THE ROLE OF SPACE IN REVENUE MANAGEMENT

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Service providers face the risk of losing revenue if physical capacity does not match the demand requiring its use, so operating with the optimal physical supply profile is essential to maximizing revenue. Research on how to determine this physical supply has not always accounted for the space required to house it, and has typically assumed that: the optimal supply mix can be accommodated by the available space, the existing number of inventory units within the space is appropriate, and inventory units are homogeneous in terms of the space they occupy. The research that has addressed the use of space in Revenue Management sometimes incorporates space as a constraint to the problem, but other times uses space as the decision variable. Therefore, testing whether there is a revenue difference between these two space outlooks in situations where these key assumptions do not hold is warranted.

A simulation model using data from a casual, full-service restaurant was developed to compare the impact of incorporating space in these two ways into the Revenue Management problem. A full-factorial experimental design created 36 distinct simulation scenarios, with these two space outlooks serving as the primary factor, and three other factors providing a range of operating conditions. For each scenario, all possible table mixes were enumerated, simulated, and ranked according to total revenue. The top revenue-generating table mix under the two space methods were paired at every level of the other factors and revenue differences were analyzed.

Results from the simulation experiment did not reveal any systematic revenue difference between the two space methods when the tables used at a restaurant were of standard size or larger. When the tables were smaller than standard size and the restaurant experienced extremely high demand, using space as the decision variable generated a significant revenue benefit over incorporating space as a constraint. To make these findings accessible to practitioners and because published means for determining the optimal physical supply profile do not always recommend table mixes that fit in the available space, table mix heuristics developed by Kimes and Thompson (2005) were modified to account for both methods of incorporating space. The size of the tables used by the restaurant and the seating rules followed affected which heuristic recommended the most lucrative supply mix.

BIOGRAPHICAL SKETCH

Kristin Rohlfs began her academic career at The University of Texas at Austin and earned a Bachelor of Business Administration degree in both Finance and Business Honors, graduating first in her class with highest honors in 1997. Kristin subsequently received a Master of Management in Hospitality degree from Cornell University in 2000. She again graduated with highest honors after writing a Master's monograph entitled, "Measuring the Financial Performance of the US Lodging Industry: A New Perspective on the Last Decade," that was recognized as a finalist in graduate research at Cornell's School for Hospitality Management.

Prior to returning to Cornell for her Ph.D, Kristin worked as a consultant for the Hospitality Finance group at Arthur Andersen and as an analyst for the Hospitality Research Group of PKF Consulting. Kristin began her hospitality career in restaurants during high school, and worked as a Front Desk and Reservations Sales agent throughout college.

Kristin has had research published in the Center for Hospitality Research report series, the Cornell Hotel and Restaurant Administration Quarterly, Lodging magazine, and various on-line hospitality websites. Her paper in the CQ, "Customers' Perceptions of Best Available Hotel Rates" was a finalist for best paper in 2006. Kristin has also consulted for Harrah's casinos in Restaurant Revenue Management, where she helped to design a revenue management program for their buffet operations.

To my adorable and amazing son, Ray; his namesake, my missed father, Ray; and my incredible, loving, and wonderfully patient husband, Stefan.

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CHAPTER 1: INTRODUCTION AND RESEARCH OBJECTIVES

In general, managing the capacity of a service operation entails using available supply to satisfy the needs of customers in a profitable manner. One aspect of supply is the physical inventory units put into operation to fulfill requests for service, generate revenues, and fit into the actual space available to process customers. Ensuring that the optimal amount and mix of this physical capacity put into use is an essential component in maximizing the revenue potential of service, and understanding how to determine this level and mix of supply is the broad topic of this study. This chapter provides background for this research problem in terms of how it is connected to the field of Revenue Management; the real-world context in which this study is conducted is also described. Three specific research questions are posed that, once answered through experimentation and analysis of results, will give insight into the impact on a service system of operating with the most advantageous, realistic level and mix of physical supply. The organization of this dissertation is also presented, including a brief synopsis of the content covered in each of the chapters.

Research Background

Many service-based businesses operate with a supply base that contains a mix of physical and nonphysical resources. The physical inventory of a service – rooms at a hotel, vehicles of a car rental company, treatment rooms in a spa, or tables at a restaurant – is used in conjunction with employees and atmosphere to fulfill the needs of customers. Once established, the amount and type of physical inventory used by a service is often inflexible and can constrain the output the system can produce since no inventory buffers exist between what customers want and what service companies provide (Sasser, 1976; Talluri and van Ryzin, 2005). For instance, a hotel built with

100 rooms can sell a maximum of 100 rooms per night, regardless of the availability of nonphysical resources such as employees or computing power.

Therefore, a service provider faces the risk of not capturing all potential revenue if the physical capacity it has available does not match the demand requiring its use. At a specific point in time, each physical inventory unit has a revenue-generating opportunity that, in most cases, will be lost forever if not used since services cannot be inventoried for sale at another time (Kimes and Chase, 1998). Additionally, revenue-producing requests for a service are oftentimes forfeited if no accompanying physical inventory component is readily available. To manage a potential imbalance between supply and demand, service companies often use demand and capacity management practices to influence how and when service requests materialize and how requests are processed as they arrive.

Revenue Management (RM) is a well-known and widely-used field that combines elements of both demand and capacity management to address service situations in which limited supply is available to fulfill demand from a variety of customer segments. The principal goal of RM is to maximize the possible revenue that can be generated by a set of physical inventory units over a certain time period (Kimes, 1989). An RM system operationalizes this goal by allocating physical supply to demand categories that are differentiated by various combinations of price, physical inventory features, and intangible operating policies (Kimes, 1989; Kimes and Chase, 1998). These supply categories are then used to serve multiple segments of customers with different needs.

For instance, hotel RM systems distribute rooms to various rate and length of stay buckets that are also differentiated by qualities such as room type and cancellation policy. As such, the same hotel room is used to serve business or leisure guests, short- or long-term customers, and discount or convenience-oriented patrons in a way that maximizes the revenue brought to the property. In a similar manner, restaurants use their available dining room to accommodate different types of customers, such as parties of two or parties of eight and business meetings or romantic couples.

Generally, the smallest and most frequently occurring physical inventory unit of a particular service operation serves as the basis for allocating the existing total supply into these demand-based categories (Kimes, 1989; Talluri and van Ryzin, 1998). Examples of the smallest inventory unit are coach seats on an aircraft, standard rooms of a hotel, and chairs or seats in a restaurant. Many times, however, seemingly identical physical inventory units are not actually homogeneous. Standard hotel rooms have differing numbers and types of beds, such as one king, one queen, or two doubles. Likewise, seats in a restaurant dining room are situated at a variety of table types such as banquettes and rounds and numerous table sizes, ranging from one-tops to twelve-tops or larger.

An additional characteristic that further makes these physical inventory units non-homogeneous is the amount of space required to accommodate each unit of inventory. For example, a Cadillac Escalade takes up more area on a rental car lot than does a BMW Mini Cooper. Similarly, an eight-top table at a restaurant occupies more space than a two-top. Therefore, a restaurant using a dining room area that cannot be easily expanded or altered may be able to capture more revenue if it has the number and mix of tables and seats available that best accommodates its customer base.

In these types of service situations where standard inventory units are spatially non-homogeneous, traditional capacity and revenue management techniques may produce the maximum possible revenue for the inventory units in operation, but not for the total potential revenue-generating space of the business under study. The overriding purpose of this research is to therefore understand how incorporating space into the revenue management problem impacts the supply profile of an operation and its ability to produce the highest possible expected revenue.

Research Context

Exploring this units-versus-space inventory issue requires comparing the performance of a system in which physical units are the basis of inventory allocation to the performance of the same system but with space as the basis for inventory allocation. The system under study consequently needs to use a mix of spatially non-homogeneous, perishable, and relatively inflexible physical inventory within a mostly fixed area. Additionally, the system should either currently use Revenue Management or have the characteristics necessary to be able to properly use RM, such as stochastic demand, demand that is easy to segment, and fairly low marginal costs (Kimes, 1989). Several service businesses including hotels, rental cars companies, airlines, casinos, and restaurants fit this description.

Of these service systems, a restaurant is chosen as the context in which to study the units-versus-space inventory problem. A restaurant can more easily alter the level and mix of its physical inventory – seats at tables – than a hotel can add or subtract beds in rooms or an airline can change the mix of seats it offers on planes. While all of the services mentioned can benefit from this type of research in the earliest phases of capacity planning, a restaurant can more immediately use the results of this study to improve operations since the cost to modify the seats and tables in dining room is not exorbitant ("Tables and Bases," 2008; Kimes, 2004; Kimes and Thompson, 2004).

Restaurateurs have long expressed interest in managing both their kitchen and dining room capacities to serve as many guests as possible while maintaining the desired level of customer service (Muller, 1999; Sill and Decker, 1999). Recently, restaurant operators have begun experimenting with capacities of their establishments in order to best move customers through the dining experience (Prewitt, 2007). Operators are particularly interested in understanding how capacity can be changed to minimize occupancy costs, maximize revenue-generating space, or both (Prewitt, 2007).

Researchers have already published several studies providing tools and techniques helpful in managing a restaurant's existing dining room capacity. Thompson (2002) examined the capacity of a restaurant in terms of the level of flexibility to combine smaller tables to fit large parties that would capture the most revenue. Kimes and Thompson (2004) studied the mix of capacity at a full-service restaurant and found that better matching physical supply to customer demand positively impacted revenue. They found that allocating the existing number of seats to the mix of 2-top, 4-top, 6-top, and 8-top tables that best matched demand for tables of those sizes, regardless if the restaurant currently owned that particular mix of tables, was a profitable venture.

In these studies, the authors were interested in determining how to serve more customers without increasing the number of seats in the subject facilities. Therefore, the optimal mix of capacity was based on the pre-determined level of capacity in the restaurant. Additionally, supply was assumed to be spatially homogeneous in that all seats required the same amount of dining room space, regardless of the table size to which they were allocated. While these studies are seminal in examining how to best use the existing physical capacity of a service, this type of supply research could be augmented by taking space considerations into account at the earliest stages of capacity allocation and also simultaneously determining the physical capacity level and mix of a service business that optimizes revenue potential.

Research Questions

A number of questions arise when comparing a restaurant situation from a perspective of space instead of the established viewpoint of seats as the basic physical inventory unit. The following questions give insight into the broad impact of this comparison:

1. To what extent is revenue impacted if capacity is allocated based on space instead of inventory units?

Basic physical inventory units, such as seats at a restaurant, appear identical but are, in fact, spatially diverse depending on how they are allocated to various revenue-generating entities, such as restaurant tables. Published capacity allocation research recognizes this issue and handles it by allowing slightly-below-optimal solutions to be adopted (Kimes, 2004; Kimes and Thompson, 2004; Kimes and Thompson, 2005). This adjustment is the result of allocating the existing number of seats to different tables without initially taking into account whether or not the table mix can actually fit in the dining room space available. Factoring in space considerations before allocating inventory units may alleviate or reduce this problem and result in a table mix that better accommodates customers and thus generates more money. It may also lead to a capacity level that is better matched to the level of demand.

2. How is existing capacity changed when supply is measured by space instead of units?

Allocating space to tables in a restaurant entails determining the net amount of space that is available to seat customers and then establishing the best mix of physical supply to meet demand. By using a space-as-inventory outlook, the current number of seats used by a restaurant may change as the operation is now constrained by available space instead of existing seats. An increase in the number of seats would expectedly lead to a categorical increase in revenue as more customers could be served in the same time frame. However, the optimal table mix under a space allocation rule could possibly use fewer seats than its seat inventory counterpart. This situation leads to the third research question.

3. Can revenue actually increase if the number of physical capacity units in operation is decreased?

Some restaurant chains have begun decreasing the size of their facilities – in terms of both space and number of seats – with the results of maintaining and sometimes even increasing revenues (Prewitt, 2007). However, no mention is made if these higher profits were achieved by simply cutting out excess capacity. Restaurants operating at high utilization rates do not have excess capacity, especially during peak periods. Owners and operators of capacity-constrained facilities could more confidently participate in the trend to downsize if the optimal table mix produced under a space allocation rule were to use fewer seats but achieve higher revenue.

Organization of the Dissertation

In this chapter, the background leading to this research, including ties to several fields within Operations Management, was presented. Details regarding why a restaurant operation was chosen as the context for this study were also provided. Three specific questions that give insight into the affect on a restaurant operating system of redefining inventory as space instead of units serve as the basis for this study and will be answered through controlled experiments.

Chapter 2 provides a review of the literature pertaining to both the broad issues and specific subjects associated with this research. Aspects of many different research streams are relevant to this problem; capacity planning, capacity management, revenue management, and restaurant revenue management literature are discussed.

The research methods used to address the objectives of this study are described in Chapter 3. A simulation model is developed to mimic the operations of a real-world test site, and is validated using actual operational data. A full-factorial experimental design is proposed, as are the statistical methods to be used to analyze the simulation output.

The results of the simulation experiment and accompanying analyses are presented in Chapter 4. Insights gained from the findings are linked to existing restaurant revenue management research in Chapter 5, which details the primary contribution of this study. Chapter 6 then presents the conclusions of the study, including additional contributions of the research to the Service Operations Management and Revenue Management literature, the implications of the study findings for practitioners, and the limitations of this study and how they provide avenues for future research.

CHAPTER 2: LITERATURE REVIEW

The goal of this research is to determine if defining the physical inventory of a service operation as space instead of capacity units, such as seats in a restaurant, leads to changes in revenues and total capacity. Aspects of many different research streams are relevant to this problem, and literature associated with each topic is reviewed in this chapter. Capacity planning and its relationship to capacity management are discussed. The importance and complexity of concurrently managing the supply and demand of a service business are presented, as is an overview of the Revenue Management tools and techniques that have emerged to take advantage of supply and demand imbalances. Literature pertaining to Revenue Management aspects of restaurants is also covered since a restaurant provides the research context for this study. Lastly, a review of how space has been considered in Revenue and Operations Management problems is given.

Capacity Defined

At first glance, capacity seems to be a straightforward notion where the total capacity of a system is the realistic amount of output its operations can produce (Klein and Long, 1973). However, several ways of defining and measuring capacity exist, making it a complex and longstanding focus of research. Various disciplines employ more specific definitions of capacity to reflect the unique characteristics of their fields. For instance, telecommunications uses channel capacity (Verdu and Han, 1994) and tourism considers carrying capacity (Lindberg et al., 1997). Further, total capacity can be determined by different methods such as the point at which full inputs are required or the point at which a bottleneck develops (Klein and Long, 1973).

Because of their perishable nature, services generally define total capacity as the maximum output that can be produced in a specified time period given a predefined level of all relevant inputs (Lovelock, 1992). Total capacity of a service is therefore a function of several factors, including the space available to build and maintain an operation, the physical and non-physical resources required to execute the service offerings, and the time allotted to provide the service (Lovelock, 1992; Klassen and Rohleder, 2001). As such, measuring total service capacity and how well it is utilized has often been done by focusing on the smallest unit of inventory for sale, such a hotel room or a restaurant seat.

Capacity Planning

In broad terms, capacity planning entails determining the supply profile of a business so as to best accommodate expected customers. This long-term planning occurs in the earliest stages of building or remodeling a business (Bahl et al., 1987) as well as throughout the lifetime of an ongoing operation (Olhager et al., 2001). The objective of capacity planning is to establish the appropriate types and levels of supply that minimize the costs of operating a business while still satisfying demand for goods or services (Eppen et al., 1989).

Capacity planning is often classified as the first stage of a two-stage stochastic decision problem (Fine and Freund, 1990; Bish and Wang, 2004). In this stage, a business makes risky, long-term, and costly investment decisions based upon uncertain demand forecasts and vague expectations of future operating conditions (Dangl, 1999; Olhager et al., 2001). The second stage of the stochastic decision problem is capacity management; literature on this subject is discussed later in this chapter.

Facets of Capacity Planning

Research in capacity planning has largely focused on helping businesses determine where and how to efficiently and inexpensively create or assemble products (Koopmans, 1951; Eppen et al., 1989; Fine and Freund, 1990; Jordan and Graves, 1995). As such, much capacity planning literature pertains to large-scale issues including the number and location of production or service facilities (Eppen et al., 1989; ReVelle and Eiselt, 2005) as well as the physical size of each location (Paraskevopoulos et al., 1991). An over-investment in facilities leads to idle capacity if actual demand falls below what is expected, while under-investing in supply results in foregone revenues if a higher level of demand materializes (Balachandran et al., 1997; Gu, 2003).

Capacity planning also involves designing the actual service or production system to be housed by the facilities. The design of a system entails establishing how inputs will be transformed into outputs, and businesses often struggle with balancing costs, quality, and productivity when planning these production processes (Banker and Morey, 1993; Armistead and Machin, 1998). Process design entails combining aspects of marketing, operations, product design and mix, human resources, materials procurement and handling, customer relationship management, and sales into a functioning system (Chase, 1981; Delaunay, 1999; Pullman and Moore, 1999; Olhager et al., 2001). It also entails configuring the layout of a facility to optimize the way in which raw materials flow through the production process so all aspects of the physical facility are utilized in the most profitable manner and customers (Tompkins and Reed, 1976; Bozer et al., 1994; Pagell and Melnyk, 2004).

A significant aspect of process design and planning is determining the amount of flexibility that should be built into the delivery system. Flexibility is often defined as the extent to which resources can be shared in the production of a variety of goods or services (Fine and Freund, 1990). Because operating with flexible resources is costly, the most beneficial level of flexibility for an operation is one in which the trade-off between higher production costs is offset by the potential benefits of being able to react to changes in the level or mix of demand (Jordan and Graves, 1995; van Mieghem, 1998). When resources have a high level of commonality, optimizing the use of the resource is more lucrative than trying to minimize the production costs (Balachandran et al., 1997).

Capacity Planning for Services

For a service operation, the combination of physical and nonphysical supply determines the total capacity of a service operation. Many capacity planning researchers have focused on nonphysical supply, or the role that employees play in service capacity planning (Hueter and Swart, 1998; Sill and Decker, 1999; Thompson, 1998; Thompson, 1999). Research regarding the physical supply of services is often concerned with service process design and engineering Back-of-House (BOH) operations for maximum efficiency (e.g. Levitt, 1972; Collier, 1995; Bowen and Youngdahl, 1998; van Merode et al., 1998; Pagell and Melnyk, 2004) or revising Front-of-House (FOH) operations for optimal customer response (Bitner, 1992; Ward et al., 1992; Robson, 1999; Namasivayam and Lin, 2004; Hassanien and Baum, 2002; Hill et al., 2002). There is limited research, however, on developing the physical supply of a service facility.

Physical Supply of Services

In a service operation, the size of a service facility is typically determined by corporate standards, site-specific qualities, best practices benchmarking, or competitor profiles (Banker and Morey, 1993; Bradach, 1997; Phillips and Appiah-Adu, 1998; Tzeng et al., 2002). Capacity planning for services involves also involves determining the appropriate level and mix, as well as configuration, of physical supply units that will be made available to accommodate customer demand (Mabert, 1986). For instance, a hotel must determine how many square feet of real estate it will occupy, as well as the total number of rooms it will offer, and how many of these rooms should have one or two beds. Decisions regarding physical supply units define the number and type of customers that can be served and are critical in setting both the maximum profits a business can achieve and the expectations of customers in terms of operating qualities such as wait time and crowdedness (Banker and Morey, 1993).

Level of Physical Supply

Researchers disagree on the amount of physical capacity that is optimal for a service operation. Wenders (1971) posited that excess capacity serves to stave off competition, while Ng et al. (1999) and Ittig (2002) argued that operating with unused capacity aids in attracting new customers and satisfying current ones. Alternatively, Lovelock (1984) and Desiraju and Shugan (1999) contended that insufficient capacity can lead to increased profits with proper management of prices. Regardless of the view on the advantages of excessive demand or supply, taking strategic, proactive measures in planning and managing capacity is crucial for long-term business success.

Very few academic studies have been published that specify tools and techniques to help service operations determine the appropriate amount of physical supply. Mabert

(1986) developed a linear program to determine the amount of equipment required to operate a check processing center. Berman et al. (1993), Berman and Kim (1999), and Berman and Sapna (2000) studied the allocation of predetermined inventory to automotive repair bays, but stopped short of determining the optimal number of these service areas. Pak et al. (2003) modeled a flight segment that had a shifting level of capacity instead of a fixed number of seats and found that revenues increased when seat supply was flexible.

Determining the optimal amount of total physical supply is especially crucial for service businesses that cannot readily alter the physical aspect of their operation (Cook et al., 1999). For instance, a hotel cannot easily build an additional room to house one more guest, and a casino cannot add another blackjack table to its gaming floor if governing regulations do not allow it. Conversely, some service operations have a higher level of flexibility in physical supply and can more easily alter total capacity to accommodate customers. A restaurant would likely be able to add another table to its dining room or a spa could use a facial room to deliver a massage if necessary. Incorporating flexibility into capacity planning adds complexity as it requires determining the extent to which different physical supply units can be used to accommodate a variety of demand (Fine and Freund, 1990).

Mix of Physical Supply

The mix of different physical supply units offered affects both revenue and customer behavior (Netessine et al., 2002; Pak et al., 2003; Kimes and Thompson, 2004). Service businesses that do not operate with the supply mix that best matches their mix of expected demand often have to use costlier inventory to satisfy less profitable demand. For instance, a rental car company that cannot accommodate a reservation for a compact car must upgrade the customer to a mid-sized vehicle. The company forgoes the higher profit that could be made from renting out the more expensive car to another customer and possibly damages customer expectations as customers may begin to change booking behavior in anticipation of free upgrades.

As such, services may use different techniques to ensure that the mix of physical supply units in operation is appropriate. Owners and operators of hotels and resorts choose their room mix primarily based on the mix offered by direct competitors and secondarily on the mix of guests expected, such as families or single business travelers. Some airlines use adjustable curtains to change the mix of economy and business class inventory (Ringbom and Shy, 2002) to match demand and thus increase revenue and improve resource utilization. Many restaurants, however, choose a supply mix that creates the image and atmosphere suitable for an operation (Katsigris and Thomas, 1999; Baraban and Durocher, 2001) instead of a supply mix that best accommodates demand.

As discussed in the previous chapter, Kimes and Thompson (2004) addressed the supply mix problem for restaurants and used simulation to determine the optimal mix of tables to maximize Revenue per Available Seat Hour (RevPASH). They found that allocating the total number of seats to the different-sized tables in a manner that matched the supply mix to the demand mix allowed more customers to be served, decreased pre-service wait times, and ultimately generated an increase in revenues of over 3 percent. In a subsequent study, Kimes and Thompson (2005) tested numerous heuristics designed to facilitate the application of their supply mix research.

