue"))


# 2. SMA - SIMPLE MOVING AVERAGE #
library(TTR)

rd1.sma_index <- rep(0,100)
rd1.sma_mse <- rep(0,100)
rd1.sma <- matrix(nrow=100,ncol=61)
rd1.sma_0 <- matrix(nrow=100,ncol=61)

for (i in 1:100)
{
      rd1.sma_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1] # find out the
fist day biz begin to be truncated
      rd1.sma_0[i,] <- BF[i,] # Copy observed business demand to metrix rd1.sma_0
      rd1.sma[i,] <- SMA(BF[i,], n=rd1.sma_index[i]) # Calculates the arithmetic mean
of the series over the past rd1.sma_index[i] observations in BF
      rd1.sma[i,1:rd1.sma_index[i]] <- rd1.sma_0[i,1:rd1.sma_index[i]]
      rd1.sma_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.sma[i,])[rd1.sma_index[i]:61]),"F"))^2/(61-rd1.sma_index[i]+1)
}

cum_rd1.sma <- rd1.sma

for (i in 1:100)
{
            for (j in 2:61)
            {
            cum_rd1.sma[i,j] <- cum_rd1.sma[i,j-1]+rd1.sma[i,j]
            }

}

rd1.sma_error <- sum(rd1.sma_mse)/100 # average MSE
rd1.sma_error
sd(rd1.sma_mse) # standard deviation

# Cumulative plot
```

```
X11()
plot(rev(colMeans(day)),colMeans(cum_rd1.sma),xlim=c(60,0),ylim=c(min(colMeans(c
umB)),max(colMeans(cumB))),type='l',xlab='Days Before
Arrival',ylab='Demand',main='Simple Moving Average')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
      lty=c(1,1,1),
      col = c("black","red","blue"))

# 3. EMA - EXPONENTIAL MOVING AVERAGE #
library(TTR)

rd1.ema_index <- rep(0,100)
rd1.ema_mse <- rep(0,100)
rd1.ema <- matrix(nrow=100,ncol=61)
rd1.ema_0 <- matrix(nrow=100,ncol=61)

for (i in 1:100)
{
        rd1.ema_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]
        rd1.ema_0[i,] <- BF[i,] # Copy observed business demand to metrix rd1.ema_0
        rd1.ema[i,] <- EMA(BF[i,], n=rd1.ema_index[i], wilder=TRUE) # calculates an
exponentially-weighted mean giving more weight to recent observations
        rd1.ema[i,1:rd1.ema_index[i]] <- rd1.ema_0[i,1:rd1.ema_index[i]]
        rd1.ema_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.ema[i,])[rd1.ema_index[i]:61]),"F"))^2/(61-rd1.ema_index[i]+1)
}

cum_rd1.ema <- rd1.ema

for (i in 1:100)
{
                for (j in 2:61)
                {
                cum_rd1.ema[i,j] <- cum_rd1.ema[i,j-1]+rd1.ema[i,j]
                }

}

rd1.ema_error <- sum(rd1.ema_mse)/100 # average MSE
rd1.ema_error
sd(rd1.ema_mse) # standard deviation

# Cumulative plot
```

```
plot(rev(colMeans(day)),colMeans(cum_rd1.ema),xlim=c(60,0),ylim=c(min(colMeans(c
umB)),max(colMeans(cumB))),type='l',xlab='Days Before
Arrival',ylab='Demand',main='Exponential Moving Average')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
      lty=c(1,1,1),
      col = c("black","red","blue"))

#For EMA, wilder=FALSE (the default) uses an exponential smoothing ratio of 2/(n+1),
while wilder=TRUE uses Welles Wilder's exponential smoothing ratio of 1/n.

# 4. DEMA - DOUBLE EXPOENTIAL MOVING AVERAGE #
library(TTR)

rd1.dema_index <- rep(0,100)
rd1.dema_mse <- rep(0,100)
rd1.dema <- matrix(nrow=100,ncol=61)
rd1.dema_0 <- matrix(nrow=100,ncol=61)

for (i in 1:100)
{
        rd1.dema_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]
        rd1.dema[i,] <- DEMA(BF[i,], n=rd1.dema_index[i]-rd1.dema_index[i]/2)
        rd1.dema[i,1:rd1.dema_index[i]] <- BF[i,1:rd1.dema_index[i]]
        rd1.dema_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.dema[i,])[rd1.dema_index[i]:61]),"F"))^2/(61-rd1.dema_index[i]+1)
}

cum_rd1.dema <- rd1.dema

for (i in 1:100)
{
                for (j in 2:61)
                {
                cum_rd1.dema[i,j] <- cum_rd1.dema[i,j-1]+rd1.dema[i,j]
                }

}

rd1.dema_error <- sum(rd1.dema_mse)/100 # average MSE
rd1.dema_error
sd(rd1.dema_mse) # standard deviation