For any service, however, optimizing the supply mix may not maximize revenues if the amount of physical supply in use is not optimal itself. The appropriate method for determining the total amount of physical inventory units to offer is to vary the number and mix of units until return on investment or net present value goals are achieved (Ozer, 1996; Stephani K. Robson, personal communication, December 2007). This method is complex, since space and inventory units of an operation are simultaneously established, and costly, since specialized consulting firms are typically involved in performing this type of capacity analysis.

Link between Capacity Planning and Capacity Management

Capacity planning is directly linked to capacity management, as the long-term decisions related to the amount and type of physical supply units to offer drive real-time capacity management. Ideally, a business could add the appropriate supply to its physical capacity during high demand periods and reduce supply accordingly during low ones (Ng et al., 1999). Since this is unrealistic, short-term control of supply is vital in ensuring realistic resource utilization and profit potential (Fine and Freund, 1990; van Mieghem, 1998; van Mieghem, 2003).

Capacity Management

Capacity management is considered the second stage of the two-stage decision problem that is often used to model resource investment and execution (Fine and Freund, 1990; van Mieghem, 1998; Bish and Wang, 2004). Capacity management literature focuses on using the supply established in the planning phase to efficiently and profitably produce goods or services once demand is realized. Traditional capacity management research concentrates on manufacturing problems such as production sequencing (Karmakar, 1987; Brennan et al., 1992), lot sizing (Karmakar, 1987), and material requirements planning (Billington et al., 1983).

More recently, capacity management studies have focused on the dynamic and simultaneous interaction, rather than sequential connection, between supply decisions and demand realizations (Olhager et al., 2001; van Mieghem, 2003). This perspective of capacity management is more relevant to services because of their immediacy and inherent lack of inventory (Sasser, 1976). Simultaneously matching the supply and demand of a service requires using techniques that manipulate how and when demand materializes and tools that recommend how much and what kind of capacity is made available to serve that demand.

Managing Supply

The goal of supply management is to utilize established capacity to accommodate demand as it materializes in real-time (Klassen and Rohleder, 2001). When supply is managed well, a service's current delivery system is able to generate incremental profit or accommodate incremental demand without compromising service standards (Sill, 1991). Two strategies for supply management – chase and constant – are frequently cited in the literature as the options available for controlling supply.

The chase strategy entails capitalizing on the flexibility of capacity to respond to demand (Sasser, 1976). Using shared equipment, scheduling short-term employees, and incorporating guest participation in the service delivery process are trademark chase management techniques (Sasser, 1976; Larsson and Bowen, 1989; Johnston, 1999). The constant strategy involves operating a fixed level of capacity that effectively provides an inventory cushion and protects an operation from ever turning away customers (Sasser, 1976; Crandall and Markland, 1996; Olhager et al., 2001). A business using a constant strategy functions under a long-run outlook and employs skilled, non-transitory employees (Sasser, 1976).

Because of the extreme nature of strictly following either the chase or the constant strategy, some researchers have recommended mixing aspects of both methods (van Mieghem, 2003). Sasser (1976) and Betts et al. (2002) argued that effectively mixing the strategies can decrease overhead costs but still provide an agile service system that can react to variable demand and better use resources. Likewise, Olhager et al. (2001) proposed a supply tracking strategy that incorporated capacity investment decisions into supply management and essentially added a supply cushion to the chase method.

Managing Demand

Demand management practices are concerned with influencing the type and timing of requests for services and essentially entail shifting demand to periods and products that are either more profitable for the operation or less taxing on the operating system (Shemwell and Cronin, 1994; Klassen and Rohleder, 2001). These practices are often used reactively, when demand exceeds supply, resulting in marked productivity, quality, and profit declines (Rhyne, 1988) or proactively, affording operators more control over the service process (Sasser, 1976). The key to demand management is accurate forecasting to maximize predictability and minimize explainable variability in peak, shoulder, and off-peak demand periods (Lovelock, 1984; Rhyne, 1988). Examples of demand management practices include taking reservations, which gives an operation control over the arrival of demand to a service system and allows for controlled queuing is a way to inventory demand for a service, and adjusting pricing and product offerings at certain times, which defers demand to shoulder and off-peak periods (Lovelock, 1984; Radas and Shugan, 1998; Sill, 1999).

Jointly Managing Supply and Demand

Because of the instantaneous interaction between supply and demand in service businesses, a systems approach to managing capacity is often recommended, with the goal of balancing potentially conflicting supply and demand objectives (Rhyne, 1988; Crandall and Markland, 1996; Pullman and Thompson, 2003). A service system is directly exposed to fluctuations in demand, while the efficient operation of the system directly impacts customer perceptions of the service outcome and future demand (Rhyne, 1988; Showalter and White, 1991; Klassen and Rohleder, 2001). Many researchers have proposed strategies for this joint supply-demand management problem that both accounted for the capacity of an operation and the influence a business can have on demand (Crandall and Markland, 1996; Klassen and Rohleder, 2002; Pullman and Thompson, 2003).

Revenue Management

Revenue Management (RM) combines elements of both supply and demand management to address situations in which demand outstrips supply. On the supply side, RM is concerned with maximizing the revenue of an operation on a granular level by focusing on the current and potential revenue generated by each unit of capacity for a specified time frame (Talluri and van Ryzin, 2005). To do so requires not only knowledge of the level, patterns, segments, and value of demand but also an understanding of how to maintain customer satisfaction while influencing customer behavior and manipulating price (Weatherford and Bodily, 1992; Kimes and Wirtz, 2003). Businesses that benefit from the use of RM have relatively high fixed costs with relatively low variable costs, perishable supply, moderately fixed capacity, and demand patterns that are time-variable, predictable, and easy to segment (Kimes, 1989). The following sections briefly summarize the literature pertaining to the strategy, technical, and operational components of an RM system, with particular attention given to how capacity is defined and managed.

Revenue Management Strategy

The practice of RM is rooted in the uncertainty associated with selling decisions about when to sell, what to sell, and how much to charge (Talluri and van Ryzin, 2005). In essence, using RM gives businesses a framework for balancing available supply with expected demand (Upchurch et al., 2002). The goal of an RM program is to capture the maximum possible revenue for a generally fixed set of physical inventory units over a certain time period by determining which customers to serve with the limited capacity (Kimes, 1989). Operations with variable, demand-based pricing and predictable, or preferably fixed, service duration are best situated to take advantage of the principles of RM (Kimes and Chase, 1998).

Technical Aspects

The technical issues of RM, and the majority of this research can be categorized into forecasting, optimization, and overbooking categories. The focus of this study relates closely to the optimization literature and loosely to the overbooking research since both of these streams relate to the optimal use of capacity, but it does not relate well to the forecasting publications. Topics associated with forecasting research include demand modeling (Talluri and van Ryzin, 2004), techniques for unconstraining demand (McGill, 1995; Orkin, 1998), and various forecasting methods (Weatherford and Kimes, 2003; Boyd and Bilegan, 2003). A comprehensive review of forecasting literature is offered by McGill and van Ryzin (1999).

Overbooking

Overbooking is concerned with determining the amount to which the total number of physical capacity units should be artificially inflated when planning for an operational period, such as a flight leg or a hotel night. Mathematical models to calculate the appropriate level of overbooking are found in Rothstein (1971), Ladany (1976), Liberman and Yechiali (1978), Bitran and Gilbert (1996), Chatwin (1998), Subramanian et al. (1999), and Karaesmen (2004). Overbooking essentially optimizes the volume rather than mix of sales, since the optimal mix of customers would not include cancels or no-shows (Talluri and van Ryzin, 2005). In this respect, overbooking can be costly if the total capacity of a service is comprised of a mix of capacity units that have different revenue-generating abilities (Desiraju and Shugan, 1999; Pak et al., 2003). Additionally, the negative outlook customers associate with overbooking stresses the importance of setting the correct number of capacity units that should be made available for sale (Bailey, 2007; Wangenheim and Bayon, 2007).

Allocation

The optimization/allocation component of RM is concerned with partitioning the physical supply of a service to various demand categories differentiated by price, physical inventory features, and intangible operating policies (Kimes and Chase, 1998). The objective of the allocation element in an RM program is to determine the timing and number of inventory units that should be made available to these demand categories in a way that optimizes revenue. By doing this, a business is able to control which requests for service to accept and which to reject, thus essentially optimizing its demand mix (Talluri and van Ryzin, 2005).

Much of the optimization/allocation literature presents mathematical models with an array of assumptions and solution approaches to determine the optimal way to allocate supply. For a discussion of these models, refer to Glover et al. (1982), Belobaba (1987), Kimes (1989), Brumelle et al. (1990), Curry (1990), Brumelle and McGill (1993), Bodily and Weatherford (1995); Talluri and van Ryzin (1998), Subramanian (1999), van Ryzin and McGill (2000), Zhao and Zheng (2001), and deBoer et al. (2002).

A common assumption of these allocation models is that most capacity units are homogeneous (Curry 1990; Bodily and Weatherford, 1995; Talluri and van Ryzin, 1998; Talluri and van Ryzin, 2005; Cooper et al., 2006). In reality, service capacity units are all heterogeneous since they can command different prices from different customers (Talluri and van Ryzin, 2005). As such, the menu, or mix, of service products and the physical resources required for the delivery of different services, offered to diverse segments of customers is vital to the RM problem (Gallego and van Ryzin, 1997; Kimes and Thompson, 2004). This study directly addresses the impact that non-homogeneous inventory has on maximum achievable revenue.

Revenue Management in Operation

Many companies in various service-based industries successfully use RM strategies in all or parts of their operations. Airlines traditionally used RM on a leg-by-leg basis but have only more recently adopted practices to maximize revenues for origin-destination pairs which represent a more system-wide approach to RM (Boyd and

Bilegan, 2003). The hotel industry uses RM to allocate rooms supply to consumer demand, but most hotels have not applied RM principles to ancillary revenue-generating functions such as meeting rooms (Kimes and McGuire, 2001). Furthermore, golf courses (Kimes, 2000), non-profit organizations (Metters and Vargas, 1999), and restaurants (Kimes et al., 1998; Kimes et al., 1999), and have successfully implemented individual RM programs. As a restaurant is the setting for this study, restaurant RM literature is discussed in depth below.

Restaurant Revenue Management

Like most industries, the restaurant industry often faces an imbalance between supply and demand. When demand is too low to fill available seats, restaurants must try to attract additional customers, but when demand exceeds capacity, the problem becomes more complicated as the operation would like to serve as many of the most profitable customers as possible. A Restaurant Revenue Management (RRM) program shares the same overall goal and structure of the more widespread airline and hotel RM programs in that historical data is used to develop strategies that will allow the restaurant to capture the maximum possible revenue over a certain time period using its existing physical capacity (Kimes, 1989; Kimes et al., 1998).

The techniques used to deploy RRM largely involve modifying operations and policies to make duration more predictable (Sill and Decker, 1999; Noone et al., 2007), finding ways to make price more variable (Kimes and Wirtz, 2003; Susskind et al., 2004), and altering the level and mix of capacity units made available to accommodate demand (Thompson, 2002; Kimes and Thompson, 2004; Kimes and Thompson, 2005). Additionally, a restaurant provides a functional service (a meal is purchased and consumed), but it also fulfills social and cultural needs of customers, adding a behavioral dimension to restaurant services (Robson, 1999; Andersson and Mossberg, 2004). Common practices associated with RRM include couponing (Taylor and Long-Tolbert, 2002), time-based discounting (Susskind et al., 2004), understanding and controlling service duration (Noone et al., 2007), and optimizing the way in which supply is utilized to meet demand (Kimes and Thompson, 2004).

Restaurant Supply and Related Research

Following the definition of total service capacity used by Lovelock (1992), the total capacity of a restaurant can be defined as the maximum number of diners that can be served at a dinner period given predetermined levels of all the resources required to process customers. These resources include the FOH employees needed to serve customers, the availability of ingredients to make menu items, the ability of the kitchen facilities and employees to produce timely and quality food, the actual space devoted to seating customers, and the amount and type of tables and chairs offered (Sill, 1999; Robson and Kimes, 2004). The research relevant to this study pertains to how the capacity units within the given space are best used to generate revenue.

As previously discussed, Kimes and Thompson (2004; 2005) addressed how the mix of tables impacted achievable revenue and developed models to help operations determine their optimal table mix. Analogous to this work is the research of Bertsimas and Shioda (2003) in matching customers to supply through allocation of arrivals to tables. They tested several different optimization-based RRM models to control the arrival of customers to a restaurant and determined that violating the customary first-come-first-served (FCFS) seating rule for walk-in customers increased revenues without increasing wait times.

Research Gaps

Most of these studies have addressed the lack of research directly related to RRM and the fact that while the number of RRM publications has been growing, research opportunities still exist (Robson, 1999; Bertsimas and Shioda, 2003; Kimes and Thompson, 2004). One such gap in the literature pertains to capacity planning and determining how many physical capacity units should be put into operation. While Kimes and Thompson (2005) and Bertsimas and Shioda (2003) used capacity management techniques to deploy the existing number of seats to any table mix (not the existing one), they assumed the number of seats that could be used was given and fixed at the current number in operation.

Another gap in the literature relates to the non-homogeneity of physical capacity units used by a service. As previously discussed, the common assumption of many RM models that capacity units are homogeneous is not realistic; identical units can have different revenue-generating abilities, so the way in which these units are used to serve customers impacts profitability (Talluri and van Ryzin, 2005). In most restaurant environments, seats – the most granular unit of capacity, since each customer occupies one seat for the duration of service – are all the same. In fact, from an operator's viewpoint, the true measure of restaurant inventory, however, is the availability of a seat for the duration of a meal experience (Kimes et al., 1998). However, these seats are situated at non-homogeneous tables that differ in shape, location, and most importantly, size since table size determines the number of customers that can be accommodated for the duration of a meal.

The research that has been published regarding how to ensure that tables are optimally used has thus far assumed that each table size is proportional to its number of seats

(Bertsimas and Shioda, 2003; Kimes and Thompson, 2004). This assumption does not always hold, as different table sizes often use different amounts of space per seat. For instance, a 2-top table at a restaurant usually requires more room on a per person basis than does a 4-top table (Stephani K. Robson, personal communication, May 2006). This study addresses this issue of the non-homogeneous spatial requirements for different table sizes.

Use of Space

In general, Operations Management research regarding the use of physical space has been largely concerned with capacity planning issues such as sizing a new facility (Banker and Morey, 1993; Bitran and Caldentey, 2003), expanding an existing operation (Luss, 1982), or configuring a given facility in a way that maximizes throughput (Smith and Daskalaki, 1988). Capacity management problems, specifically those associated with Revenue Management, also have a space component. Space (e.g., square footage) is the common element among spatially-diverse capacity units (e.g., restaurant tables or hotel rooms), and as such, focusing on space may provide new insight into how an operation can effectively use its most basic supply resource.

A few RM studies have given notable consideration to the use of space in the Revenue Management problem. As previously discussed, Pak et al. (2003) determined how utilizing airline capacity that could be physically converted between economy or business-class seats impacted revenues on a flight segment. Essentially, the authors studied how redefining flight capacity to include the amount of space required to house diverse inventory units had a beneficial effect on revenue. Additionally, Kimes and McGuire (2001) used space as a component in studying the revenue management of hotel meeting rooms. They determined that space was an integral aspect of this specific RM problem because of the opportunity cost associated with using of a portion of a divisible meeting room and obstructing the potential sale of the entire space. Further, Kimes and Robson (2004) began exploring how to determine the optimal layout of restaurant tables in a given space of a restaurant and found that both table location and type impacted service duration and customer spending.

Another area of RM in which the role of space has been explicitly studied is revenue management of cargo and retail businesses. These types of operations use physical space as the inventory unit allocated to different categories of demand. In cargo RM, the available shipping space is partitioned to demand based on the weight, volume, and position of freight that needs to be accommodated (Kasilingam, 1996; Billings et al., 2003). Similarly, retail RM allocates the total shelf space of a store to product categories, each of which does not necessarily require an amount of space proportional to its size or profitability. Product category shelf space is subsequently allocated to individual items that also are not always identical in size or revenue contribution (Yang and Chen, 1999). No published studies have applied the idea of using space as the basic inventory unit allocation unit to pure services, such as restaurants and hotels.

Connecting ideas from these studies leads to the premise that space is a basic resource that should be taken into account in the Revenue Management problem, especially when physical capacity units are non-homogeneous in terms of the amount of space they require to be put into use to generate revenue. A restaurant environment is a good testing ground for studying this, as restaurant tables are non-homogeneous in both size and space required per person. Additionally, because space has been treated differently in RM literature – merely a component of meeting room RM versus the inventory unit under study in cargo and retail RM – testing whether there is a revenue difference between these two space outlooks is warranted.

Summary

This chapter has presented an extensive review of the existing literature related to the research problem addressed in this study. As this problem focuses on the use of supply in a restaurant setting, many aspects of capacity were reviewed, including capacity planning, capacity management, and balancing supply and demand. A discussion of Revenue Management, the specific field of capacity management designed to take advantage of supply-demand imbalances, and the application of Revenue Management to restaurant operations were also presented. Finally, the scant literature pertaining to space in the context of capacity management or Revenue Management was reviewed. The following chapter explains the methodology used in determining how space should be included in the Restaurant Revenue Management problem.

CHAPTER 3: METHODOLOGY

Service operators strive to optimize their service delivery systems to create the most profit possible while satisfying and delighting their customers. Both physical inventory and the actual space that accommodates this inventory comprise the material Front-of-House component of a service operation. Determining the level and mix of inventory that produces the maximum revenue and advantageously uses the available space is integral in optimizing a service delivery system.

In this chapter, a simulation model is developed to examine how differing definitions, levels, and mixes of spatially non-homogeneous inventory impact the operations of a restaurant system. Results from the simulation address the three specific research questions posed in Chapter 1: (1) How is revenue impacted if capacity is allocated based on space instead of inventory units? (2) To what extent is existing capacity changed when supply is measured by space instead of units? (3) Can revenue actually increase if capacity is decreased?

Simulation

Simulation is an appropriate method to use when the economic or opportunity costs of experimenting in a live environment are too high. Repeatedly altering the established system to test different research scenarios is intrusive and impractical. A computer simulation replicates the system and allows for the assessment of various operational changes without disrupting the actual business and creating confusion.

Simulation can mimic the complex, unpredictable, stochastic events, such as customer and employee behavior, which comprise a multifaceted service system like a restaurant. By randomly sampling from distributions based on observed patterns from actual operations, simulation can actually model variable service processes quite closely. Additionally, operational aspects not related to the proposed research questions can be controlled so that alternate systems can be tested and compared on an equal basis.

Simulation studies based on empirical problems found in service organizations allow researchers to examine realistic situations, evaluate the impact of different practices, and provide managers with practical solutions without interrupting the current service process (Shafer and Smunt, 2004). Simulation modeling has been successfully used to study operational issues in a variety of service situations, such as optimal location of a city's ambulance service (Savas, 1969) and network design at a shipping company (Cheung et al., 2001).

The complex interaction of supply and demand that characterizes effective capacity management of a service business makes simulation an especially attractive analytical tool for testing capacity management techniques. Brennan et al. (1992) examined how several operational procedures impacted a health facility's ability to effectively use available capacity to process patients in a way that minimizes wait time. Pullman and Thompson (2003) used simulation to determine the profit impact of upgrading and expanding capacity at a ski resort while simultaneously securing more control over customer demand. Pagell and Melnyk (2004) simulated the supply layout of a health clinic and tested various alternatives to maximize efficiency and decrease variability.

The established use of simulation to evaluate capacity management techniques in a dynamic service environment indicates that simulation is an appropriate research method for this study. The focus of the study is a full-service restaurant, which is characterized by multiple interactions among and between employees, customers, and physical surroundings. The overall project plan for this simulation study has five steps:

1. Identify the system components to include in the model and determine the performance measures to be collected;
2. Design the baseline model, accounting for key steps as well as assumptions of the restaurant system, and code the model using empirical data collected from the test restaurant;
3. Validate the baseline model to ensure it matches the operation of the actual restaurant system;
4. Develop and simulate alternate scenarios; and
5. Analyze outputs of alternate scenarios.

System Components and Performance Measures

This simulation study is based on the operation of an anonymous, full-service, well-established, casual restaurant located in an urban area of southern New York State. The outlet is open seven days a week for dinner service and is also open for brunch on Sunday. It has 32 tables, a sizeable and popular bar, and a moderately-sized kitchen. Currently, the restaurant has a total of 116 seats; its table mix is comprised of ten 2-top tables, nineteen 4-tops, two 6-tops, and one 8-top.

The simulation models dinner service on both Friday and Saturday since the restaurant is typically operating at or near capacity at those times. The simulation is terminating and does not use a warm-up time in order to best reflect the immediacy and variability of restaurant operations. The model has a random duration that begins when the restaurant opens for dinner at 5:00 pm and ends when all tables are empty, which is generally at least an hour after the kitchen stops serving at midnight.

Model Inclusions and Exclusions

The focus of this study is how revenue-generating space and the tables and seats it situated within the space is used and reused at the restaurant during peak operating periods. The flow of customers dictates when and for how long space is occupied, so customer movement through the restaurant serves as the base of the simulation. The model accounts for both the seating and bussing processes, which together essentially account for the set-up time required to prepare the dining room space to be utilized.

Although the actions of hosts, wait staff, and bussers are contained in the model, these employee resources are not explicitly modeled. In reality, the number of employees available to perform FOH functions rarely impedes the flow of customers to tables because floor managers at the test restaurant regularly greet and seat guests, deliver food and drinks, and clear and reset tables. Since the number and availability of FOH employees is not central to the problem of space usage, specifically modeling them in the simulation is effectively redundant and would only add unnecessary complexity.

Back-of-House (BOH) operations are also not explicitly included in the simulation. Kitchen operations are assumed to vary proportionally with Front-of-House (FOH) business. Further, customers are not involved in the BOH, so omitting this area from the simulation allows the focus of the model to remain on the flow customers through the restaurant and how effectively space is used to accommodate them.

Performance Measures

Several measures must be collected to assess the performance of the simulation against actual operations and to also evaluate different scenarios against each other. The performance measures collected in this study are:

1. Total revenue;
2. Total number of customers served;
3. Total number of customers lost;
4. Table utilization (occupancy) – total and by table type;
5. Seat utilization (occupancy) – total and by table type;
6. Hourly RevPASH (Revenue per Available Seat Hour);
7. Hourly RevPAST (Revenue per Available Space-Time Unit, here it is Revenue per Available Net Square Foot Hour);
8. Average wait time of customers by party size; and
9. 85th percentile of customer wait times.

The principal measure used to both benchmark the baseline model against actual operations and compare alternate systems is total revenue, as generating the highest revenue possible is the foundation of a profit-seeking business. The customers served and lost measures serve as gauges to ensure the simulated systems are practical and reasonable. The occupancy, RevPASH, and RevPAST metrics give an indication of how effectively the restaurant is using its supply to satisfy demand and generate revenue. Customer management is represented by the wait measures collected.

Design, Assumptions, and Coding of Baseline Model

The model was built and run in ServiceModel (2005), a simulation product directed at service businesses. ServiceModel was chosen as the software for this study primarily because it has the capability to dynamically change inputs for different simulation runs, but also because users can tailor the software by building additional code on top of the existing program. ServiceModel is flexible enough to allow for all key processes of the restaurant system to be modeled. This software is also accessible, cost effective, and user-friendly so models and results can be understood and used by academic researchers, industry analysts, or knowledgeable practitioners.

Operational data from the test restaurant served as the basis for much of the input data for the model. Transaction records for over 1580 parties gathered from the restaurant's Point-of-Sale (POS) system on seven different weekends were used to calculate party size, spend data, and duration figures. Timing studies of 160 tables done on two separate weekends provided the data for the bussing times used.

Simulation models do not need to exactly replicate the system they model. Rather, they should mimic the system under study to the extent that results in the live environment will be equivalent to those found in the simulation (Naylor and Finger, 1967). Building too much detail into the simulation may be unnecessarily time consuming and add irrelevant complexity to the model. Thus, simplifying assumptions are made to create a manageable, focused model that ensures accurate results.

The baseline model represents the flow of customers through the restaurant. Four distinct, consecutive stages – Arrival, Seating, Dining, and Exit – ultimately combine to form the restaurant system. These stages comprise the movement of customers through the outlet and represent when seats and tables are in use by either customers or employees. Figure 3.1 is a schematic of how customers move through these four stages; design, assumption, and coding decisions for each stage follow.

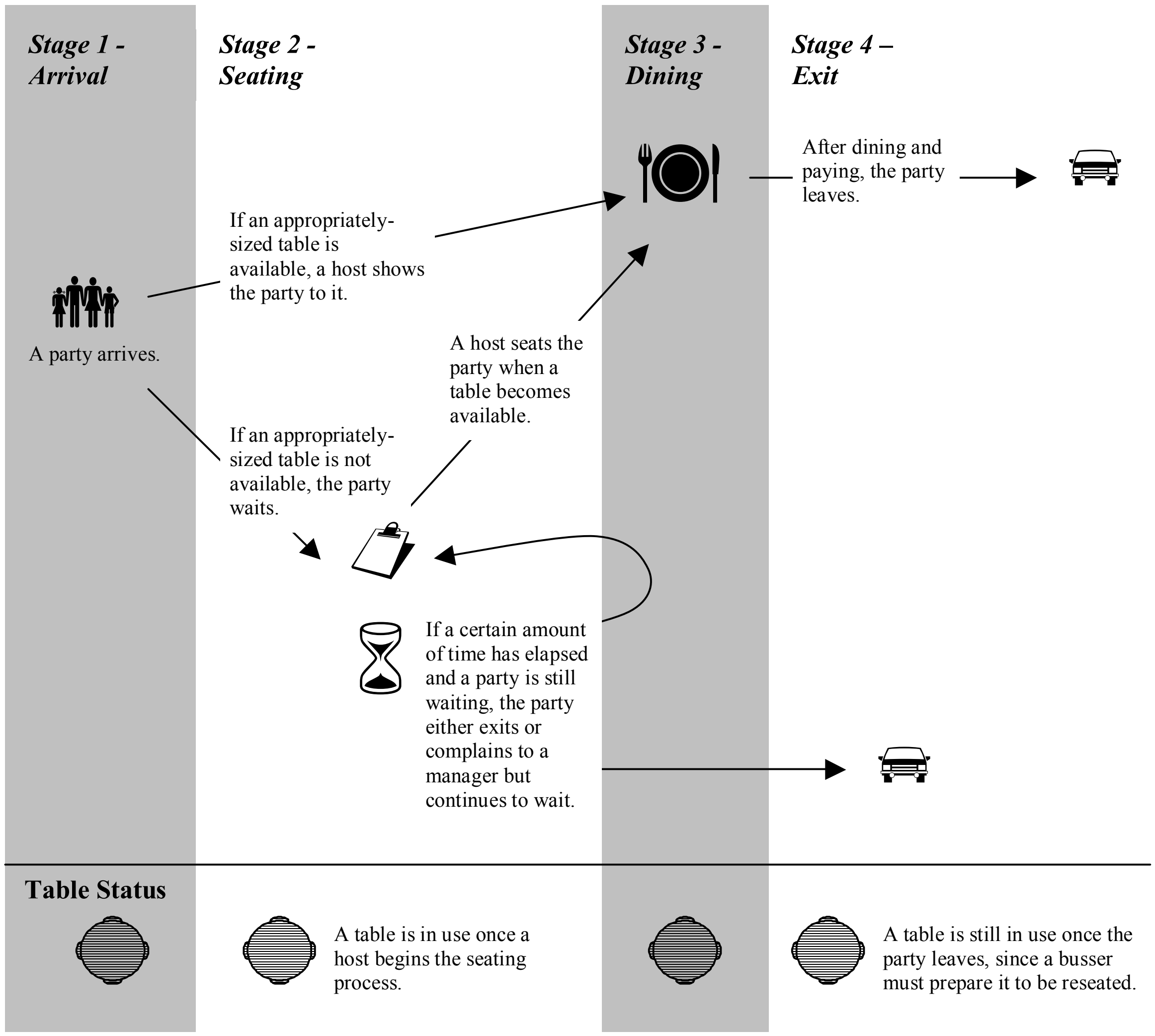

Figure 3.1: Model Schematic

<u>*Stage 1 – Arrival of Customers to the Restaurant*</u>

Design and Assumptions. The rate at which customers arrive to the outlet over a typical Friday-Saturday night period is unknown. One way to approximate customer arrival times is to use the time at which a server opens a check in the POS system. However, this method proves to be inappropriate for this study due to the limited number of weekends for which data is available. Additionally, the restaurant reports that the wait time for a table during peak hours on Friday and Saturday nights typically ranges from 5 to 45 minutes, so the time a party's check is opened in the POS system is not indicative of the time party arrived at the outlet. A known non-stationary Poisson process is used instead to model the arrival rates of customers.

A non-stationary Poisson process is often used to approximate arrivals to a system that is characterized by time-of-day effects, with greater or fewer arrivals occurring during different time periods (Green and Kolesar, 1991; White, 1999). Additionally, simulation studies in the field of Operations Management often include models built either partly or fully with empirically-based, but ultimately artificially generated, data (Shafer and Smunt, 2004). Assumed input data does not compromise the validity of a model or impede in the comparison of alternate systems as long as the data is representative of the service system under study and provided that results are proven to be statistically significant (Klassen and Rohleder, 2002).

The arrival process used in this model replicates the flow of customers into the establishment over 15-minute increments. Arrival rates vary by time, but the same rates are used for both Friday and Saturday nights. The arrival rates assumed for the simulation are generated based on a reasonable pattern for dinner service on a typical weekend at this particular establishment. This pattern is derived based on conversations with a panel of professionals familiar with restaurant operations, including an employee of the test restaurant, two managers from similar establishments, a 20-year veteran restaurant owner, two hospitality educators with a combined 14 years experience in teaching, consulting, and researching, and an independent restaurant consultant specializing in balancing operational efficiency with customer service.

`Figure 3.2 graphs the arrival rates used. The rate of arriving parties starts small at the 5:00 pm opening of the restaurant, gradually increases to the peak period occurring from 7:15 pm to 8:30 pm, and declines slowly at first and then rapidly at later hours in the night. The most popular arrival time is between 7:45 pm and 8:00 pm, while the least popular time is between 11:45 pm and 12:00 am, just before the kitchen closes.

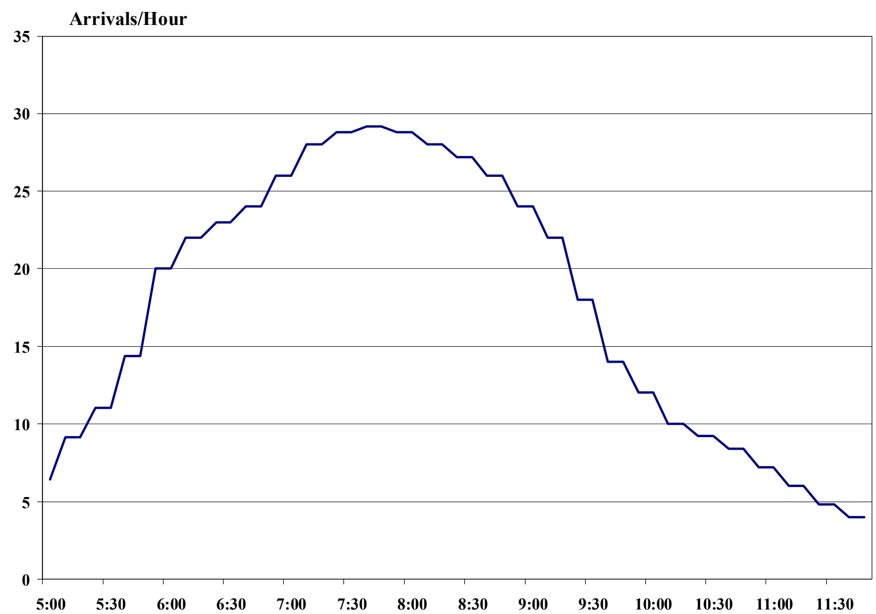

Figure 3.2: Non-Stationary Poisson Arrival Rate Function

Parties are assumed to arrive with all members ready to be seated and served. In reality, parties may arrive piecemeal, go directly to the bar instead of the host stand, balk, or not wait if they are considered a VIP. All arriving parties are processed on a first-come-first-served (FCFS) basis; reservations and call-ahead seating are not used.

Coding. The simulation code mimics the thinning method for generating a non-stationary Poisson process (Lewis and Shedler, 1979). Parties enter the system according to an exponential distribution and are accepted into the system with a probability based on their time-dependent arrival rate. Parties that are rejected at the arrival stage never fully enter the system and do not affect any performance measure.

Each arriving party is randomly assigned a party of size 1, 2, 3, 4, 5, 6, 7 or 8 according to the restaurant's current distribution of party sizes, given in Table 3.1. Over 60% of the restaurant's customers are in parties of one or two and fewer than 2% are in parties with seven or eight. Parties larger than 8 are not included in this model as they provide only a miniscule amount of business at the test restaurant.

Table 3.1: Customers by Party Size

Party Size	Percentage of Total Parties
1	11.2%
2	52.9%
3	16.2%
4	12.2%
5	3.9%
6	2.0%
7	1.0%
8	0.7%

Stage 2 – Seating Parties at Available Tables

Design and Assumptions. The seating process at the restaurant is straightforward; a party enters the outlet and proceeds to a table if an appropriately-sized one is immediately available. If an appropriately-sized table is not available, the party waits until one becomes available; at that time, the party moves to its table. A table sits idle while waiting for its assigned party to be seated. Parties are seated at available tables with consideration of fitting party size to table size. For instance, a party of two is given preference to be seated at a two-top, but would be seated at a four-top if no two-tops are available; however, the party would likely never be seated at an eight-top since the large table would overwhelm the party size.

The time it takes to seat customers once a table becomes available is variable. The seating process depends on several factors, including the speed at which patrons and employees walk, the crowdedness of the restaurant at the time of seating, the number of people in the party that must be gathered and led through the restaurant, and the location of the table being seated. Table 3.2 gives the durations for the seating process used in the simulation model. These times are assumed, as they are derived from a simple observation of the seating process at the test restaurant over two nights.

Table 3.2: Seating Duration by Party Size

Party Size	Average Seating Duration (minutes)	Standard Deviation of Seating Duration (minutes)
1 or 2	1.5	1.0
3 or 4	2.0	1.5
5 or 6	2.5	1.5
7 or 8	3.0	2.0

Since the restaurant is empty at the beginning of each night of operation, customers arriving in the first few hours are usually seated immediately with no wait. Once tables fill and customers are required to wait, some decide to renege, or wait awhile but leave before being seated and served.

Coding. Tables are assigned according to the rules given in Table 3.3, with priority given to seating a party at a table best matching the party's size. In the model, all parties are processed on a strict FCFS basis. In reality, hosts have discretion over what party to seat at which table and may not exactly follow these assignment rules.

Table 3.3: Table Assignment Rules

Party Size	Priority Table Size	Allowable Table Sizes
1	2	2, 4
2	2	2, 4, 6
3	4	4, 6
4	4	4, 6, 8
5	6	6, 8
6	6	6, 8
7	8	8
8	8	8

Each party is assigned a random duration for the seating process. This assignment is based on a lognormal distribution with the average and standard deviation parameters given above. A lognormal distribution has been shown to be a good approximation for service times (De Kok and Tijms, 1985; Brown et al., 2005) and is therefore assumed to be a reasonable distribution to use for this seating process.

Some parties that arrive at the restaurant do not get seated since they choose to renege, or abandon the queue after waiting for a certain amount of time. According to Hwang and Lambert (2005), restaurant customers will wait for around 48 minutes before becoming so dissatisfied that they either contact a manager to complain or simply leave. The number of people in a party would likely influence this threshold time. It is therefore assumed that the higher the number in a party, the longer the party will wait before potentially reneging because more people have invested time in the dining experience.

The simulation is coded to randomly assign each party a renege time from a uniform distribution based on the times and assumed standard deviations given in Table 3.4. A coefficient of variation of 0.2 is selected as the basis for the standard deviation calculations because it gives a realistic range of wait time thresholds within one standard deviation. For instance, the threshold for a party of four is between 42 and 63 minutes. Several other values for the CV are considered, but they give either too tight of a wait threshold range to be realistic or too large of a number at the high end of the range to be reasonable.

Table 3.4: Wait Threshold by Party Size

Party Size	Average Wait Threshold (in minutes)	Standard Deviation of Wait Threshold (in minutes) based on Different CVs			
		CV = 0.1	CV = 0.2	CV = 0.3	CV = 0.4
1	45.5	4.55	9.10	13.65	18.20
2	47.9	4.79	9.58	14.37	19.16
3	50.3	5.03	10.06	15.09	20.12
4	52.8	5.28	10.56	15.84	21.12
5	55.5	5.55	11.10	16.65	22.20
6	58.2	5.82	11.64	17.46	23.28
7	61.1	6.11	12.22	18.33	24.44
8	64.2	6.42	12.84	19.26	25.68

It is assumed that half of all parties reaching their threshold renege time will leave, while the other half will complain to a manager but continue waiting until their table is ready. This 50-50 split of the renege/continue-to-wait option was chosen because it provides a realistic balance between wait times and the number of customers that renege due to a long wait. A higher renege percentage leads to an unrealistic number of customers that enter, wait, and eventually leave, while a lower renege percentage leads to unrealistic average wait times.

<u>Stage 3 – Dining</u>

Design and Assumptions. Once a party is seated, it occupies the table for the duration of a meal. The data used to calculate dining duration in this study is from the Point-of-Sale (POS) system. Dining duration is calculated from the time a check is opened in the system to the time it is closed by running a credit card or accepting a cash payment. Although dining duration can be affected by a number of factors, including the experience level of the server, the staffing levels on the floor, the load on the kitchen, and the preferences of the customers in the party, it is assumed that all of these factors were accounted for in the overall dining duration from the POS data.

Dining duration by party size is given in Table 3.5. The data was checked for extreme outliers, such as cases when a server neglected to close the check for several hours, or if a check was opened and then closed within several minutes. As expected, larger parties tend to have longer dining durations than smaller parties. The average duration for parties of one or two is just over 1 hour, while parties of eight average about 90 minutes. High variability characterizes the dining duration for all party sizes.

Table 3.5: Dining Duration by Party Size

Party Size	Average Dining Duration (in minutes)	Standard Deviation of Dining Duration (in minutes)
1	68.8	31.7
2	63.0	20.7
3	67.4	21.0
4	73.3	22.6
5	81.2	23.0
6	86.5	29.4
7	78.1	23.3
8	90.9	30.8

Duration times calculated by POS data are not completely accurate. At the beginning of the meal, it takes time for the server to approach a table, take drink orders, and enter relevant data into the POS. At the end of the meal, diners may linger after they have paid. Thus, a party may be sitting at the table longer than the POS data indicates.

To better reflect the amount of time a table is occupied, pre-dining duration times are included in the simulation. The activities occurring at a table after a party is seated but before the party's check is opened in the POS system include being greeted by the server, receiving water, hearing nightly specials, and placing drink orders. Table 3.6 shows pre-dining duration times used in the simulation. These times are assumed; they are derived from a simple observation of the dining process at the test restaurant over two nights.

Table 3.6: Pre-Dining Duration by Party Size

Party Size	Average Pre-Dining Duration (in minutes)	Standard Deviation of Pre-Dining Duration (in minutes)
1 or 2	2	1.0
3 or 4	3	1.5
5 or 6	4	2.0
7 or 8	5	2.5

The amount of revenue generated by each customer depends on party size. Smaller parties tend to have both a slightly higher and more variable average per person than larger parties. Table 3.7 gives the average spend per person data for the test site.

Table 3.7: Average Spend per Person by Party Size

Party Size	Average Spend per Person	Standard Deviation of Spend per Person
1	$23.74	$14.57
2	$23.73	$11.37
3	$22.85	$10.61
4	$24.54	$10.93
5	$22.64	$9.57
6	$22.73	$10.64
7	$21.92	$8.60
8	$22.07	$8.27

Coding. Every party that is seated receives three randomly assigned variables – pre-dining duration, dining duration, and spend per person. Since pre-dining duration data is assumed, its actual distribution is unknown. Therefore, a lognormal distribution is used to model the pre-dining process; as stated earlier, a lognormal distribution approximates service times reasonably well. Distributions by party size are fitted to duration to model the amount of time a party uses a table. Likewise, distributions by party size are fitted to per person spend to model the revenue each customer in the party generates. These distributions, given in Table 3.8, are calculated by Stat::Fit, the statistical fit software attached to ServiceModel. An Anderson-Darling goodness of fit test is used to assess the hypothesized distributions against the observed data.

Table 3.8: Distributions Used for Modeling Duration and Spend

Party Size	Dining Duration	Goodness-of-fit p-value	Spend per Person	Goodness-of-fit p-value
1	Lognormal	0.959	Lognormal	0.811
2	Loglogistic	0.449	Gamma	0.211
3	Lognormal	0.911	Gamma	0.746
4	Lognormal	0.989	Gamma	0.900
5	Weibull	0.993	Beta	0.949
6	Weibull	0.924	Beta	0.774
7	Lognormal	0.982	Normal	0.959
8	Lognormal	0.940	Weibull	0.978

All of the goodness-of-fit p-values for both duration and per person spend are well above a 0.10 alpha value, indicating that there is no evidence to reject the hypotheses that the data come from the distributions in Table 3.8.

Stage 4 –Exiting of Customers; Preparing Tables to be Reseated

Design and Assumptions. At this stage of the operation, customers have already dined and paid and are simply exiting the dining room. Once a party vacates its table, however, the table is not immediately available to be put back in use. The table must be cleared, cleaned, and set with plates and silverware rollups before it is ready to be reseated.

The time it takes to prepare a table to be reseated is shown in Table 3.9. These figures represent the time between customer departure and the time a table is ready to be reseated, and include notifying a host of the empty table. Bussing durations were gathered from a time study of 160 tables over two different weekends. Since these timings reflect bussing operations during peak periods when customers are waiting, it is rare that a table sits empty and dirty for a significant amount of time before it is cleared and cleaned.

Table 3.9: Bussing Duration by Table Size

Table Size	Average Bussing Duration (in minutes)	Standard Deviation of Bussing Duration (in minutes)
2	2.57	2.08
4	3.24	3.87
6	3.74	4.11
8	4.36	4.74

As would be expected, smaller tables take a shorter amount of time to clear and prep than larger tables. All tables have a high variation in bussing time, due largely to the amount of pre-bussing, or the clearing of dishes and accompaniments, that is completed by the table's server before the party departs.

Coding. Once a party leaves, each empty and dirty table receives a random bussing duration. This duration differs by table size and is based on the average and standard deviation parameters given previously. All bussing durations are also assumed to be lognormally distributed.

Model Verification and Validation

To effectively test alternate supply-demand scenarios, a baseline simulation model must first perform similarly to the real restaurant. The model must accurately represent both the inputs to and the outputs from the system under study. Verification of a baseline model occurs once the simulation code is free of bugs and input parameters for the model correspond equivalently to actual system inputs. This baseline model is verified; it has been thoroughly debugged and produces average figures for party size, dining duration, average spend, and bussing duration that match the actual data gathered from the test restaurant.

Input-Output Validity

A baseline model is considered valid if it is an accurate representation of the actual operating system. Validation of a model occurs if key outputs from the simulation match actual operating data, demonstrating that the structure of the model translates inputs to outputs similarly to the way the actual system operates. To validate the baseline model for this study, multiple replications (104), representing the weekend dinner operation of the test restaurant over one year, were run.

As shown below in Table 3.10, the simulation model is validated since the structure of the model produces outputs that correspond closely to outputs from the actual operating system. Total revenue, the primary performance measure being used to compare alternate systems, falls within 0.5 percent of the actual revenue generated over an average Friday-Saturday night dinner service. Also, the total number of customers served, another performance measure, generated by the baseline model falls within 0.2 percent of the actual number of customers served over the operating period at the sample site.

Table 3.10: Validation of Baseline Model

	Model	Actual	Hypothesis Test	Conclusion
Total Revenue	\$14,183	\$14,114	H_0: Revenue = 14,114 H_A: Revenue $\neq$ 14,114	Fail to reject H_0 at $\alpha = 0.05$
Total Customers Served	608	609	H_0: Customers = 609 H_A: Customers $\neq$ 609	Fail to reject H_0 at $\alpha = 0.05$

These null hypotheses characterize a valid model; if the data generated from the simulation model can be used to accept the null hypothesis, then the output measures produced from the model are consistent with the output generated by the actual system. Hypothesis tests for both the total revenue and total customer measures indicate a failure to reject the null hypotheses at a conservative alpha of 0.05. The power of the test for both measures exceeds 0.90, signifying that the probability of accepting an invalid model is low. Therefore, the baseline simulation model is considered an accurate representation of the restaurant operations under study and can be used confidently to test alternate systems.