# Cumulative plot
```

```
plot(rev(colMeans(day)),colMeans(cum_rd1.dema),xlim=c(60,0),ylim=c(min(colMeans(
cumB)),max(colMeans(cumB))),type='l',xlab='Days Before
Arrival',ylab='Demand',main='Double Exponential Moving Average')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(cum_rd1.dema),type='l',col='purple')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
     lty=c(1,1,1),
     col = c("black","red","blue"))

#DEMA is calculated as:
#DEMA = (1 + v) * EMA(x,n) - EMA(EMA(x,n),n) * v(with the cor-responding wilder
and ratio arguments).
# 6. BP - Booking Profile #

rd1.bp_index <- rep(0,100)
rd1.bp_mse <- rep(0,100)
rd1.bp_0 <- rep(0,61)
rho.bp <- rep(0,61)
rd1.bp <- matrix(nrow=100,ncol=61)

# Using cumulative data
cum_rd1.bp <- S50B

for (i in 1:100)
{
        rd1.bp_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]

        rd1.bp_0 <- colMeans(cumNB)
        for(j in rd1.bp_index[i]:61)
        {
                rho.bp[j] <- rd1.bp_0[j]/rd1.bp_0[j-1]
                cum_rd1.bp[i,j] <- S50B[i,j-1]*rho.bp[j]
        }
        for (j in 1:61)
        {
         if (j==1)
         {
                rd1.bp[i,1] <- cum_rd1.bp[i,1]
         }
         else
         {
                rd1.bp[i,j] <- cum_rd1.bp[i,j]-cum_rd1.bp[i,(j-1)]
         }
        }
```

```
	rd1.bp_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.bp[i,])[rd1.bp_index[i]:61]),"F"))^2/(61-rd1.bp_index[i]+1)

}


rd1.bp_error <- sum(rd1.bp_mse)/100 # average MSE
rd1.bp_error
sd(rd1.bp_mse) # standard deviation

# Cumulative plot
plot(rev(colMeans(day)),colMeans(cum_rd1.bp),xlim=c(60,0),ylim=c(min(colMeans(cu
mB)),max(colMeans(cumB))),type='l',xlab='Days Before
Arrival',ylab='Demand',main='Booking Profile')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
      lty=c(1,1,1),
      col = c("black","red","blue"))


# 7. PU - Pick Up #

rd1.pu_index <- rep(0,100)
rd1.pu_mse <- rep(0,100)
cum_rd1.pu <- S50B
inc_rd1.pu <- matrix(nrow=100,ncol=61)

for(i in 1:100)
{
	rd1.pu_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]
	for(j in (rd1.pu_index[i]:61))
	{
	 cum_rd1.pu[i,j] <- S50B[i,(rd1.pu_index[i]-
1)]+(sum(NB[,rd1.pu_index[i]:j])/100)
	}
	for (j in 1:61)
	{
	 if (j==1)
	 {
		inc_rd1.pu[i,1] <- cum_rd1.pu[i,1]
	 }
	 else
	 {
```

```
                inc_rd1.pu[i,j] <- cum_rd1.pu[i,j]-cum_rd1.pu[i,(j-1)]
            }
          }
          rd1.pu_mse[i] <- (norm(as.matrix((oldB[i,]-
inc_rd1.pu[i,])[rd1.pu_index[i]:61]),"F"))^2/(61-rd1.pu_index[i]+1)


}

rd1.pu_error <- sum(rd1.pu_mse)/100 # average MSE
rd1.pu_error
sd(rd1.pu_mse) # standard deviation

# Cumulative plot
plot(rev(colMeans(day)),colMeans(cum_rd1.pu),xlim=c(60,0),ylim=c(min(colMeans(cu
mB)),max(colMeans(cumB))),type='l',xlab='Days Before
Arrival',ylab='Demand',main='L/B Ratio=1/1, Truncation Level=50%')
points(rev(colMeans(day)),colMeans(cum_rd1.bp),type='l',col='green')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("PU","BP","Real","Truncated"),
      lty=c(1,1,1,1),
      col = c("black","green","red","blue"))
abline(v=(61-min(rd1.dema_index)),col=4,lty=2)
text(40, 35, "Historical Demand",
    cex = 1.2)
text(10, 20, "Forecast Period",
    cex = 1.2)

# 8. EM - Expectation Maximization #
library(RM2)

rd1.em_index <- rep(0,100)
rd1.em_mse <- rep(0,100)
rd1.em <- rep(0,61)

for(i in 1:100)
{
          rd1.em_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]

          # GENERATE REAL DEMAND
          rdemand <- NB[i,]
          # GENERATE BOOKING LIMITS
          bl <- BF[i,]
          # GENERATE OBSERVED DEMAND
```

```
	demand <- rdemand * (rdemand <= bl) + bl * (rdemand > bl)
	# IDENTIFIED PERIODS WITH CONSTRAINED DEMAND: 1 -
CONSTRAINED DEMAND
	names(demand) <- as.character(as.numeric(rdemand>bl))
	# UNTRUNCATE DEMAND
	rd1.em_0 <- EM(demand,eps=0.005)

	rd1.em <- rd1.em + rd1.em_0$demand;

	rd1.em_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.em_0$demand)[rd1.em_index[i]:61]),"F"))^2/(61-rd1.em_index[i]+1)