Face Validity

The other seven metrics included in this study (total customers lost, table utilization, seat utilization, RevPASH, RevPAST, average wait by party size, 85th percentile of customer waits by party size) are used to establish the face validity of the model, as most cannot be directly compared to actual operating results due to the lack of data. The tables below illustrate that all of these measures are reasonable and have at least face validity.

Table 3.11 shows that the total number of customers lost over the Friday-Saturday night dinner service is around two percent of the total amount of customers who enter the restaurant system. The panel of industry professionals previously described agree that this number of reneges is realistic for peak operating periods over two nights.

Table 3.11: Total Customers Lost – Baseline Model

Party Size	Customers Served	Customers Lost
1	26	1
2	245	6
3	114	2
4	114	2
5	48	1
6	30	0
7	17	0
8	14	0
Total	608	12

Table occupancy rates generated by the baseline model for all table types used at the sample restaurant are given in Figure 3.3. These occupancies are both logical and realistic; overall table occupancy climbs during the first two hours of service, peaks at 90 percent within the 8-9PM hour, and gradually declines afterwards.

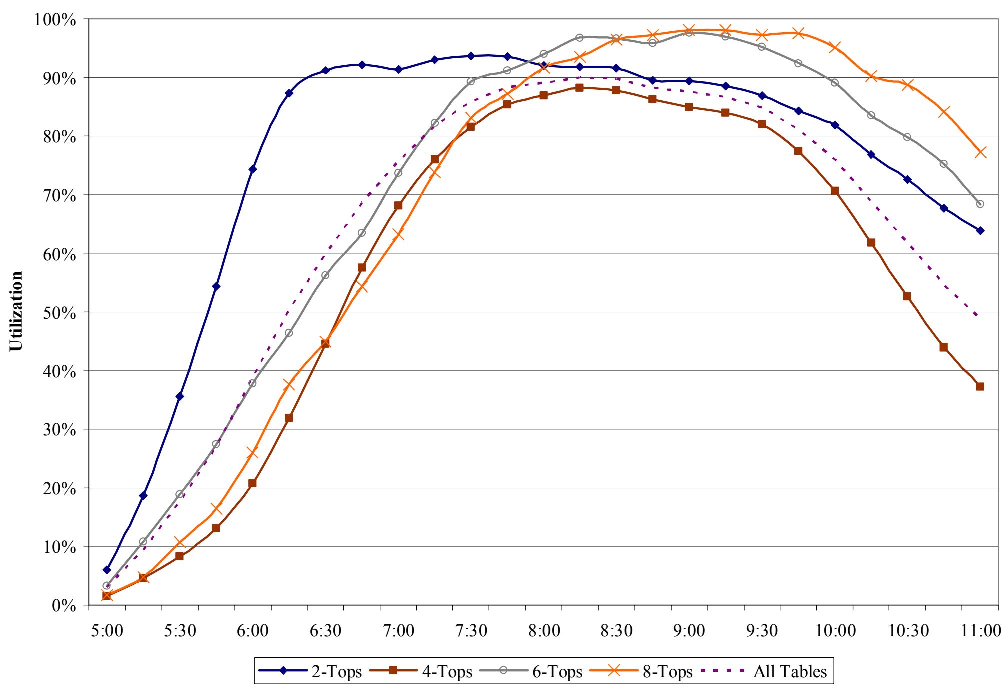

Figure 3.3: Table Occupancy – Baseline Model

Figure 3.4 shows the seat occupancy rates generated by the baseline simulation for the test restaurant. These rates also appear to have face validity, as they reflect typical seat occupancies for a weekend dinner service. As expected, seat occupancies are systematically lower than table occupancies, reflecting the seating rules outlined previously and the fact that the restaurant only uses tables with an even-number of seats, but serves both even-numbered parties and parties with an odd-number of guests.

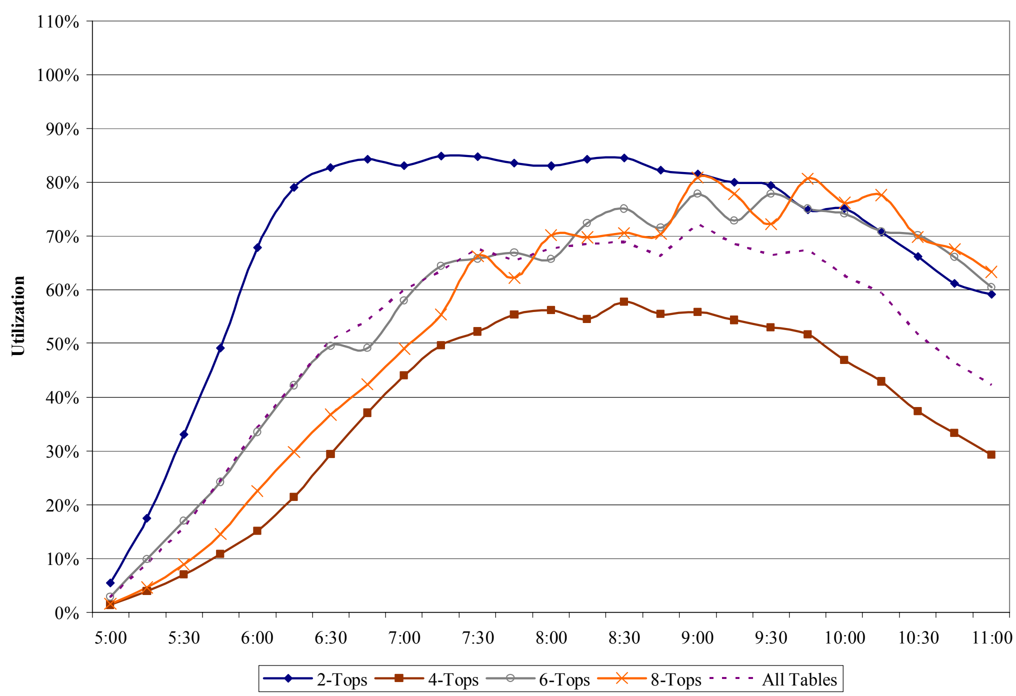

Figure 3.4: Seat Occupancy – Baseline Model

The baseline output for hourly RevPASH is given in Table 3.12. RevPASH is calculated by dividing the number of available seats into the revenue generated over an hour. Comparing the baseline RevPASH to the actual numbers calculated from the POS data for Friday and Saturday night dinner service confirms face validity.

Hypothesis testing of RevPASH would be redundant; RevPASH is derived from total revenue, which has already been shown to validate the baseline model.

Table 3.12: RevPASH – Baseline Model

Hour	Model RevPASH	Actual RevPASH	Difference
5 – 6 PM	$5.38	$5.07	-$0.31
6 – 7 PM	$10.33	$10.66	$0.33
7 – 8 PM	$12.42	$12.20	-$0.22
8 – 9 PM	$10.94	$11.59	$0.65
9 – 10 PM	$10.03	$10.34	$0.31
10 – 11 PM	$5.69	$6.50	$0.81
11 – 12 AM	$2.73	$3.69	$0.96

Table 3.13 shows the results from the baseline model for the RevPAST performance measure. Two RevPAST measures are provided, as RevPAST can be calculated by either dividing the number of square feet available for accommodating tables into the revenue generated over an hour or by dividing the number of square feet used to accommodate tables into the revenue generated. Only estimates for the square footage of the test restaurant, its tables, and its seats are available, so the RevPAST from the model cannot be directly compared to the actual RevPAST. Additionally, RevPAST is currently not a standard Revenue Management metric, making it impossible to gauge if the baseline output is reasonable and realistic. RevPAST, however, is generated from total revenue, which has validated the simulation model. This indicates that RevPAST figures are likely credible, at least for comparison purposes across simulation scenarios.

Table 3.13: RevPAST – Baseline Model

Hour	Model RevPAST (calculated using square feet available)	Model RevPAST (calculated using square feet used)
5 – 6 PM	$0.41	$0.42
6 – 7 PM	$0.87	$0.89
7 – 8 PM	$0.99	$1.02
8 – 9 PM	$0.94	$0.97
9 – 10 PM	$0.84	$0.87
10 – 11 PM	$0.53	$0.54
11 – 12 AM	$0.30	$0.31

Table 3.14 gives the average and 85th percentile of customer waits generated by the baseline simulation. Of the industry professionals consulted, three are familiar with the test restaurant and agree that these wait time results seem plausible, but low. Since actual wait times are unknown and since this performance measure is calculated in the same manner for each simulation scenario tested, a low baseline result does not impede in the ability to compare the effects of alternate systems.

Table 3.14: Average and Maximum Wait – Baseline Model

Party Size	Average Wait (in minutes)	85th Percentile of Wait Times (in minutes)
1	5.72	13.00
2	6.04	13.19
3	6.31	14.33
4	5.68	13.12
5	6.15	15.59
6	4.91	0.00*
7	6.54	0.00*
8	5.92	0.00*
*Because of the small number of large parties and the existing number of large tables at the test restaurant, the 85th percentile of waits for parties of 6-8 is 0.		

Develop and Simulate Alternate Scenarios

The power of simulation as a research tool lies in being able to change key elements of the existing system and scientifically gauge how the chosen performance measures will react. Classic, statistical experimental design is employed to develop the alternate scenarios that will be tested to answer the research questions at hand.

A simulation experiment with only one varied input factor is unrealistic, as the results produced will only be valid under the assumed operating conditions. Therefore, creating and using a more complex experimental design introduces random variation which in turn produces results that are robust across a range of reasonable and realistic operating characteristics modeled by the simulations (Kleijnen et al., 2005). A robust statistical design approach for simulation experiments entails determining which input factors are important to an experiment and to what extent these input factors should be varied (Kleijnen et al., 2005).

Inputs considered important are those that are central to the purpose of the research and that, when moderately and realistically changed, significantly affect output measures among the alternative scenarios simulated (Kelton, 2000). The levels of important input factors represent the reasonable changes that could be expected of these inputs in the realistic operating environment depicted in the simulation. Inputs that impact output measures in a similar manner across all scenarios can be fixed at a reasonable level and considered model assumptions or parameters.

Full-Factorial Design

The inputs to the simulation experiments used in this study fall into three categories: supply, demand, and customer/operational behavior. As matching supply and demand is the purpose of this research, the inputs associated with supply and demand are the important factors that are varied. The inputs related to the behaviors of customers and operations, including arrival patterns, seating rules, duration measures, and spend figures, are held constant at reasonable levels and considered assumptions.

This experiment has a four-factor (2x3x2x3) full-factorial design. Supply-related factors are method of inventory allocation and table size proportion. Demand-related factors are level of peak demand and demand mix. Details regarding each of the four input factors are provided in following sections, but are briefly given here to establish the study's experimental design:

- Supply-related factors –
    1. Method of inventory allocation refers to the way in which inventory is defined and distributed in the test restaurant. The two methods considered are seats-to-tables (with space constraint) and space-to-tables. In the seats-to-tables method, seats are considered the smallest common inventory unit and are apportioned to tables of differing sizes. In the space-to-tables method, square footage is the smallest common inventory element and is allocated to tables of various sizes.
    2. Table supply proportion denotes the amount of space taken up by differently-sized tables. Standard, narrow, and wide levels of proportion are considered.
- Demand-related factors –
    1. The peak demand input factor, representing the amount of demand realized at the test restaurant over Friday and Saturday dinner periods, is tested at its current level and at 117.645% of the current level.
    2. Demand mix, which refers to the composition of party sizes at the test

site, is evaluated at its current party size mix, a mix skewed to smaller party sizes, and a mix skewed to larger party sizes.

The primary concern for this study is the impact of method of inventory allocation on service operations, so the total revenue produced by the two methods serves as the basis for comparison. Each simulation run is differentiated by its supply mix and whether this mix is determined by the space-to-tables or seats-to-tables allocation method. The supply mix scenario producing the highest revenue for every combination of the table size proportion, demand level, and demand mix inputs is determined. This revenue is compared for the two inventory allocation methods to evaluate if one method consistently outperforms the other. Figure 3.5 is a visual representation of the total revenue comparison resulting from this experimental design.

		Method of Inventory Allocation (Seats-to-Tables or Space-to-Tables)				
Demand Mix	Current	revenue difference	revenue difference	revenue difference	100%	Demand level
		revenue difference	revenue difference	revenue difference	117.6%	
	Skewed smaller	revenue difference	revenue difference	revenue difference	100%	
		revenue difference	revenue difference	revenue difference	117.6%	
	Skewed larger	revenue difference	revenue difference	revenue difference	100%	
		revenue difference	revenue difference	revenue difference	117.6%	
		Standard	Narrower	Wider		
		Table Space Proportion				

Figure 3.5: Comparison of Allocation Methods

The additional eight performance measures (total number of customers served, total number of customers lost, table utilization – total and by table type, seat utilization – total and by table type, hourly RevPASH, hourly RevPAST, average wait by party size, 85th percentile of waits by party size) from the top revenue-generating scenarios for both inventory allocation methods are also collected and compared for every combination of the other three input factors. In all, this experimental design produces 162 comparisons that indicate how using a seat allocation rule or a space allocation rule impacts system performance under a variety of operating conditions.

Experimental Factors

Method of Inventory Allocation

As previously stated, the two methods of inventory allocation tested are seats-to-tables and space-to-tables. The seats-to-tables method is the current inventory allocation approach used by researchers and practitioners employing RRM. Seats are the basic inventory unit and are distributed to tables of varying sizes according to the demand pattern of the restaurant. The space-to-tables method, however, allocates the net square footage required by a table to different sizes of tables. Square feet are the inventory units to be allocated to tables of different sizes.

Seats-to-Tables (with Space Constraint) Method: Under this inventory allocation method, the theoretical capacity of the test restaurant is distributed to tables. Theoretical capacity refers to the existing number of seats that are available to serve customers, which currently totals 116. The purpose of testing differing table mixes is to determine the mix that best accommodates demand and thus generates the most revenue.

Finding this optimal table mix required testing every possible supply profile. MATLAB (2005) software was used to generate all table configurations using tables of two, four, six, and eight. The number of scenarios produced was 1735.

However, all of these supply scenarios using the full complement of 116 seats may not fit into the dining space of the test restaurant. The dining room area available to seat customers is determined based on the physical space occupied by a restaurant, as well as the theme and décor of the establishment. On average, the dining room of a full-service, upscale casual outlet has 1 square foot of useable dining space for each 0.265 square foot space used elsewhere in the front-of-house, such as in the restroom or coat check areas. This is known as the FOH gross factor (Stephani K. Robson, personal communication, July 2006); the FOH gross factor used for this study is this standard 1.265 measure. Useable dining space corresponds to space net of all stairs, poles, and other impediments.

The restaurant used in this study has a total useable FOH area of 1800 square feet; applying the FOH gross factor described above indicates that the facility has 1423 net square feet of dining space. While the actual dining room was not specifically measured, a tour of the restaurant and discussions with the industry professionals consulted confirmed that this is a reasonable figure to use.

Table 3.15 gives the standard square footage requirements to accommodate different table types. These figures represent the full planning square required for each table size. A planning square includes the physical size of a table top, the size and number of chairs at a table, the area needed to accommodate patrons in the chairs at the table when occupied, and the area needed for staff to circulate the table during service. The test site operates with typical, commonplace restaurant tables and chairs; these standard figures are representative of its space requirements and thus appropriate to employ.

Table 3.15: Standard Square Footage Requirements

Table Size	Square Feet
2-top	31.50
4-top	43.75
6-top	78.63
8-top	81.00

Source: S.K. Robson, personal communication, July 2006

Each of the 1735 table mixes was checked for spatial-feasibility to determine which mixes actually fit in the square footage available for seating. Under the seats-to-tables method, 43 percent, or 744 mixes, used the total existing theoretical capacity (116 seats) and had a total square footage that is less than or equal to the 1423-square-foot dining area. To keep the focus of this study on inventory units and maximum achievable revenue, the physical arrangement of tables was not considered.

The majority of all supply scenarios that used the total 116 seats are not spatially feasible. Over 57 percent, or 991, of the table mixes generated exceeded the square footage of the dining area. Because these scenarios could represent high revenue-generating supply profiles, they must be adjusted to fit into the available dining space. While adjusting these scenarios will decrease the existing total capacity at the test outlet, the seats may be used more often and thus contribute more to total profit.

A logical way to modify the table mixes of these scenarios is to use a simple heuristic designed to give a spatially-feasible result for each initial table mix that is spatially-infeasible. Essentially, this heuristic applies consistent rules for determining which tables to remove from a mix in order to create a supply profile that maximizes the total square footage available. The heuristic used is given by the following integer-program (IP).

Variable: $x_i = \#$ of tables with i seats

Parameters: p_i = required space for a table with i seats

P = total dining room space available

y_i = # of tables with i seats given by enumeration

Maximize: $$\sum_i p_i x_i \quad (1)$$

Subject to: $$\sum_i p_i x_i \leq P \quad (2)$$

$$x_i \leq y_i \quad \forall i \quad (3)$$

$$x_i \geq 0, \text{integer} \quad \forall i \quad (4)$$

When applied to the 991 seats-to-tables scenarios that were initially spatially-infeasible, the heuristic provided 456 unique, spatially-feasible table mixes. These reworked scenarios use between 90 and 114 seats and between 1346.2 and 1423 square feet of available dining space.

Based on the initial spatially-feasible enumerated scenarios and the scenarios made feasible through the heuristic, a total of 1200 supply profiles are simulated for the seats-to-tables (with space constraint) inventory allocation method.

Space-to-Tables Method: Instead of distributing the total number of seats to different-sized tables, the space-to-tables inventory allocation method allocates the available dining space to tables. Under this method, the existing total square footage available to accommodate the planning squares required for tables of various sizes is distributed to every possible table mix. The feasible set of table mixes is defined as the mixes of space in which the square footage allocated to different table sizes sum to the usable, available square foot capacity of the dining area. The purpose of testing differing table mixes is to determine the mix that best accommodates demand and thus generates the most revenue.

Finding this optimal table mix requires testing every possible supply profile. As space is the unit being allocated, the spatial feasibility issue in the seats-to-tables method is not a concern. However, requiring the supply mixes to perfectly sum to the available square footage of the dining area would likely lead to no feasible mixes. To alleviate this problem, a range of space is used to determine feasible options. Clearly, an operation would like to accommodate its highest revenue-producing table mix. Therefore, the maximum space that can fit tables is the total net dining space, which has been previously given as 1423 square feet for the test restaurant. A supply mix that takes up too little space is also problematic since useable space that could generate revenue at some times would be left empty. Therefore, to ensure that all available space is used, feasible supply mixes under the space-to-tables allocation method are those that never leave as much free space as would fit the smallest table. The minimum space that can fit tables in the test restaurant is thus 1391.5 square feet.

Using the average planning square figures given previously in Table 3.15 and a total space range of 1391.5 – 1423 square feet, 2115 supply profiles are generated using MATLAB software. These scenarios use table combinations comprised of between 90 and 140 seats.

This enumeration of table mixes based on space requirements will be completed a total of three times. As stated, these initial 2115 supply profiles are based on the average planning square figures presented previously in Table 3.15. The table space proportion input factor, described in the following section, involves changing these planning square figures to accommodate tables that are either narrower or wider than average. Because table mixes under the space-to-tables allocation method depends on the space each table type requires, all possible mixes must be generated for each table space proportion tested.

Table Space Proportion

The table space proportion input factor accounts for how close table sizes are to being proportional to the number of seats that comprise each table. This proportionality is measured by space per person. Industry professionals often discuss public restaurant space requirements in terms of space per person and gross dining room space requirements in terms of space per seat (Baraban and Durocher, 2001; Hesser, 2000). These per person or seat figures vary widely based on the type, atmosphere, location, and price point of an individual restaurant. Allotments range from 8 to 20 square feet per seat for a casual, mid-priced, sit-down outlet like the restaurant used in this study (Baraban and Durocher, 2001; S.K. Robson, personal communication, July 2006).

However, these per person or per seat numbers assume that the space required by various table sizes is proportional to the number of seats comprising each table size. Under this assumption, a restaurant using a spatial requirement of 15 square feet per person would have 2-top tables that take up 30 square feet, 4-top tables that take up 60 square feet, and 6-tops that take up 90 square feet. Restaurants with perfectly proportional spatial requirements for tables commonly use one or two different table sizes and combine adjacent tables as needed to accommodate differing party sizes.

Whether taking into account space requirements per person, the dimensions of different-sized table tops, or the full and actual space needed for different tables sizes, smaller tables generally require more space per person than larger tables. As previously described, this actual space is the planning square for tables of different sizes and includes not only the actual size of the table and chairs, but also the area around the table used by either customers or employees. No industry standard exists for the exact size of planning squares for various-sized tables. Like the per person seat figures described above, the amount of space required for planning squares depends on a restaurant's operating and marketing characteristics, such as service style, location, and industry segment (S.K. Robson, personal communication, July 2006).

To account for the impact that different planning square sizes may have on optimal seat or space inventory allocation, table space proportion is varied at three levels. The first level represents supply situations in which the space needed to accommodate different-sized tables is not proportional to the seats at tables; instead, it is an average amount for a mid-priced, casual, full-service restaurant (S.K. Robson, personal communication, July 2006). Another level corresponds to supply scenarios with differing table space requirements that are nearly proportional to the number of seats at a table. Conversely, the third table space proportion input level relates to supply situations in which space requirements for different table sizes are far from proportional to the number of seats that comprise a table. The proportionality of table spaces used for each level of this input is included in Table 3.16.

Table 3.16: Table Space Proportions

Table Type	Average Amount Scenario*			Nearly Proportional Scenario/Wider Tables*			Far from Proportional Scenario/Narrower Tables*		
	Planning Square Size	Per Person Space	% of Per Person Space of 2-top	Planning Square Size	Per Person Space	% of Per Person Space of 2-top	Planning Square Size	Per Person Space	% of Per Person Space of 2-top
2-top	31.50	15.75	100%	30.00	15.00	100%	31.00	15.50	100%
4-top	43.75	10.94	69.4%	56.00	14.00	93.3%	32.00	8.00	51.6%
6-top	78.63	13.11	83.2%	87.00	14.50	96.7%	60.00	10.00	64.5%
8-top	81.00	10.13	64.3%	110.00	13.75	91.7%	79.00	9.88	63.7%

*Sizes are given in square feet

As previously stated, all possible table mixes are generated under the space-to-tables allocation method for each of the average, nearly proportional, and far from proportional table space scenarios. The number of scenarios simulated under the average planning square proportion is 2115, while the scenarios simulated for the nearly proportional and far from proportional planning square requirements number 1133 and 3764, respectively.

Under the seats-to-tables method, the enumeration step is completed only once. However, each supply enumeration is tested for initial spatial feasibility and then run through the IP heuristic three separate times. The resulting number of table mixes to be simulated is 1200 for the average planning square table space proportion scenarios, 509 for the nearly proportional table space proportion scenarios, and 1620 for the far from proportional table space proportion scenarios.

Peak Demand

To capture the demand aspect of the problem entailing matching supply to demand in a stochastic service operating environment, demand is varied at two levels. Since capacity management techniques such as those associated with Revenue Management are beneficial under conditions in which demand exceeds supply, only peak nights of Friday and Saturday are modeled. As discussed previously, the restaurant has fairly high table utilization during the busiest hours of these nights, so the operating system can be considered strained under the current supply condition in which tables are of standard size. It follows that the operating system is also taxed under the current demand level when tables are close to proportional, or effectively larger than the ones currently used, since fewer tables will be able to fit in the given space. However, when tables are far from proportional, a greater number of tables can fit in the available dining room space. Because of this, the current level of demand will likely not constrain supply and should therefore be artificially inflated to ensure that the operating system is taxed. For the scenarios in which the table space proportion factor is far from proportional, the 100% level of demand is adjusted to be 115% of current demand.

The current, observed level of demand on these peak nights serves as the first level of demand tested. Kimes and Thompson (2004) found that the optimal capacity mix under a seat to table allocation method without space constraint varied under differing demand volumes, so a demand increase of 17.645% from the current level is also tested for all table space proportions. This percentage increase is derived from published studies that test, to some degree, how a service business reacts to increases in demand. Kimes and Thompson (2004), Pullman and Thompson (2002), and Radas and Shugan (1998), all tested the impact on a customer-based service operating system to a demand increase ranging from 5 to 20 percent.

While 17.645% is an ample increase in demand, a supply configuration which better matches demand should be able to either accommodate additional demand or decrease current wait times during peak times in which capacity is already constrained (Kimes and Thompson, 2004; Pagell and Melnyk, 2004). The reaction of both the seats-to-tables and space-to-tables allocation methods to this demand increase will give an indication of the sensitivity of these allocation options to possible changes in demand.

Demand Mix

The best mix of supply for different-sized inventory units will likely vary with the mix of demand for the range of sizes. Therefore, three party size mixes mix are tested for each of the allocation methods. Thompson (2002) and Kimes and Thompson (2005) altered the overall average party size to test different party size mixes. For this research, the different levels for mix of demand are determined by benchmarking the distribution of party sizes of several outlets similar to the test restaurant. Aside from using the current party size mix as one level of the demand mix input variable, two other demand mix scenarios are tested. Based on the demand mixes from the five benchmarked outlets, one level is skewed to having an additional number of smaller party sizes than the current demand mix and the third level is skewed to having an additional number of larger party sizes than the current mix. Table 3.17 shows the derivation of the demand mixes.

Table 3.17: Demand Mix Inputs

Party Size	Outlet 1	Outlet 2	Outlet 3	Outlet 4	Outlet 5	Current Level	More Smaller Parties	More Larger Parties
1	7.5%	17.7%	10.0%	8.0%	6.6%	11.2%	13.0%	8.0%
2	59.9%	51.9%	63.7%	50.2%	66.0%	52.9%	58.0%	52.0%
3	16.0%	15.4%	14.8%	17.2%	9.7%	16.1%	14.0%	16.0%
4	10.3%	9.0%	6.9%	16.0%	11.7%	12.2%	10.5%	16.0%
5	3.4%	2.7%	2.7%	4.2%	2.5%	3.9%	2.5%	3.5%
6	1.6%	1.7%	0.8%	2.5%	2.2%	2.0%	1.0%	2.5%
7	0.5%	0.8%	0.4%	0.8%	0.7%	1.0%	0.5%	1.0%
8	0.8%	0.8%	0.7%	0.9%	0.6%	0.7%	0.5%	1.0%
Average Party Size	2.53	2.39	2.36	2.73	2.50	2.58	2.39	2.72

Replications and Runs

Accounting for the two supply inputs (method of inventory allocation and table space proportion) and the two demand inputs (level and mix of demand), 62,046 unique scenarios are run through the simulation model for 104 replications each. All replications use common random numbers for the various simulation components and all replications have the same initial conditions.

Each run of the model takes 30 seconds on a Windows-based personal computer with a 2.0 GHz processor. Using three dedicated computers, the total run time for the simulation study is just over seven days.

Output Analysis

The table mixes for each of the two methods of inventory allocation, at every combination of factor levels for the other three inputs, are ranked according to the average total revenue generated over the 104 replications run. All performance measures are collected for the top performing mix for each of the 36 scenarios. Since all scenarios and simulation runs are independent and a full-factorial experimental design is used, all observations are independent and from a normally distributed population of responses. Thus, statistical inference procedures are suitable for analyzing the simulation output data.

A point estimate for the difference in each pair of means for the top total revenue table mix scenario is calculated and a 95% confidence interval is established, yielding a set of 18 confidence intervals. Intervals including zero show that no difference in revenue exists between the two methods of inventory allocation for the given levels of the table space proportion, level of demand, and mix of demand factors. For the family of intervals not including zero, the sample means are further analyzed using a multiple comparison procedure to determine whether or not one of the inventory allocation methods is statistically better than the other.

To concurrently examine all the data for all of the scenarios comprising the total experiment, a four-way ANOVA is calculated. The response variable is total revenue and the four main factors are method of inventory allocation, table space proportion, demand level, and demand mix. A multi-factor ANOVA is an appropriate method to model observations that result from an experiment that has a randomized design, produces multiple replications, and has factors that possibly interact in a non-additive manner. Pairwise comparisons and linear contrasts are used to investigate the significant and interesting results arising from the ANOVA. In total, these output analyses are designed to provide a full complement of metrics that show how the two inventory allocation methods affect the operating characteristics of the test restaurant and whether one method consistently outperforms the other across a variety of conditions.

Summary

The chapter detailed the methodology proposed to determine the revenue impact of managing the physical space of a service business instead of the physical inventory. The simulation and experimental design together produce a 95% confidence interval for the difference in mean total revenue between a space allocation rule and an inventory allocation rule. The next chapter presents the results of executing the simulation study presented and analyzing the data according to the methods discussed above.

CHAPTER 4: RESULTS

The focus of this chapter is to analyze the simulation results in a way that fully explores the general purpose of this study, which is to determine how revenue is impacted by defining inventory in terms of space instead of units. The specific research questions posed in Chapter 1 are addressed:

1. To what extent is revenue impacted if capacity is allocated based on space instead of inventory units?
2. How is existing capacity changed when supply is measured by space instead of units?
3. Can revenue actually increase if capacity is decreased?

This chapter begins with a statistical analysis of the total revenue generated through simulation by the two methods of inventory allocation under study: the seats-to-tables method (hereafter abbreviated "SEATS") and the space-to-tables method (hereafter abbreviated "SPACE"). The statistical significance of these revenue findings is then discussed, followed by an analysis of how the two allocation methods impact capacity. The other eight performance measures collected from the simulation are then compared for SEATS and SPACE.

Running the Simulation Model

The simulation model designed and validated in Chapter 3 was used to mimic restaurant operations according to a four-factor, full-factorial experimental design. The factors included in the study – method of inventory allocation, table space proportion, demand level, and demand mix – were varied at different levels to account for a range of operating conditions, thus creating 36 distinct simulation scenarios.

Recall from the previous chapter that the method of inventory allocation is the primary factor under study. SEATS considered seats to be the unit of inventory in a restaurant, and all possible table mixes were determined by allocating the existing number of seats at the test restaurant to 2-top, 4-top, 6-top, and 8-top tables. SPACE considered the space required by tables to be the unit of inventory, and thus determined possible table mixes by allocating the existing amount of square footage in the dining room to the various table sizes.

The additional three factors tested in the simulation were included to ascertain how different operating scenarios affected the simulation results. The demand-related factors included two demand levels (for standard and close to proportional space scenarios, 100% and 115%; for far from proportional table space scenarios, 117.645% and 132.645%). In addition, three different levels of party size mix (the current party size mix, a mix skewed towards more smaller parties, and a mix skewed from its current state towards more larger parties) were tested.

The table space proportion factor was less straightforward; three different levels were used to test the extent to which results were impacted when tables accommodated the same number of people, but required different amounts of space. The complexity of this factor was due to how these space requirements were determined; in essence, the three levels of table space proportion tested – standard, far from proportional, and close to proportional – all used approximately the same size 2-top table. However, the sizes of the 4-top, 6-top, and 8-top tables varied due to how close the table sizes were to being proportional to the number of seats that comprise each table. Therefore, the far from proportional level used the smallest 4-tops, 6-tops, and 8-tops, the standard proportional level used slightly larger tables, and the close to proportional level used the largest tables. For clarity, the table space proportions will henceforth be called "standard," "far/small," and "close/large."

All feasible table mixes, determined for each of the 36 simulation scenarios through the enumeration procedures described in Chapter 3, were run through the appropriate scenarios and replicated 104 times. The complete simulation experiment therefore contained 62,046 runs and over 6.4 million replications of a two-night dinner service at the test restaurant. Appendix A provides a summary of input factors and the combinations tested for each scenario. For every run of the simulation, the nine performance measures – total revenue, customers served, customers lost, table occupancy, seat occupancy, RevPASH, RevPAST, average wait by party size, and 85th percentile of waits by party size – were collected and averaged over the 104 replications. For each of the 36 scenarios, the simulation runs were then ranked according to average total revenue, and the top revenue-producing table mix for every factor level combination was identified.

These top revenue scenarios were then paired by the inventory allocation factor so one-to-one comparisons could be made between SEATS and SPACE at every level of the demand, demand mix, and table space proportion factors. For example, Scenario Pair 1&19 represents a comparison of the top performing table mix generated by SEATS (Scenario 1) and SPACE (Scenario 19) under the current level of demand, the current mix of demand, and the current table space proportion. Table 4.1 gives the top table mix and its associated revenue and capacity measures under the two methods of inventory allocation for each pair of simulation scenarios.

Table 4.1: Top Revenue-Producing Table Mixes Generated Under Each Scenario

SEATS Scenarios									*SPACE Scenarios*								
Scenario	**Revenue**	**2-tops**	**4-tops**	**6-tops**	**8-tops**	**Total Seats**	**Total Tables**	**Square Footage Used**	**Scenario**	**Revenue**	**2-tops**	**4-tops**	**6-tops**	**8-tops**	**Total Seats**	**Total Tables**	**Square Footage Used**
1	$14,689	19	9	0	5	114	33	1397.3	**19**	$14,729	14	15	0	4	120	33	1421.3
2	$13,812	18	8	1	5	114	32	1400.6	**20**	$13,812	18	8	1	5	114	32	1400.6
3	$15,493	16	10	4	2	112	32	1418.0	**21**	$15,493	16	10	4	2	112	32	1418.0
4	$17,040	14	13	3	2	114	32	1407.6	**22**	$17,040	14	13	3	2	114	32	1407.6
5	$16,068	21	10	2	2	110	35	1418.3	**23**	$16,068	21	10	2	2	110	35	1418.3
6	$17,817	15	12	2	3	114	32	1397.8	**24**	$17,842	17	11	0	5	118	33	1421.8
7	$17,096	21	10	3	2	116	36	1309.0	**25**	$17,376	4	23	8	1	156	36	1419.0
8	$16,135	24	7	4	2	116	37	1366.0	**26**	$16,222	24	11	0	4	124	39	1412.0
9	$17,866	18	11	2	3	116	34	1267.0	**27**	$18,276	1	26	5	3	160	35	1400.0
10	$19,315	21	10	3	2	116	36	1309.0	**28**	$20,154	4	26	5	2	158	37	1414.0
11	$18,633	24	10	2	2	116	38	1342.0	**29**	$19,024	14	20	3	2	142	39	1412.0
12	$20,048	19	11	3	2	116	35	1279.0	**30**	$21,232	7	24	3	3	152	37	1402.0
13	$14,431	17	6	4	2	98	29	1414.0	**31**	$14,431	17	6	4	2	98	29	1414.0
14	$13,579	19	10	2	1	98	32	1414.0	**32**	$13,708	17	9	2	2	98	30	1408.0
15	$15,099	14	10	0	4	100	28	1420.0	**33**	$15,131	13	9	2	3	98	27	1398.0
16	$16,313	18	9	3	1	98	31	1415.0	**34**	$16,340	15	10	2	2	98	29	1404.0
17	$15,658	21	9	2	1	98	33	1418.0	**35**	$15,709	18	10	1	2	98	31	1407.0
18	$16,804	18	9	3	1	98	31	1415.0	**36**	$16,847	13	11	2	2	98	28	1400.0

Revenue Comparison between Inventory Allocation Methods

Figure 4.1 contains the point estimate and confidence interval for the difference in mean revenue generated by the top-revenue producing table mix under each SEATS and SPACE pair under all factor levels.

		Method of Inventory Allocation					
Demand Mix		SEATS	SPACE	SEATS	SPACE	SEATS	SPACE
Current		Scenario 1	Scenario 19	Scenario 7	Scenario 25	Scenario 13	Scenario 31
	100%	Point Estimate = -$40		Point Estimate = -$281		Point Estimate = $0	
		95% CI = (-$284,$205)		95% CI = (-$607,$46)		95% CI = N/A	
		Scenario 4	Scenario 22	Scenario 10	Scenario 28	Scenario 16	Scenario 34
	115%	Point Estimate = $0		Point Estimate = -$839		Point Estimate = -$26	
		95% CI = N/A		95% CI = (-$1,123,-$555)		95% CI = (-$291,$239)	
Skewed smaller		Scenario 2	Scenario 20	Scenario 8	Scenario 26	Scenario 14	Scenario 32
	100%	Point Estimate = 0		Point Estimate = -$86		Point Estimate = -$129	
		95% CI = N/A		95% CI = (-$360,$187)		95% CI = (-$353,$95)	
		Scenario 5	Scenario 23	Scenario 11	Scenario 29	Scenario 17	Scenario 35
	115%	Point Estimate = $0		Point Estimate = -$392		Point Estimate = -$51	
		95% CI = N/A		95% CI = (-$584,-$182)		95% CI = (-$283,$181)	
Skewed larger		Scenario 3	Scenario 21	Scenario 9	Scenario 27	Scenario 15	Scenario 33
	100%	Point Estimate = $0		Point Estimate = -$411		Point Estimate = -$32	
		95% CI = N/A		95% CI = (-$698,-$123)		95% CI = (-$271,$207)	
		Scenario 6	Scenario 24	Scenario 12	Scenario 30	Scenario 18	Scenario 36
	115%	Point Estimate = -$26		Point Estimate = -$1,184		Point Estimate = -$43	
		95% CI = (-$324,$272)		95% CI = (-$1,464,-$904)		95% CI = (-$245,$160)	
	Demand Level	Standard		Far/Smaller		Close/Larger	
		Table Space Proportion					

Figure 4.1: 95% Confidence Intervals for the Difference in Mean Revenue between SEATS and SPACE

The top-performing table mix was identical between SEATS and SPACE in five instances; further, nine of the confidence intervals include zero. These results indicate that no statistically significant difference in revenue exists between the two inventory allocation methods for the levels of the table space proportion, amount of demand, and mix of demand characterized by these fourteen scenario pairs. However, the 95% confidence intervals for Scenario Pairs 9&27 through 12&30 were all less than zero, indicating that SPACE generated revenues that were statistically greater than revenues produced by SEATS. The approximate revenue benefit under SEATS and the operating characteristics that produce this revenue benefit are as follows:

- For Scenario Pair 9&27, the revenue gain under SEATS was approximately $123 to $698. The test restaurant used far from proportional, or effectively smaller/more closely situated tables, experienced demand at 115% of the current amount of demand, and had a demand mix skewed towards a greater number of larger parties, with an average party size of 2.72.
- For Scenario Pair 10&28, the revenue gain under SEATS was approximately $555 to $1,123. The test restaurant used far from proportional, or effectively smaller/more closely situated tables, experienced demand at roughly 132% of the current amount of demand, and had a demand mix based on the existing mix, with an average party size of 2.58.
- For Scenario Pair 11&29, the revenue gain under SEATS was approximately $182 to $584. The test restaurant used far from proportional, or effectively smaller/more closely situated tables, experienced demand at roughly 132% of the current amount of demand, and had a demand mix skewed towards a greater number of smaller parties, with an average party size of 2.39.
- For Scenario Pair 12&30, the revenue gain under SEATS was approximately $904 to $1,464. The test restaurant used far from proportional, or effectively

smaller/more closely situated tables, experienced demand at roughly 132% of the current amount of demand, and had a demand mix skewed towards a greater number of larger parties, with an average party size of 2.72.

There are two explanations for the significant revenue differences observed for these four Scenario Pairs; one relates to the combination of factor levels used in these particular Scenario Pairs, while the other pertains to the table mixes tested by the simulation. In regard to the factor levels, for these four Scenario Pairs, the table space proportion was at the far/smaller level, so the number of seats that can fit in the restaurant is at its maximum. The SEATS scenarios (9, 10, 11, and 12) were all constrained by the 116 seats currently used at the test site whereas the SPACE counterparts (scenarios 27, 28, 29, and 30) were able to use many more seats.

Additionally, the gross amount of demand introduced into the operating system was at its highest for these four instances. For Scenario Pair 9&27, although the demand level was at its current state (recall that 115% was used as the base case for the far/small table space proportion scenarios), the demand mix was skewed towards larger parties. For the other three scenario pairs, the demand level was at its increased state (recall that 132% was used as the higher demand case for the far/small table space proportion scenarios). Therefore, the combination of using smaller tables and experiencing extremely high demand magnifies the difference in the number of seats put into use between the two methods of inventory allocation and results in the SPACE method outperforming the SEATS method under these circumstances.

In regard to the table mixes tested by the simulation, an explanation as to why there is no difference between revenue under SEATS and SPACE for fourteen scenario pairs –

and why there is a revenue difference for Scenario Pairs 9&27 through 12&30 – concerns the table mixes input into the simulation for each scenario. If the same or very similar table mixes are tested for each method of inventory allocation, then it is not unexpected that the output would be the same or similar. As shown in Table 4.2, the number of unique mixes for the SEATS never surpassed 10 percent of the total table mixes tested in all scenarios.

Table 4.2: Similarity of Table Mixes Input into Simulation

Scenarios	Total Number of Table Mixes Enumerated			Of the Total Table Mixes Enumerated			Actual Total Number of Mixes Tested
				Number of Identical Mixes between Two Inventory Allocation Methods	Number of Unique Mixes		
	SEATS	SPACE	Sum		SEATS	SPACE	
1 to 6 and 19 to 24	1,200	2,115	3,315	617	583	1,498	2,698
7 to 12 and 25 to 30	1,620	3,764	5,384	235	1,385	3,529	5,149
13 to 18 and 31 to 36	509	1,133	1,642	266	243	867	1,376

Scenario Pairs	Total Number of Mixes in Top 10%, Ranked by Revenue	Within the Top 10% of All Table Mixes				
		Revenue Range	Percentage Identical for Both Allocation Methods	Percentage Similar* for Both Allocation Methods	Percentage Unique to Allocation Method	
					SEATS	SPACE
1 & 19	270	$14,453 - $14,729	51.1%	0.0%	2.6%	46.3%
2 & 20	270	$13,484 - $13,728	48.1%	6.7%	5.2%	40.0%
3 & 21	270	$15,165 - $15,493	40.7%	11.1%	5.9%	42.2%
4 & 22	270	$16,633 - $17,040	56.3%	5.9%	4.1%	33.7%
5 & 23	271	$15,685 - $16,068	61.3%	3.0%	3.7%	32.1%
6 & 24	270	$17,353 - $17,842	48.9%	11.9%	3.3%	35.9%
7 & 25	515	$14,546 - $14,767	0.0%	3.1%	6.0%	90.9%
8 & 26	515	$13,537 - $13,757	5.0%	8.5%	9.7%	76.7%
9 & 27	515	$15,287 - $15,604	0.0%	0.0%	8.2%	91.8%
10 & 28	515	$17,067 - $17,376	0.0%	0.4%	0.0%	99.6%
11 & 29	515	$15,943 - $16,222	0.8%	3.1%	5.0%	91.1%
12 & 30	515	$17,915 - $18,277	0.0%	0.0%	0.0%	100.0%
13 & 31	138	$14,096 - $14,431	31.9%	21.7%	4.3%	42.0%
14 & 32	138	$13,287 - $13,708	33.3%	14.5%	1.4%	50.7%
15 & 33	138	$14,704 - $15,131	26.1%	20.3%	5.8%	47.8%
16 & 34	138	$15,726 - $16,340	43.5%	8.7%	3.6%	44.2%
17 & 35	138	$15,160 - $15,710	39.1%	14.5%	2.9%	43.5%
18 & 36	138	$16,300 - $16,847	40.6%	13.0%	5.8%	40.6%

*Similar is defined as any pair of table mixes, with one mix from each inventory allocation method, that meet two requirements:

1. The *net* difference between the total seats is between 0 and 4 .
2. Only one set of consecutive table sizes constitute this difference.

Examples of pairs of similar table mixes (in the format of 2s/4s/6s/8s) are: 14/15/3/2 & 14/14/3/2; 13/15/2/2 & 13/14/3/2

Examples of pairs of dissimilar table mixes are: 10/10/3/5 & 10/10/3/6; 11/11/4/2 & 11/13/4/1

At least half of the table mixes simulated for the standard and close/large table space proportions (Scenarios 1 – 6 and 9 – 24 and Scenarios 13 – 18 and 31 – 36) were either identical or notably similar. However, when the tables were of far/small proportion, very few of the top 10 percent of table mixes tested were identical or even similar between SEATS and SPACE, and for five of the six far/small proportion scenarios, over 90 percent of the top performing table mixes were unique to the SEATS factor. Table 4.2 above recaps the table mixes simulated for all three table space proportions, and summarizes the top 10 percent of table mixes, as ranked by total revenue, simulated for both SEATS and SPACE.