}

rd1.em_result<- rd1.em/100

cum_rd1.em <- rd1.em_result

for (i in 2:61)
{

		cum_rd1.em[i] <- cum_rd1.em[i-1]+rd1.em_result[i]


}

rd1.bp_error <- sum(rd1.em_mse)/100 # average MSE
rd1.bp_error
sd(rd1.em_mse) # standard deviation

# Cumulative plot
plot(rev(colMeans(day)),cum_rd1.em,xlim=c(60,0),ylim=c(min(colMeans(cumB)),max(c
olMeans(cumB))),type='l',xlab='Days Before Arrival',ylab='Demand',main='Expectation
Maximization')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
      lty=c(1,1,1),
      col = c("black","red","blue"))


# 9. PD - Projection Detruncation #
library(RM2)
```

```
rd1.pd_index <- rep(0,100)
rd1.pd_mse <- rep(0,100)
rd1.pd <- rep(0,61)

for(i in 1:100)
{
	rd1.pd_index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]

	# GENERATE REAL DEMAND
	rdemand <- NB[i,]
	# GENERATE BOOKING LIMITS
	bl <- BF[i,]
	# GENERATE OBSERVED DEMAND
	demand <- rdemand * (rdemand <= bl) + bl * (rdemand > bl)
	# IDENTIFIED PERIODS WITH CONSTRAINED DEMAND: 1 -
CONSTRAINED DEMAND
	names(demand) <- as.character(as.numeric(rdemand>bl))
	# UNTRUNCATE DEMAND
	rd1.pd_0 <- PD(demand,eps=0.005)

	rd1.pd <- rd1.pd + rd1.pd_0$demand;

	rd1.pd_mse[i] <- (norm(as.matrix((oldB[i,]-
rd1.pd_0$demand)[rd1.pd_index[i]:61]),"F"))^2/(61-rd1.pd_index[i]+1)

}

rd1.pd_result<- rd1.pd/100

cum_rd1.pd <- rd1.pd_result

for (i in 2:61)
{

		cum_rd1.pd[i] <- cum_rd1.pd[i-1]+rd1.pd_result[i]


}

rd1.bp_error <- sum(rd1.pd_mse)/100 # average MSE
rd1.bp_error
sd(rd1.pd_mse) # standard deviation

# Cumulative plot
```

```
plot(rev(colMeans(day)),cum_rd1.pd,xlim=c(60,0),ylim=c(min(colMeans(cumB)),max(c
olMeans(cumB))),type='l',xlab='Days Before Arrival',ylab='Demand',main='Projection
Detruncation')
points(rev(colMeans(day)),colMeans(cumB),type='l',col='red')
points(rev(colMeans(day)),colMeans(S50B),type='l',col='blue')
legend("topleft", legend=c("Detruncated","Real","Truncated"),
      lty=c(1,1,1),
      col = c("black","red","blue"))


###### END: APPLY DETRUNCATION METHOD TO TRUNCATED DATA ######

############## BEGIN: CALCULATE ROM ##############

index <- rep(0,100)

# absolute increase #

sum.sa <- rep(0,100)
sum.sma <- rep(0,100)
sum.ema <- rep(0,100)
sum.dema <- rep(0,100)
sum.bp <- rep(0,100)
sum.pu <- rep(0,100)
sum.em <- rep(0,100)
sum.pd <- rep(0,100)


for (i in 1:100)
{
        index[i]<-which(S50B[i,]==ceiling(cumB[i,61]*rho))[1]

        sum.sa[i]   <- cum_rd1.sa[i,61]-cum_rd1.sa[i,index[i]]
        sum.ema[i]  <- cum_rd1.ema[i,61]-cum_rd1.ema[i,index[i]]
        sum.sma[i]  <- cum_rd1.sma[i,61]-cum_rd1.sma[i,index[i]]
        sum.ema[i]  <- cum_rd1.ema[i,61]-cum_rd1.ema[i,index[i]]
        sum.dema[i] <- cum_rd1.dema[i,61]-cum_rd1.dema[i,index[i]]
        sum.bp[i]   <- cum_rd1.bp[i,61]-cum_rd1.bp[i,index[i]]
        sum.pu[i]   <- cum_rd1.pu[i,61]-cum_rd1.pu[i,index[i]]
        sum.em[i]   <- cum_rd1.em[61]-cum_rd1.em[index[i]]
        sum.pd[i]   <- cum_rd1.pd[61]-cum_rd1.pd[index[i]]

}

# Average absolute increase #
```

```
rev.sa <- mean(sum.sa)
rev.sa

rev.sma <- mean(sum.sma)
rev.sma

rev.ema <- mean(sum.ema)
rev.ema

rev.dema <- mean(sum.dema)
rev.dema

rev.bp <- mean(sum.bp)
rev.bp

rev.pu <- mean(sum.pu)
rev.pu

rev.em <- mean(sum.em)
rev.em

rev.pd <- mean(sum.pd)
rev.pd


############## END: CALCULATE ROM ##############
```