Sensitivity of Simulation Output

An important observation that emerged over the course of conceptualizing and running these simulations relates to the demand level factor. As previously described, the current demand/100% level had to be augmented for the far from proportional scenarios to ensure that the restaurant system was truly taxed and thus operating under excess demand/constrained supply, which are the principal conditions necessary to benefit from Revenue and Capacity Management techniques. The current demand level/100% for the standard and close to proportional scenarios was assumed to be sufficient to strain the system and create the excess demand/constrained supply conditions.

However, when some of these scenarios were rerun with different random number seeds, the simulation results changed, meaning that the top-performing table mixes and associated revenues for the scenarios varied from that given in Table 4.1. Although the change in revenue was less than 1 percent, this indicates that there is some lack of stability in the top-performing table mix at low demand levels which could be alleviated in further research by increasing the current/100% level for all table space proportions.

Full Experimental Analysis

A four-way ANOVA, with total revenue as the response variable, was calculated to further understand how and when the revenue produced under SEATS and SPACE differed statistically. This type of full experimental analysis served to concurrently examine all simulation scenarios and determine if any of the individual factors, or a combination of some or all of them, impacted revenue.

The standard procedure for analyzing an ANOVA was followed, starting with initially testing all interactions and factor effects using separate F tests, continuing with testing significant interactions starting at the highest order, and ending with further exploration of all interesting and significant findings. Since 15 separate F tests were computed simultaneously when determining the p-value for each interaction and factor in the general ANOVA table, Kimball's inequality was used to ensure that the error rate for this family of F tests does not exceed a reasonable rate. The Kimball inequality indicates that each individual F-test must be analyzed at a significance level of 0.007 to ensure that error rate for the overall experimentwise error does not exceed 0.10. Results from the ANOVA are in Table 4.3.

Table 4.3: Four-way ANOVA

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Method of Allocation (SEATS, SPACE)	1	36181104	36181104	36181104	29.78	0.000
TableSpaceProportion (standard, far, close)	2	6985616579	6985616579	3492808290	2875.18	0.000
DemandLevel (100%, 115%)	1	4756561080	4756561080	4756561080	3915.47	0.000
DemandMix (current, skew small, skew large)	2	1654307509	1654307509	827153755	680.89	0.000
*Method*TableSpaceProportion*	2	52871909	52871909	26435955	21.76	0.000
*Method*DemandLevel*	1	7235795	7235795	7235795	5.96	0.015
*Method*DemandMix*	2	4663591	4663591	2331795	1.92	0.147
TableSpaceProportion DemandLevel*	2	75644453	75644453	37822227	31.13	0.000
TableSpaceProportion DemandMix*	4	33779363	33779363	8444841	6.95	0.000
*DemandLevel*DemandMix*	2	1958516	1958516	979258	0.81	0.447
*Method*TableSpaceProportion* DemandLevel*	2	16004731	16004731	8002365	6.59	0.001
*Method*TableSpaceProportion* DemandMix*	4	12008537	12008537	3002134	2.47	0.043
*Method*DemandLevel* DemandMix*	2	1471548	1471548	735774	0.61	0.546
TableSpaceProportion DemandLevel*DemandMix*	4	5315328	5315328	1328832	1.09	0.358
*Method*TableSpaceProp* DemandLevel*DemandMix*	4	1600678	1600678	400169	0.33	0.858
Error	370	4504525054	4504525054	1214813		
Total	3743	18149745776				
S = 1102.19		R-Sq = 75.18%		R-Sq(adj) = 74.95%		

The individual F tests indicated that no third-order interaction is present; one second-order interaction (MethodofAllocation-TableSpaceProportion -DemandLevel) was significant at p<0.007. The interaction plots for the factors of this second-order interaction are in Figure 4.2. The plots do not display much deviation from parallel curves, suggesting that the significance of this interaction may be due to a difference in scale. To test this, log and square root transformations of the data were completed; both transformations made this second-order interaction insignificant at p<0.007.

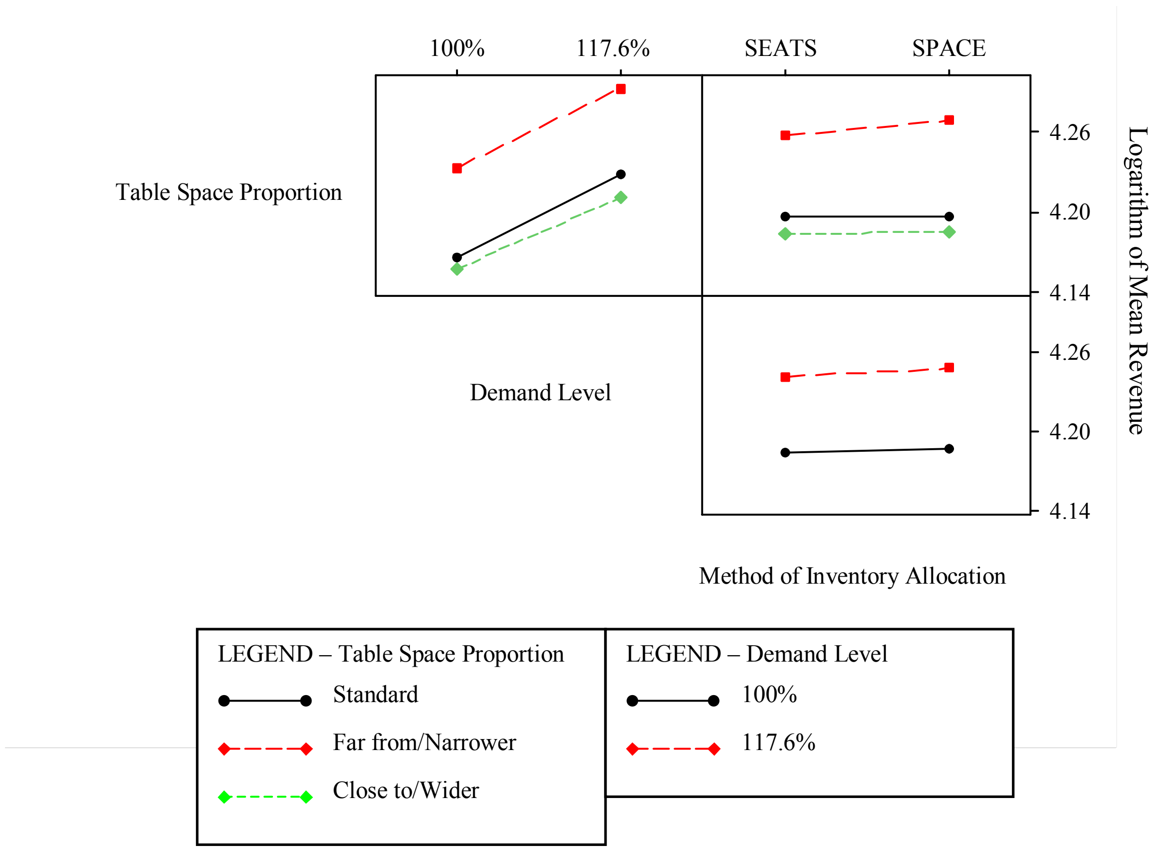

Figure 4.2: Interaction Plot for Method of Allocation & Table Space Proportion & Demand Level Interaction

The ANOVA also indicated that three first-order interactions (MethodofAllocation and TableSpaceProportion; TableSpaceProportion and DemandLevel; TableSpace-Proportion and DemandMix) were significant at $p<0.007$. The same data transformations were completed to determine the importance of these interactions. The TableSpaceProportion and DemandMix interaction was transformable and thus insignificant. However, the MethodofAllocation and TableSpaceProportion interaction and the TableSpaceProportion and DemandLevel interaction were nontrans-formable and both remained significant at $p<0.001$, indicating that the nature of these interaction effects must be fully investigated. The interaction plots for these two factor pairs are included in Figure 4.2 above; these interactions are nontransformable, so their logarithm-transformed plots are identical in scope to their original plots.

Statistical Comparisons and Contrasts

The nature of each of the two significant interactions is revealed through comparisons and contrasts of treatment means. An explanation of the six pairwise comparisons calculated, the estimated treatment means used in the calculations, and the confidence intervals for the comparisons are provided in Appendix B. As these comparisons were not determined prior to conducting the experiments of this study, Scheffé's method is appropriate to use to control experimentwise error rate.

The 95% confidence intervals for the family of comparisons associated with the MethodofAllocation-TableSpaceProportion interaction indicate that more revenue is generated under the SPACE method for tables that are far from proportional/smaller, whereas no statistical revenue difference exists between the two methods at the other two table space proportions. This finding is expected, as SPACE is unconstrained by the number of seats it can use and effectively operates with more supply than does SEATS and can serve a larger number of customers that generate additional revenue. The 95% confidence intervals for the family of comparisons associated with the TableSpaceProportion-DemandLevel interaction indicate that for all table space proportions, mean revenue when demand is at its current level is lower than mean revenue when demand increases by 17.645%. Expectedly, the restaurant makes more money under high demand conditions, regardless of the sizes of the tables used.

Linear contrasts are used to determine which table space proportion benefits the most from higher demand. A description of the three contrasts calculated, the point estimates used in the calculations, and the confidence intervals for the contrasts are in Appendix C. Scheffé's method is used again to control overall error rate when calculating these contrasts. The linear contrasts reveal that the gain in revenue for higher demand situations is greatest for far/small tables and lowest for close/large tables.

Summary of Statistical Analyses

The simulation experiment revealed that the table space proportion factor determined whether a consistent and systematic revenue difference existed between the SEATS SPACE methods of inventory allocation. More specifically, for standard-sized tables and close/large tables, there is no revenue advantage between SEATS and SPACE, regardless of the level of demand or how party sizes generating roughly the same average party size are skewed. The same conclusion does not hold for far/small tables, especially under high demand conditions in which additional customers are introduced to the system either via a skew towards larger party sizes or a strict increase in all arriving parties.

Impact on Capacity Level and Mix

For all scenario pairs, the maximum difference in the total number of tables is 3 (Scenario Pair 18&36), the maximum difference in the total number of seats is 44 (Scenario Pair 9&27), and the maximum difference in the total square footage used is 133 (also Scenario Pair 9&27). Table 4.4 highlights the maximum difference in these three capacity measurements for each of the table space proportions tested. It is interesting to note how little the number of tables used differs between SEATS and SPACE, even in the majority of the far/small scenarios where the number of seats and square footage used differs dramatically.

Table 4.4: Summary of Capacity Measures Associated with the Top Revenue-Producing Table Mixes

	SEATS							*SPACE*							
Scenario Pair	2-tops	4-tops	6-tops	8-tops	Total Seats	Total Tables	SF Used	2-tops	4-tops	6-tops	8-tops	Total Seats	Total Tables	SF Used	
Table Space Proportion: Standard															
1 & 19	19	9	0	5	114	33	1397.3	14	15	0	4	120	33	1421.3	† ◊
2 & 20	18	8	1	5	114	32	1400.6	18	8	1	5	114	32	1400.6	
3 & 21	16	10	4	2	112	32	1418.0	16	10	4	2	112	32	1418.0	
4 & 22	14	13	3	2	114	32	1407.6	14	13	3	2	114	32	1407.6	
5 & 23	21	10	2	2	110	35	1418.3	21	10	2	2	110	35	1418.3	
6 & 24	15	12	2	3	114	32	1397.8	17	11	0	5	118	33	1421.8	* ◊
Table Space Proportion: Far/Smaller Tables															
7 & 25	21	10	3	2	116	36	1309.0	4	23	8	1	156	36	1419.0	
8 & 26	24	7	4	2	116	37	1366.0	24	11	0	4	124	39	1412.0	*
9 & 27	18	11	2	3	116	34	1267.0	1	26	5	3	160	35	1400.0	† ◊
10 & 28	21	10	3	2	116	36	1309.0	4	26	5	2	158	37	1414.0	
11 & 29	24	10	2	2	116	38	1342.0	14	20	3	2	142	39	1412.0	
12 & 30	19	11	3	2	116	35	1279.0	7	24	3	3	152	37	1402.0	*
Table Space Proportion: Close/Larger Tables															
13 & 31	17	6	4	2	98	29	1414.0	17	6	4	2	98	29	1414.0	
14 & 32	19	10	2	1	98	32	1414.0	17	9	2	2	98	30	1408.0	
15 & 33	14	10	0	4	100	28	1420.0	13	9	2	3	98	27	1398.0	† ◊
16 & 34	18	9	3	1	98	31	1415.0	15	10	2	2	98	29	1404.0	
17 & 35	21	9	2	1	98	33	1418.0	18	10	1	2	98	31	1407.0	
18 & 36	18	9	3	1	98	31	1415.0	13	11	2	2	98	28	1400.0	*

*** Denotes the maximum difference in the number of tables used under the two inventory allocation methods for the group of table space proportions**

† Denotes the maximum difference in the number of seats used under the two inventory allocation methods for the group of table space proportions

◊ Denotes the maximum difference in the square footage used under the two inventory allocation methods for the group of table space proportions

Additional Performance Measures

Eight additional performance measures – number of customers served, number of customers lost, RevPASH, RevPAST, table occupancy, seat occupancy, average wait by party size, and 85th percentile of waits by party size, were collected for each top revenue-performing scenario. While total revenue is the primary performance measure used to characterize and rank all table mixes simulated for all scenarios in this experiment, the operating conditions produced by the top revenue generating table mixes must be feasible and realistic. Notable observations on each of the performance measures associated with the top total revenue scenario under both methods of inventory allocation are provided below; the eight performance measures for all scenarios can be found in Appendix D.

Number of Customers Served

In 67% of the scenarios, the difference in the number of customers served under both SEATS and SPACE is marginal and ranges from 0 to 4 customers. This result is mostly expected, since the number of customers served logically follows the amount of revenue generated, and revenue does not differ either practically or statistically for over three quarters of the scenario pairs. All of the scenarios exceeding a difference of 4 customers served used tables that were far from proportional/smaller. In each of these instances, a generally sizeable amount of additional seats was used under SPACE to accommodate these additional customers, although difference in the number of tables used was not substantial.

Number of Customers Lost

The number of customers lost under SEATS and SPACE differs by over 5 customers in five of the six scenario pairs which use far from proportional tables. In all of these cases, SPACE turns away fewer customers, even though the total number of tables used by both allocation methods is similar. The most interesting observations related to lost customers are Scenario Pairs 9&27 through 12&30; in these cases, the number of tables used under SPACE is greater than the tables used under SEATS by only 1 or 2, whereas between 12 and 37 additional customers are lost under SEATS.

RevPASH

RevPASH is higher for SEATS scenarios in which the number of seats used is lower than the seats used in the corresponding SPACE scenarios (Scenario Pairs 1&19, 6&24, and 7&25 through 12&30), regardless of the revenue benefit seen from using the space method. This is expected, as the fewer number of seats used to generate roughly the same amount of revenue would each have to contribute more money to the total. Additionally, the instances in which RevPASH under SPACE method is higher than RevPASH for SEATS (Scenario Pairs 14&32 and 16&34 through 18&36) are expected since SPACE revenue is slightly higher under these scenarios, while the number of seats used is the same.

RevPAST

The RevPAST performance measure is calculated in two ways; one way assesses how the total 1422.925 square feet of dining room space available is used to generate revenue over two nights of a 7-hour dinner service. The other method follows the how RevPASH is measured in that the total square feet of dining room space actually used serves as the basis of the calculation. In regards to the first calculation, overall RevPAST does not differ between SEATS and SPACE by more than once cent for Scenario Pairs 1&19 through 8&26 and Scenario Pairs 13&31 through 18&36 because the revenues generated for these scenario pairs do not significantly differ between the two methods of inventory allocation. As expected, RevPAST is higher under SPACE for the scenario pairs that exhibited a revenue difference between SEATS and SPACE (Scenario Pairs 9&27 through 12&30). Looking at RevPAST from the standpoint that includes the space actually used also yields expected results. When the amount of space used differs considerably for paired scenarios, RevPAST is higher for the scenario using less space, whether or not its revenue is significantly lower.

Table Occupancy

In general, the table occupancy performance measure does not yield unexpected results. For the scenario pairs using tables of standard or larger proportion, occupancy rates are higher for the allocation method that uses fewer tables. For the scenarios using smaller tables, peak table occupancy is generally higher under SPACE, regardless of the number of tables used, because a significantly greater number of seats are used in these scenarios, allowing more customers to be processed and fewer customers to be turned away. While all table occupancies are close to 90 percent or higher for all scenarios during the peak operating hour, total occupancy for either method of allocation rarely surpasses 95 percent. This indicates that the test restaurant may be able to process more demand; however, a greater number of reneges would also result which could lead to potentially negative consequences.

Seat Occupancy

Seat occupancies are generally higher under SEATS. This is an expected result, as SEATS scenarios often use fewer seats to process basically the same number of customers. This finding is most pronounced when far/smaller tables are used, even though considerably fewer customers are processed under SEATS; in these scenario pairs the SPACE method uses between 8 and 44 additional seats.

Average Wait by Party Size

The average wait times by party size are quite similar under the two inventory allocation methods for most scenarios. The average wait time is consistently lower under SPACE for Scenario Pairs 8& 26 through 12&30 because the number of tables in use is greater under SPACE. Wait times are lower under SEATS in Scenario Pairs 14&32 and 17&34 for the same reason, although on a smaller scale. Neither method produced unrealistic or infeasible average wait times in any operating condition.

85th Percentile of Wait by Party Size

The results for the 85th percentile of wait times by party size follow the exact same trend as the findings associated with the average wait times. As expected, when more tables are available, fewer parties experience a longer wait. Due to the seating rules used and the priority given to matching party sizes with the appropriate table size, large parties rarely wait for more than a few minutes under any operating conditions.

Summary

The results of performing the simulation study proposed in the Methodology section were detailed in this chapter. Based on these findings, revenue and capacity are not significantly impacted when restaurant capacity is allocated based on space instead of seats and tables are of standard proportion or larger. However, when tables are smaller than standard, the SPACE method outperforms the SEATS method. The following chapter specifically answers the three research questions at the center of this research and translates the insights gained from the simulation experiment into both practical and academic contributions.

CHAPTER 5: DISCUSSION

Based on the analyses presented in Chapter 4, the questions serving as the premise of this research are answered. The insights gathered from these answers are then translated into a useful research contribution by augmenting two table mix models developed by Kimes and Thompson (2005) to account for space. Both of these models are modified in two ways, and the recommended table mixes are compared for all eighteen operating scenarios. This chapter concludes with a discussion of which modified table mix model ultimately produces the most lucrative table mix.

Research Questions Answered

To what extent is revenue impacted if capacity is allocated based on space instead of inventory units?

When the tables used in a restaurant are of standard size or larger, revenue is not significantly impacted when capacity is allocated based on a space-as-inventory rule instead of a seats-as-inventory rule. These findings are not entirely unexpected; space was accounted for as an after-the-fact constraint in the SEATS method. When the number of seats used in the top-performing table mix under SPACE was close to the current number of seats used in the restaurant, using the SPACE method with a before-the-fact constraint had no significant benefit.

When the tables used are smaller than standard size, the results are not as straightforward. In these instances, when demand is heightened through either a strict increase in the number of arriving parties or an increase in the amount of larger parties introduced into the operating system, the SPACE method produces a table mix that generates a statistically higher amount of revenue than the table mix garnered from the

SEATS method. Although the number of tables used does not differ dramatically between SEATS and SPACE in these cases, the number of seats put into operation under SPACE is considerably higher, thus allowing more customers to be served and fewer customers to be turned away. However, when the number of customers introduced into the system is not increased to a very high level, this benefit of employing additional seats is lost, as there was no statistically significant difference in revenue between SEATS and SPACE.

In general, it appears that the SPACE method outperforms SEATS when the top revenue table mixes between the two differ, with this revenue benefit most apparent for the far/small table space proportion scenarios. However, for all but four of these scenarios, because there is no statistically significant revenue difference between SEATS and SPACE, the apparent superiority of the SPACE method may disappear when the scenarios are re-simulated using different random number streams or an exorbitant number of replications. Rerunning the far/small scenarios with a ten-fold increase in the number of replications and new seeds for the random number streams confirmed this.

How is existing capacity changed when supply is measured by space instead of units?

Comparing the top-performing table mixes under SEATS and SPACE to the existing table mix can only be done for the first scenario pair since it reflects the current operating conditions of the test site. Recall that the baseline capacity for the restaurant is comprised of (in the format of 2-tops/4-tops/6-tops/8-tops) 10/19/2/1, which totals 116 seats at 32 tables that occupy 1384.5 square feet of space. When supply is allocated based on units-as-inventory (SEATS), the top-performing table mix is 19/9/0/5, with a total of 114 seats at 33 tables that take up 1397.3 square feet. In comparison, when supply is allocated based on a space-as-inventory rule (SPACE), the top table mix is 14/15/0/4, with 120 seats at 33 tables using 1421.3 square feet.

Both the SEATS and SPACE recommend table mixes that are quite different from the current one, and both generate a statistically significant amount of additional revenue ($506 under SEATS and $546 under SPACE). However, there is no significant revenue difference between the two methods, which indicates that there is not just one table mix that maximizes revenue of the restaurant.

Examining the capacity differences between the two methods for the other scenarios reveals that the table mixes generated under SEATS and SPACE are often quite different, even if the differences in table, seat, and space capacity are minimal. This observation supports the research of Kimes and Thompson (2004 and 2005) that operating with the appropriate mix of tables is important. However, it suggests that there is not necessarily a single optimal table mix for an operation, but instead a selection of different table mix options that produce statistically equal revenue; the practical implications of this conclusion are discussed in the following chapter.

Can revenue actually increase if capacity is decreased?

Comparing the revenue and capacity measures of each scenario pair reveals that operating with more seats, more tables, or more dining room space does not guarantee higher revenue. While Scenario Pairs 9&27 through 12&30 indicates a correlation between additional capacity and higher revenue, the absence of a significant revenue difference in the other fourteen scenarios pairs do not support this. However, for the same reason, revenue does not categorically increase with a decline in capacity either.

An interesting observation related to this research question is seen in the far/small table space proportion scenarios. In all of these cases, the amount of dining room space used varies greatly between SEATS and SPACE even though the number of tables does not differ notably for any of the scenarios, including the significant Scenario Pairs 9&27 through 12&30. This finding indicates that although the tables in a restaurant are the actual capacity units that process parties of customers, the number of seats and the amount of space used are the critical factors in determining the capacity of a restaurant in terms of the number and mix of tables that should be offered.

Research Insight – Modified Table Mix Models

The insights gained from answering these research questions confirm that when inventory is perishable, operating with the mix of inventory that not only matches demand but also appropriately uses available space positively impacts revenue. This finding is translated into a useful academic and practical contribution by building on the research conducted by Kimes and Thompson (2005). The remainder of this chapter describes how published table mix models were modified to account for space and which models yielded the best results in differing situations.

Existing Table Mix Model: NaïveIP-A

Kimes and Thompson (2005) tested a number of heuristics designed to make determining the optimal table mix of a restaurant accessible for operators to use and implement. While these heuristics ranged in complexity, the simplest model, NaïveIP-A, produced robust results, with revenues within 1% of maximum. This NaïveIP-A model, reproduced below, recommends a table mix that minimizes the deviation between the number of seats that ideally matches demand and the actual number of seats put into operation.

NaïveIP-A Model

Variables:

s_i^- = shortage of seats between the actual and ideal number allocated to each table size, where i = 2, 4, 6, or 8

s_i^+ = surplus of seats between the actual and ideal number allocated to each table size, where i = 2, 4, 6, or 8

x_i = number of tables with i seats, where i = 2, 4, 6, or 8

Parameters:

Seats = total number of seats available for use

NDBIdealSeats$_i$ = ideal number of seats for each table size i, determined by estimating the proportion of Total Demand from customers entering the restaurant system for i under seating rules in which each party is seated at the smallest table size that can accommodate the party. The calculation for NDBIdealSeats$_i$, where j = 2, 4, 6, or 8, is:

$$\text{Seats*} \frac{i * \% \text{ of Total Demand to be seated at } i}{\sum_j \left(i * \% \text{ of Total Demand to be seated at } i\right)}$$

Minimize: $$\sum_i (s_i^- + s_i^+) \tag{5}$$

Subject to: $$ix_i + s_i^- - s_i^+ = \text{NDBIdealSeats}_i \quad \forall\, i \tag{6}$$

$$\sum_i ix_i \le \text{Seats} \tag{7}$$

$$x_i \ge 0, \text{integer } \forall\, i \tag{8}$$

Several modifications to this Naïve model that included duration and value information were tested, but none of these more complex models resulted in table mixes that produced significantly higher revenue. However, the authors suggested that accounting for missing factors such as table assignment rules could enhance the model. One factor not tested was space and how incorporating the available dining room space and the space required by each different table size impact the usefulness and results of the model. In fact, after running the NaïveIP-A model for every combination of the demand level-demand mix-table space proportion factors, the importance of including space was underscored as none of the recommended table mixes fit in the allowable dining room space for 12 of the 18 operating scenarios.

Modified NaïveIP-A Table Mix Models

To determine the best manner in which to incorporate space into the model, the NaïveIP-A heuristic was modified and tested in two ways. The NaïveIP-A(1) model has the same objective function and constraints, but includes an added constraint that implicitly ensures that the sum of the space used by each recommended table fits into the space available. The NaïveIP-A(2) model is similar in structure to the original model, but explicitly considers space in the objective function instead of in a constraint. This model variation uses the square footage of the planning square for each table size, which includes the space taken up by the table top, accompanying chairs, and necessary area for movement, as the decision variables. As such, the objective of this model variation is to minimize the deviation between the number of square feet that ideally matches demand and the actual number of square feet put into operation. Accordingly, the NaïveIP-A(2) model does not have a constraint regarding the number of seats that can be used. Both full models are given below:

NaïveIP-A(1) Model

Additional Parameters:

Space = total amount of dining room square footage available for use

p_i = square footage of the planning square required to fit each table size *i*, where *i* = 2, 4, 6, or 8

Minimize: (5)

Subject to: (6), (7), (8)

$$\sum_i x_i p_i \leq \text{Space} \quad (9)$$

NaïveIP-A(2) Model

Variables:

ss_i^- = shortage of space between the actual and ideal amount allocated to each table size, where *i* = 2, 4, 6, or 8

ss_i^+ = surplus of space between the actual and ideal amount allocated to each table size, where *i* = 2, 4, 6, or 8

Additional Parameter:

NDBIdealSpace_i = ideal amount of space for each table size *i*, determined by estimating the proportion of Total Demand from customers entering the restaurant system for *i* under seating rules in which each party is seated at the smallest table size that can accommodate the party. The calculation for NDBIdealSpace_i, where *j* = 2, 4, 6, or 8, is:

$$\text{Space} * \frac{p_i * \%\text{ of Total Demand to be seated at } i}{\sum_j \left(p_i * \%\text{ of Total Demand to be seated at } i\right)}$$

Minimize: $$\sum_i (ss_i^- + ss_i^+) \quad (10)$$

Subject to: (8), (9)

$$ix_i + ss_i^- - ss_i^+ = \text{NDBIdealSpace}_i \quad \forall i \quad (11)$$

The results of running the NaïveIP-A(1) and NaïveIP-A(2) models for the three different demand mixes and three different table space proportions tested are provided in Table 5.1 below. Because these models do not account for demand level, the table mixes are the same for the two levels of demand under each of the table space proportions, but the revenue given by the simulation differs.

When the recommended table mixes vary between the two models (16 scenarios), the NaïveIP-A(2) model outperforms the NaïveIP-A(1) model in 15 instances and produces 4.3% higher revenues on average. Additionally, under the existing operating conditions of the test site (Scenario 1), the revenue associated with the table mix identified by NaïveIP-A(2) model is $154 higher than the revenue generated by the restaurant's current table mix, while revenue produced by the table mix recommended by the NaïveIP-A(1) model is $612 lower.

However, concluding that restaurateurs should use the NaïveIP-A(2) model to explicitly consider space when determining the table mix of a restaurant is not defendable. The table mixes recommended by the model are markedly different from the top-performing table mixes as determined through complete enumeration. More importantly, the accompanying revenues are significantly below the maximum revenues yielded by enumeration, with the NaïveIP-A(2) revenue averaging only 92.6% of maximum. These revenue differences are included in Table 5.1 below, and the differences in the recommended table mixes can be found in Appendix E. The suboptimal revenues produced by the modified NaiveIP-A models indicate that further examination and modification of existing heuristics is warranted; the following section explores if including duration in the heuristics produces table mixes and associated revenues that more closely match the results of enumeration and simulation.

Table 5.1: Results of the NaïveIP-A(1) and NaïveIP-A(2) Table Mix Models

	NaïveIP-A(1)								NaïveIP-A(2)								
Scenario	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	Maximum Achievable Revenue, determined by Complete Enumeration
1	26	10	2	0	104	38	1413.76	$13,502	23	10	2	1	106	36	1400.26	$14,268	**$14,729**
2	31	10	0	0	102	41	1414.00	$12,278	28	10	1	0	102	39	1398.13	$12,752	**$13,812**
3	23	12	2	0	106	37	1406.76	$14,096	22	11	2	1	108	36	1412.51	$14,869	**$15,493**
4	26	10	2	0	104	38	1413.76	$15,479	23	10	2	1	106	36	1400.26	$16,190	**$17,040**
5	31	10	0	0	102	41	1414.00	$14,237	28	10	1	0	102	39	1398.13	$14,525	**$16,068**
6	23	12	2	0	106	37	1406.76	$16,180	22	11	2	1	108	36	1412.51	$16,753	**$17,842**
7	26	11	2	1	116	40	1357.00	$16,493	27	12	2	1	122	42	1420.00	$16,447	**$17,376**
8	31	11	1	0	112	43	1373.00	$14,704	31	11	1	0	112	43	1373.00	$14,704	**$16,222**
9	23	12	2	1	114	38	1296.00	$16,843	25	13	2	1	122	41	1390.00	$16,939	**$18,276**
10	26	11	2	1	116	40	1357.00	$18,516	27	12	2	1	122	42	1420.00	$18,632	**$20,154**
11	31	11	1	0	112	43	1373.00	$16,635	31	11	1	0	112	43	1373.00	$16,635	**$19,024**
12	23	12	2	1	114	38	1296.00	$19,069	25	13	2	1	122	41	1390.00	$19,214	**$21,232**
13	26	11	0	0	96	37	1396.00	$12,041	22	10	2	0	96	34	1394.00	$13,375	**$14,431**
14	30	9	0	0	96	39	1404.00	$11,929	26	9	1	0	94	36	1371.00	$12,466	**$13,708**
15	22	12	1	0	98	35	1419.00	$12,535	20	11	2	0	96	33	1390.00	$13,951	**$15,131**
16	26	11	0	0	96	37	1396.00	$14,120	22	10	2	0	96	34	1394.00	$15,207	**$16,340**
17	30	9	0	0	96	39	1404.00	$13,919	26	9	1	0	94	36	1371.00	$14,283	**$15,709**
18	22	12	1	0	98	35	1419.00	$13,847	20	11	2	0	96	33	1390.00	$15,957	**$16,847**

Existing Table Mix Model: NaïveIP-B

An explanation for the revenue differences observed between the NaiveIP-A model variations and the maximum revenue achieved through complete enumeration is that both NaïveIP-A variations consistently include more 2-tops and fewer 8-tops in their recommended table mixes than complete enumeration does. Kimes and Thompson (2005) addressed this effect in their NaïveIP-B model by accounting for differences in dining duration, or the time parties of varying sizes require the use of a table. The NaïveIP-B model somewhat reduced the tendency of the NaïveIP-A model to not exclude larger tables, even when the demand mix is heavily skewed towards smaller parties. While this model underperformed its simpler counterpart, it still produced table mixes that generated revenue within 1.5% of the maximum. With the exception of the first constraint, the NaïveIP-B model is the same as the NaïveIP-A model.

NaïveIP-B Model

Altered Parameter:

DBIdealSeats_i = ideal number of seats for each table size i, determined by estimating the proportion of total demand – adjusted for duration – for i under seating rules in which each party is seated at the smallest table size that can accommodate the party. The calculation for DBIdealSeats_i, where j = 2, 4, 6, or 8, is:

$$\text{Seats} * \frac{i * \sum_{z} (\text{\% of Total Demand for } i \text{ from party size } z * \text{Average duration of party size } z)}{\sum_{j,z} (i * \text{\% of Total Demand for } i \text{ from } z * \text{Average duration of party size } z)}$$

Minimize: (5)

Subject to: (7), (8)

$$ix_i + s_i^- - s_i^+ = \text{DBIdealSeats}_i \qquad \forall\, i \tag{12}$$

Modified NaïveIP-B Table Mix Models

Not all of the table mixes recommended by the existing NaïveIP-B model fit in the allowable dining room space. Two variations of the NaïveIP-B model that incorporate the available dining room space were tested.

NaïveIP-B(1) Model

Minimize: (5)

Subject to: (8), (9), (12)

$$ix_i + s_i^- - s_i^+ = \text{DBIdealSeats}_i \qquad \forall\, i \qquad (13)$$

NaïveIP-B(2) Model

Altered Parameter:

DBIdealSpace$_i$ = ideal amount of space for each table size i, determined by estimating the proportion of total demand – adjusted for duration – for i under seating rules in which each party is seated at the smallest table size that can accommodate the party. The calculation for DBIdealSpace$_{i,}$ where j = 2, 4, 6, or 8, is:

$$\text{Space} * \frac{p_i * \sum_{z} (\text{\% of Total Demand for } i \text{ from party size } z * \text{Average duration of party size } z)}{\sum_{j,z} (p_i * \text{\% of Total Demand for } i \text{ from } z * \text{Average duration of party size } z)}$$

Minimize: (10)

Subject to: (8), (9)

$$ix_i + ss_i^- - ss_i^+ = \text{DBIdealSpace}_i \qquad \forall\, i \qquad (14)$$

Running the NaïveIP-B(1) and NaïveIP-B(2) models for the three different demand mixes and three different table space proportions had the desired result of including fewer smaller tables and a greater number of larger tables; Table 5.2 provides these results. When the recommended table mixes varies (16 scenarios), the NaïveIP-B(2) model consistently produces higher revenues than the NaïveIP-B(1) model, with an average revenue benefit of 5.2%. However, the revenues generated from the table mixes produced by the NaïveIP-B(2) model are below the revenues yielded by enumeration, with the NaïveIP-B(2) revenue averaging 96.0% of maximum. The differences between the NaïveIP-B(2) model and the results from complete enumeration are included in Appendix E. Because a considerable amount of revenue is unclaimed if this model is used as it currently stands, additional model modifications must be tested to determine a more compelling and useful heuristic. The following section explores if including practical seating rules in the heuristics produces table mixes and associated revenues that more closely match the results of enumeration and simulation.

Table 5.2: Results of the NaïveIP-B(1) and NaïveIP-B(2) Table Mix Models

	NaïveIP-B(1)								NaïveIP-B(2)								
Scenario	**2-tops**	**4-tops**	**6-tops**	**8-tops**	**Seats**	**Tables**	**Total SF**	**Revenue**	**2-tops**	**4-tops**	**6-tops**	**8-tops**	**Seats**	**Tables**	**Total SF**	**Revenue**	**Maximum Achievable Revenue, determined by Complete Enumeration**
1	24	11	2	0	104	37	1394.51	$13,512	22	11	2	1	108	36	1412.51	$14,214	**$14,729**
2	29	11	0	0	102	40	1394.75	$12,173	26	10	2	0	104	38	1413.76	$13,126	**$13,812**
3	21	12	3	0	108	36	1422.39	$14,253	20	12	2	1	108	35	1393.26	$14,962	**$15,493**
4	24	11	2	0	104	37	1394.51	$15,525	22	11	2	1	108	36	1412.51	$16,398	**$17,040**
5	29	11	0	0	102	40	1394.75	$14,262	26	10	2	0	104	38	1413.76	$15,468	**$16,068**
6	21	12	3	0	108	36	1422.39	$16,815	20	12	2	1	108	35	1393.26	$16,853	**$17,842**
7	23	11	3	1	116	38	1324.00	$16,820	25	12	3	1	124	41	1418.00	$16,832	**$17,376**
8	29	11	2	0	114	42	1371.00	$15,195	29	11	2	0	114	42	1371.00	$15,195	**$16,222**
9	21	12	3	1	116	37	1371.00	$17,233	23	14	3	1	128	41	1420.00	$17,620	**$18,276**
10	23	11	3	1	116	38	1324.00	$18,991	25	12	3	1	124	41	1418.00	$19,201	**$20,154**
11	29	11	2	0	114	42	1371.00	$17,997	29	11	2	0	114	42	1371.00	$17,997	**$19,024**
12	21	12	3	1	116	37	1371.00	$19,786	23	14	3	1	128	41	1420.00	$20,196	**$21,232**
13	23	11	1	0	96	35	1393.00	$12,113	20	9	2	1	96	32	1388.00	$14,027	**$14,431**
14	28	10	0	0	96	38	1400.00	$12,082	24	9	2	0	96	35	1398.00	$13,082	**$13,708**
15	21	11	2	0	98	34	1420.00	$14,054	18	10	2	1	96	31	1384.00	$14,662	**$15,131**
16	23	11	1	0	96	35	1393.00	$13,276	20	9	2	1	96	32	1388.00	$15,737	**$16,340**
17	28	10	0	0	96	38	1400.00	$14,140	24	9	2	0	96	35	1398.00	$15,291	**$15,709**
18	21	11	2	0	98	34	1420.00	$15,961	18	10	2	1	96	31	1384.00	$16,397	**$16,847**

Further Model Modification – Seating Assignment Rule

The extenuating reason that the results from the NaïveIP models vary so significantly from the complete enumeration results is due to seating assignment rules. All of the NaïveIP models operate under the assumption of strict table assignment, meaning that party sizes are only seated at their closest matching table size. Specifically, these strict assignment rules dictate that parties of 1-2 sit only at 2-tops, parties of 3-4 sit only at 4-tops, parties of 5-6 only sit at 6-tops, and parties of 7-8 only sit at 8-tops.

While seat assignment rules are not the focus of this research, to further gauge the usefulness of adding a space factor into a functional table mix heuristic, seating rules had to be addressed. In fact, Kimes and Thompson (2005) suggested that different seating rules may have an impact on their NaïveIP models. They accounted for the possibility that parties can be seated at any table size larger than the party in their calculation of the ideal number of seats for each table size. For instance, parties of 2 can be accommodated by 2-tops, 4-tops, 6-tops, or 8-tops, but parties of 6 can only be seated at either 6-tops or 8-tops.

Realistically, restaurant operators give preference to matching party and table size and rarely use certain table sizes to fit certain party sizes (for instance, a party of 1 would not be seated at an 8-top). These proclivities were reflected in the simulation model and consequently the top-performing table mixes. This more feasible type of seating assignment was translated into the NaïveIP models through the use of decreasing constants in calculating the ideal number of seats (for NaïveIP-1 variations) and the ideal amount of space to be allocated to each table size (for NaïveIP-2 variations). Table 5.3 gives the specific seating rules followed in the simulations, as well as the constants assigned to each party size at each table type used in the NaïveIP models.

Table 5.3: Party Size Constants to Account for Realistic Seating Rules

	Table Size			
Party Size	**2-top**	**4-top**	**6-top**	**8-top**
1	1	0.5	0	0
2	1	0.5	0.25	0
3	0	1	0.5	0
4	0	1	0.5	0.25
5	0	0	1	0.5
6	0	0	1	0.5
7	0	0	0	1
8	0	0	0	1

These constants were integrated into the NaïveIP model variations through the parameter that accounts for the ideal number of seats or the ideal amount of space allocated to each table size. The calculations of these updated parameters are:

$\text{NDBIdealSeatsRULE2}_i$ = ideal number of seats for each table size i under the revised seating rules, where i = 2, 4, 6, or 8; party size z = 1, 2, . . ., 8; j = 2, 4, 6, or 8; and C_{iz} = constants provided in Table 6.3:

$$\text{Seats} * \frac{i * \sum_{z} (C_{iz} * \%\ \text{of Total Demand from } z)}{\sum_{j} \left(i * \sum_{z} (C_{iz} * \%\ \text{of Total Demand from } z) \right)}$$

$\text{NDBIdealSpaceRULE2}_i$ = ideal amount of space for each table size i under the revised seating rules, where i = 2, 4, 6, or 8; party size z = 1, 2, . . ., 8; j = 2, 4, 6, or 8; and C_{iz} = constants provided in Table 6.3:

$$\text{Space} * \frac{p_i * \sum_{z} C_{iz} * \%\ \text{of Total Demand from } z)}{\sum_{j} \left(p_i * (\sum_{z} C_{iz} * \%\ \text{of Total Demand from } z) \right)}$$

DBIdealSeatsRULE2$_i$ = ideal number of seats for each table size i – adjusted for duration – under the revised seating rules, where i = 2, 4, 6, or 8; party size z = 1, 2, . . ., 8; j = 2, 4, 6, or 8; and C_{iz} = constants provided in Table 6.3:

$$\text{Seats}^* \frac{i * \sum_{z} (C_{iz} * \text{\% of Total Demand from } z * \text{Avg. duration of party size } z)}{\sum_{j} \left(i * \sum_{z} (C_{iz} * \text{\% of Total Demand from } z * \text{Avg. duration of party size } z) \right)}$$

DBIdealSpaceRULE2$_i$ = ideal amount of space for each table size i – adjusted for duration – under the revised seating rules, where i = 2, 4, 6, or 8; party size z = 1, 2, . . ., 8; j = 2, 4, 6, or 8; and C_{iz} = constants provided in Table 6.3:

$$\text{Space}^* \frac{p_i * \sum_{z} (C_{iz} * \text{\% of Total Demand from } z * \text{Avg. duration of party size } z)}{\sum_{j} \left(p_i * \sum_{z} (C_{iz} * \text{\% of Total Demand from } z * \text{Avg. duration of party size } z) \right)}$$

Accounting for the revised seating rules did not change the structure of the four models; one part of a constraint in each was simply replaced with the appropriate new Ideal Seats or Space parameter. The model names and constraint numbers are amended to reflect the use of updated seating rules; the altered constraints are:

- **NaïveIP-A(1.2)** – constraint (6) is replaced with:

$$ix_i + s_i^- - s_i^+ = \text{NDBIdealSeatsRULE2}_i \qquad \forall\, i \qquad (6.2)$$

- **NaïveIP-A(2.2)** – constraint (11) is replaced with:

$$ix_i + s_i^- - s_i^+ = \text{NDBIdealSpaceRULE2}_i \qquad \forall\, i \qquad (11.2)$$

- **NaïveIP-B(1.2)** – constraint (13) is replaced with:

$$ix_i + s_i^- - s_i^+ = \text{DBIdealSeatsRULE2}_i \qquad \forall\, i \qquad (13.2)$$

- **NaïveIP-B(2.2)** – constraint (14) is replaced with:

$$ix_i + s_i^- - s_i^+ = \text{DBIdealSpaceRULE2}_i \qquad \forall\, i \qquad (14.2)$$

All four modified NaïveIP models were rerun with the revised constraint; the results are provided below in Tables 5.4 and 5.5. For the NaïveIP-A.2 variations, the revenues of the top-performing table mix for each operating scenario generated by either model averaged within 3.0% of the maximum revenues, and ranged from 88.7% to 98.9% of the maximums. For four of the eighteen scenarios, the recommended table mix was identical for both NaïveIP-A(1.2) and NaïveIP-A(2.2). In eight of the scenarios, the NaïveIP-A(2.2) outperformed the NaïveIP-A(1.2) model by an average of 3.8%, while the NaïveIP-A(1.2) model recommended table mixes that produced an average of 2.4% greater revenues in the remaining six scenarios. The differences between the NaïveIP-A(1.2) and the NaïveIP-A(2.2) models and the results from complete enumeration are included in Appendix F.

Results from the NaïveIP-B.2 model variations were somewhat similar; the top-performing table mix for each operating scenario generated by either model averaged within 4.2% of the maximum revenues, and ranged between 88.5% and 98.5% of the maximums. The recommended table mix was identical under both model variations for two of the eighteen scenarios. In eleven scenarios, the NaïveIP-B(2.2) model outperformed the NaïveIP-B(1.2) by an average of 2.9%, while the NaïveIP-B(1.2) model recommended table mixes that produced an average of 2.5% greater revenues in five scenarios.

Table 5.4: Results of the NaïveIP-A(1.2) and NaïveIP-A(2.2) Table Mix Models with Revised Seating Rules

	NaïveIP-A(1.2)								NaïveIP-A(2.2)								Maximum Achievable Revenue, determined by Complete Enumeration
Scenario	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	
1	12	11	6	1	112	30	1412.03	$14,441	12	11	6	1	112	30	1412.03	$14,441	**$14,729**
2	18	15	2	0	108	35	1380.51	$13,219	13	11	5	1	108	30	1364.90	$13,517	**$13,812**
3	11	11	6	1	110	29	1380.53	$15,262	11	11	6	1	110	29	1380.53	$15,262	**$15,493**
4	12	11	6	1	112	30	1412.03	$16,693	12	11	6	1	112	30	1412.03	$16,693	**$17,040**
5	18	15	2	0	108	35	1380.51	$15,463	13	11	5	1	108	30	1364.90	$15,696	**$16,068**
6	11	11	6	1	110	29	1380.53	$17,360	11	11	6	1	110	29	1380.53	$17,360	**$17,842**
7	12	11	6	1	112	30	1163.00	$16,693	14	13	7	1	130	35	1349.00	$17,020	**$17,376**
8	14	11	6	1	116	32	1225.00	$15,907	16	13	7	1	134	37	1411.00	$16,041	**$16,222**
9	11	11	6	1	110	29	1132.00	$17,360	13	13	7	2	136	35	1397.00	$18,055	**$18,276**
10	12	11	6	1	112	30	1163.00	$18,201	14	13	7	1	130	35	1349.00	$19,578	**$20,154**
11	14	11	6	1	116	32	1225.00	$17,752	16	13	7	1	134	37	1411.00	$18,576	**$19,024**
12	11	11	6	1	110	29	1132.00	$18,630	13	13	7	2	136	35	1397.00	$20,645	**$21,232**
13	12	11	5	0	98	28	1411.00	$13,871	10	9	5	1	94	25	1349.00	$13,764	**$14,431**
14	14	11	3	1	98	29	1407.00	$13,322	12	9	5	1	98	27	1409.00	$13,291	**$13,708**
15	11	11	4	1	98	27	1404.00	$14,872	9	9	5	1	92	24	1319.00	$14,460	**$15,131**
16	12	11	5	0	98	28	1411.00	$15,961	10	9	5	1	94	25	1349.00	$15,395	**$16,340**
17	14	11	3	1	98	29	1407.00	$15,411	12	9	5	1	98	27	1409.00	$15,109	**$15,709**
18	11	11	4	1	98	27	1381.00	$16,628	9	9	5	1	92	24	1319.00	$15,739	**$16,847**

Table 5.5: Results of the NaïveIP-B(1.2) and NaïveIP-B(2.2) Table Mix Models with Revised Seating Rules

	NaïveIP-B(1.2)								NaïveIP-B(2.2)								
Scenario	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	Maximum Achievable Revenue, determined by Complete Enumeration
1	11	11	6	1	110	29	1380.53	$14,418	11	10	6	2	114	29	1417.78	$14,486	**$14,729**
2	13	11	5	1	108	30	1364.90	$13,517	12	11	6	1	112	30	1412.03	$13,518	**$13,812**
3	10	10	6	2	112	28	1386.28	$15,075	10	10	6	2	112	28	1386.28	$15,075	**$15,493**
4	11	11	6	1	110	29	1380.53	$16,378	11	10	6	2	114	29	1417.78	$16,533	**$17,040**
5	13	11	5	1	108	30	1364.90	$15,696	12	11	6	1	112	30	1412.03	$15,643	**$16,068**
6	10	10	6	2	112	28	1386.28	$17,220	10	10	6	2	112	28	1386.28	$17,220	**$17,842**
7	11	11	6	1	110	29	1132.00	$16,378	13	13	7	2	136	35	1397.00	$17,023	**$17,376**
8	13	11	6	1	114	31	1194.00	$15,691	15	13	7	1	132	36	1380.00	$15,953	**$16,222**
9	10	11	6	2	116	29	1180.00	$17,392	12	13	7	2	134	34	1366.00	$18,003	**$18,276**
10	11	11	6	1	110	29	1132.00	$17,882	13	13	7	2	136	35	1397.00	$19,546	**$20,154**
11	13	11	6	1	114	31	1194.00	$17,559	15	13	7	1	132	36	1380.00	$18,493	**$19,024**
12	10	11	6	2	116	29	1180.00	$18,941	12	13	7	2	134	34	1366.00	$20,576	**$21,232**
13	11	10	6	0	98	27	1412.00	$13,814	9	9	5	1	92	24	1319.00	$13,748	**$14,431**
14	12	11	5	0	98	28	1411.00	$13,012	11	9	5	1	96	26	1379.00	$13,122	**$13,708**
15	10	10	5	1	98	26	1405.00	$14,592	8	9	5	2	98	24	1399.00	$14,685	**$15,131**
16	11	10	6	0	98	27	1412.00	$15,607	9	9	5	1	92	24	1319.00	$14,460	**$16,340**
17	12	11	5	0	98	28	1411.00	$14,888	11	9	5	1	96	26	1379.00	$14,803	**$15,709**
18	10	10	5	1	98	26	1405.00	$16,436	8	9	5	2	98	24	1399.00	$15,766	**$16,847**

Recommended Table Mix Heuristics

Of the modified NaïveIP table mix models that account for revised seating rules, the NaïveIP-A.2 variations outperformed their NaïveIP-B.2 counterparts in the majority of operating scenarios. While the NaïveIP-B(2.2) model produced the top-performing table mix in four instances, the revenue benefit over a NaïveIP-A.2 model was not statistically significant. It is therefore recommended that a modified NaïveIP-A heuristic be used to determine a table mix that best uses a restaurant's resources to accommodate its demand. Table 5.6 contains the revenues associated with each model variation for all scenarios, as well as how the heuristics compare to the maximum revenues from complete enumeration.

Table 5.6: Revenue Comparison of All NaïveIP.2 Model Variations

Scenario	NaïveIP-A(1.2)	NaïveIP-A(2.2)	NaïveIP-B(1.2)	NaïveIP-B(2.2)	Top Revenue-Producing Model	Revenue Difference between Top and Recommended Models*	Recommended Model Revenue as % of Maximum
1	$14,441	$14,441	$14,418	$14,486	B(2.2)	$44	98.0%
2	$13,219	$13,517	$13,517	$13,518	B(2.2)	$1	97.9%
3	$15,262	$15,262	$15,075	$15,075	A(1.2) and A(2.2)	$0	98.5%
4	$16,693	$16,693	$16,378	$16,533	A(1.2) and A(2.2)	$0	98.0%
5	$15,463	$15,696	$15,696	$15,643	A(2.2) and B(1.2)	$0	97.7%
6	$17,360	$17,360	$17,220	$17,220	A(1.2) and A(2.2)	$0	97.3%
7	$16,693	$17,020	$16,378	$17,023	B(2.2)	$3	98.0%
8	$15,907	$16,041	$15,691	$15,953	A(2.2)	$0	98.9%
9	$17,360	$18,055	$17,392	$18,003	A(2.2)	$0	98.8%
10	$18,201	$19,578	$17,882	$19,546	A(2.2)	$0	97.1%
11	$17,752	$18,576	$17,559	$18,493	A(2.2)	$0	97.6%
12	$18,630	$20,645	$18,941	$20,576	A(2.2)	$0	97.2%
13	$13,871	$13,764	$13,814	$13,748	A(1.2)	$0	96.1%
14	$13,322	$13,291	$13,012	$13,122	A(1.2)	$0	97.2%
15	$14,872	$14,460	$14,592	$14,685	A(1.2)	$0	98.3%
16	$15,961	$15,395	$15,607	$14,460	A(1.2)	$0	97.7%
17	$15,411	$15,109	$14,888	$14,803	A(1.2)	$0	98.1%
18	$16,628	$15,739	$16,436	$15,766	A(1.2)	$0	98.7%

**Recommended models are A(2.2) for Scenarios 1-12 and A(1.2) for Scenarios 13-18*

The size of tables used in an operation, tested in this experiment as the table space proportion factor, appeared to have an impact on which NaïveIP-A.2 variation recommended the best table mix. When tables were either standard-size or smaller, the NaïveIP-A(2.2) model produced table mixes that generated revenues within 2.1% of the maximum, but the NaïveIP-A(2.1) model performed within 4.6% of the maximum. Further, when the table mix generated by the two heuristics was different (8 of the 12 scenarios), the revenue benefit of using the NaïveIP-A(2.2) model ranged from $134 to $2015; this revenue difference was statistically significant for 7 of the 8 scenarios. This finding indicates that in many instances, the NaïveIP-A(2.2) model produces table mixes that generate statistically higher revenues than any other of the NaïveIP models tested, furthermore, in the cases in which it does not generate a statistically significant revenue benefit, it does not recommend a table mix associated with a revenue disadvantage. Therefore, if using complete enumeration and simulation is inaccessible, the NaïveIP-A(2.2) model is the space-inclusive table mix heuristic recommended to determine the top-performing table mix for a restaurant using tables of standard size or smaller.

Conversely, when tables were close to proportional/larger than standard, the NaïveIP-A(1.2) model produced the top-performing table mixes, with revenues within 2.3% of the maximum revenues. For these scenarios, the revenues associated with the NaïveIP-A(2.2) recommended table mix models averaged 4.7% short of the maximum achievable revenues. Additionally, the revenue under the NaïveIP-A(1.2) model was greater than the corresponding NaïveIP-A(2.2) revenue for every scenario. This revenue benefit ranged from $31 to $890 and was statistically significant in 4 scenarios. Therefore, if using complete enumeration and simulation is inaccessible, the NaïveIP-A(2.1) model is the space-inclusive table mix heuristic recommended to determine the top-performing table mix for a restaurant using tables of larger than standard size.

The reason for the discrepancy between the NaïveIP-A.2 heuristics for the different table space proportions/table sizes is because given the same demand conditions, when tables are larger, fewer can fit into a given space and are thus at a premium. By allocating seats instead of space, the NaïveIP-A(1.2) model forced more seats and consequently more tables to be used than did the NaïveIP-A(2.2) model. Outlets with larger tables need the revenue-producing ability of each table more, and thus require the use of a heuristic that has seats as the decision variable to ensure that more tables are put into use. Conversely, outlets with smaller, and thus more tables, do not need to give as much consideration to the number of seats or tables when determining their table mix and instead should use the heuristic that has space as the decision variable, as it produced a more lucrative table mix in the majority of operating scenarios.

Summary

Because the published table mix heuristics do not always produce table mixes that can actually fit into the dining room space available, modifications of these existing heuristics that account for the amount of space tables require were tested. It was determined that incorporating practical seating rules in a heuristic was important since using a strict rule in which each party was only seated at the smallest table size that can accommodate it resulted in unrealistic table mixes that did not maximize revenues. The following chapter discusses the implications of these results and additional findings of this study for practitioners and academics; it also describes the limitations of this research and outlines several options for future study.

CHAPTER 6: CONCLUSIONS, IMPLICATIONS, AND FURTHER RESEARCH

Service capacity – the number of customers that can be processed by a service facility in a certain amount of time – is a function of several factors including availability of employees (is a clerk on duty to check in a customer?) and physical capacity units (is a car available to be rented out?). Each physical capacity unit, at a specific point in time, has a revenue-generating opportunity; if a request for a service cannot be accommodated by the physical capacity, then this revenue is lost forever (Kimes and Chase, 1998). As such, ensuring that the amount, type, and mix of physical capacity that is put into use is essential to maximizing revenues.

In many instances, physical capacity is comprised of a variety of inventory units; many Revenue Management models account for diverse inventory through demand categorization and supply allocation methods (Weatherford and Bodily, 1992; Talluri and van Ryzin, 2005; Kimes and Thompson, 2005). However, these RM programs operate under the assumptions that: (1) the number of inventory that can be put into use is fixed, and (2) all standard inventory units are homogeneous in terms of the amount of physical space each requires. These assumptions do not hold for all service environments, including restaurants since the number of physical capacity units (tables) put into operation is somewhat flexible, and these physical units are not homogeneous in the amount of space each occupies (2-tops require less space than 6-tops). Therefore, this study was conducted with the overall objective of understanding the role of physical space in Restaurant Revenue Management.

The specific research questions were: (1) How does revenue react when physical capacity units are redefined as space instead of inventory units?; (2) How does total capacity change when physical capacity is measured by space instead of units?; and (3) Can revenue increase if physical capacity decreases? These questions were tested by simulating and comparing restaurant operations in which physical inventory was defined and allocated as either the amount of space each table required or the number of seats each table used. Space was accounted for by both definitions; the difference in the SEATS and SPACE methods lied in *how* space was incorporated into the allocation problem –as the decision variable or as a constraint.

In the following sections, the contributions of this research to the Service Operations and Revenue Management literature and the implications of the study findings for practitioners are discussed. The limitations of this study and areas for future research are also addressed.

Research Contribution

The active role of space in capacity planning and capacity management has received limited attention in the Services Operations Management and Revenue Management literature. In particular, the impact on revenues of operating with spatially non-homogeneous physical inventory units within a fixed amount of space has not been established. Therefore, this study contributes to the existing literature in several ways.

From a broad perspective, this study is unique in that it included space as a factor in the revenue management problem whereas the majority of RM research has only considered duration and price as the critical strategic levers that can be manipulated to maximize revenue (e.g., Kimes, 1989). This study incorporated space in two different ways, and although that neither method produced statistically better results in every operating circumstance, both methods did recommend levels and mixes of physical capacity that not only fit into the available dining space of the test restaurant, but also yielded significantly higher revenues than achieved with the current physical inventory profile.

This research also addressed the fact that physical capacity units used in the delivery of a service are not always spatially homogeneous. While it has been long recognized that different capacity types hold different values for an operation in terms of the revenues they can generate (Talluri and van Ryzin, 2005), few studies have included space as an explicit differentiating factor when determining the level and mix of physical capacity to offer. In a restaurant environment, the literature regarding the use of physical capacity has assumed that each table size is proportional to its number of seats (Bertsimas and Shioda, 2003; Kimes and Thompson, 2004), even though this assumption does not always hold as different table sizes usually use different amounts of space per seat. The findings of this study underscored the importance of determining the optimal mix of physical inventory at a restaurant (Kimes and Thompson, 2003; Kimes and Thompson, 2004), but also showed that accounting for the amount of space required by non-homogeneous physical capacity units affects the level of supply to offer.

Another contribution to the existing literature pertains to the simultaneous planning and managing of the physical capacity units of a service that occurs when total available space and the spatial requirements of diverse inventory units are accounted for in the Restaurant Revenue Management problem. The studies that have addressed physical capacity have assumed that the number of inventory units put into operation had an upper limit of the number of seats already in use, even if this capacity was somewhat flexible in terms of how it was best configured and deployed (Kimes and Thompson, 2003; Thompson, 2002; Pak et al., 2003). A significant portion of this study did not assume that the number of seats in a restaurant was predetermined and instead tested how concurrently establishing the amount and mix of tables impacted revenue. The findings indicated that this assumption was actually critical to include when operations used physically large tables, but should be relaxed for restaurants using tables that are of standard proportion or smaller.

The primary contribution of this research, however, was more specific than these broad topics and involved augmenting existing table mix heuristics developed by Kimes and Thompson (2005) to include a space component. Chapter 5 detailed the process followed in adjusting and testing these modified models. The heuristic that produced the top revenue-generating table mix depended both on the physical size of tables and the table assignment rules used. Operations using essentially larger tables that allotted more space per person were better served by a model that incorporated space as a constraint, while a model using space as the decision variable was recommended for restaurants operating with essentially smaller tables that gave customers fewer square feet per person. Additionally, incorporating practical table assignment rules into these models was essential to them producing viable results. This particular finding validated the assertion made by both Kimes and Thompson (2004 and 2005) and Bertsimas and Shioda (2003) that seating rules play a crucial role in maximizing the revenues that can generated by a non-homogeneous supply base.

Implications for Practitioners

The insights brought about by this research regarding the impact of incorporating space into revenue management have practical implications for service providers, especially restaurateurs. First, neither of the two ways in which space was accounted for – as a constraint or as the decision variable – significantly outperformed the other when the tables used by a restaurant were of standard size or larger. However, when essentially smaller tables were used, accounting for space as the decision variable produced statistically significant higher revenues when the operating system was inundated with demand. The consequence of this finding is that operators have options for determining the amount and mix of physical capacity units to offer, which subsequently influences how total revenue-generating space is used at a facility. For instance, in one of non-significant scenarios (Scenario Pair 8&26), the top-revenue generating table mix under SEATS was 24/7/4/2, which put 116 seats into use at 37 tables and occupied 1366 square feet of dining room space. Alternatively, the table mix that generated the maximum revenue under SPACE was 24/11/0/4, which put 124 seats at 39 tables and occupied 1412 square feet of space. Obviously, these are two extremely different options for using the space at the restaurant; and a restaurateur can choose to either put the maximum number of tables into operation (the SPACE option) or can offer fewer tables (the SEATS option) and use surplus square footage for other strategic purposes such as a bakery or home-meal-replacement counter. In effect, operators can determine the highest and best use of their total space while still providing a number and mix of physical inventory units that maximizes revenues.

Additionally, similar insight applies to the two heuristics recommended in Chapter 5. These heuristics themselves were initially developed to translate research findings into useful models for practitioners; they were augmented by this study to provide an accessible way in which to determine a table mix that can actually fit into the dining room space available. Applying the same reasoning as above, the heuristics allow operators to have more options when determining the physical supply that captures the most revenue possible. For the same scenario discussed above, the recommended NaïveIP-A(2.2) model produced a 16/13/7/1 table mix that uses 134 at 37 tables and occupies 1411 square feet of dining room space. The NaïveIP-A(1.2) model yielded a 14/11/6/1 table mix that uses 116 seats, 32 tables, and 1225 square feet. Because there was not significant difference in the revenue generated by these two table mix options, restaurateurs are again provided alternatives for their physical supply profile. The primary implication of this insight is that restaurant owners can use theoretically-based, user-friendly models to help make determinations regarding the use of space and the physical capacity profile to offer. These important capacity decisions have traditionally been delegated to service facility designers and managerial judgments, and while not made in a vacuum, have not been completed with analytical support.

Study Limitations and Directions for Future Research

The structure and findings of this study provide a number of avenues for future research that address the limitations of this work. As occurs when using simulation, assumptions made to put boundaries on the model may not always hold; testing different assumptions for their affect on output measures such as revenue would extend and strengthen this study. Additionally, the results and insights of this work provide a foundation for future cross-disciplinary research between Service Operations Management and Environmental Psychology.

It was assumed in this study that the current level of demand for peak hours at the test site sufficiently taxed the system. While management reported and data confirmed that the system was operating at capacity under the existing conditions, simultaneously altering the demand and supply profiles resulted in several instances, specifically those associated with using smaller tables, in which the system was not truly stressed. Having an excess demand/constrained capacity situation is critical to the usefulness of Revenue and Capacity Management practices. Therefore, the simulation model should be tested at higher demand levels to ensure that these conditions are maintained and to determine if there are any differences in the two inventory allocation methods when the operating system is extremely stressed. Additionally, as previously stated, using different random number seeds in the simulation changed the top-performing table mix and associated maximum revenue for two scenarios. Although the revenue was not significantly different (within 1 percent), this finding indicates that the simulation model may be unstable in certain conditions.

The assumptions related to how customers arrive to and enter the restaurant may not reflect the true arrival process. As explained in the Methodology section, data from Point of Sale systems has customarily been used to model arrivals to a service system (cite). Because this data does not reflect the real arrival time of a party to the restaurant, but instead gives the time the party's check was opened in the POS, arrivals were approximated by a known non-stationary Poisson process. While modeling arrivals in this way yielded results similar to actual operations of the restaurant under study, testing the effect of POS data on simulation performance measures or collecting actual arrival data and using it to simulate restaurant operations would provide a more insightful picture as to how the timing of requests for tables of different sizes impacts the revenues associated with various table mixes.

Clearly, table assignment rules affect how well the existing and proposed table mix models work, and more research on seating rules and how they impact a restaurant's optimal table mix is warranted (Kimes and Thompson 2005). Bertsimas and Shioda

(2003) studied how to best violate the first-come-first-served rule when matching arriving customers to available tables, but they did not consider optimal table mix and also did not translate their findings into accessible models that could actually be used by practitioners. Another aspect related to seating rules and their impact on the best table mix that was not addressed in this study is table combinability, which impacts both revenue and capacity (Thompson 2002). Many restaurants opt to combine smaller tables to accommodate larger parties, and incorporating this factor into research on the use of revenue-generating space would strengthen this study.

A number of additional assumptions that merit further testing to determine their effect on revenue and capacity when including space in the revenue management problem include the order in which parties are processed, the conditions under which customers leave before being served, and the Back-of-House operations. It was assumed that neither reservations nor call-ahead seating were used. In reality, many restaurants use one or both of these practices, which affect the order of arriving customers and possibly the amount and mix of tables available to seat them. The renege process used in this study also does not reflect the true nature of restaurant operations, as parties have varying levels of tolerance for waits and may even balk before joining the queue. Although collecting actual renege and balk data for a service operation is difficult, incorporating more accurate lost customer information into the revenue management problem would lead to a greater understanding of how well revenue-generating space is used. It was also assumed that the facility's Back-of-House operations were in proportion to the Front-of-House requirements in that the kitchen would not serve as a bottleneck to serving any number or mix of customers. This assumption served to isolate the problem under study to the Front-of-House. However, a true systems approach to determining the best way to use available space warrants not only consideration of the amount of total space allocated to BOH functions, such as kitchen and storage, but also how the kitchen production reacts to changes in FOH capacity.

Replicating this type of study for other restaurant sites would serve to strengthen the results related to the field of Service Operations Management and extend the findings into other fields such as Environmental Psychology. The restaurant used as the testing ground was mid-sized, mid-priced, and casual, and catered to a generally adult customer base with its ambiance and menu. A different type or size of restaurant would possibly impact the recommended table mix because the demand base would differ; for instance, a large, family-oriented restaurant would likely have more large parties in its customer mix and thus require more large tables.

Moreover, the physical sizes of tables used by a restaurant, incorporated into this study via the table space proportion factor, vary based on the size and type of facility. Three levels of table space proportion were tested in this research, with each level using roughly the same size 2-top table but differing sizes for 4-top, 6-top, and 8-top tables. The physical size of tables used by a restaurant is a function of the type of food served, along with the associated plate sizes, accompaniments, and utensils associated with the menu, and the desired atmosphere which can range from small plate tapas to candlelit intimate to family-style dining. As such, testing different table space proportions in relation to 2-tops, as well as testing smaller and larger 2-top table sizes, may impact the table mixes recommended by the NaïveIP-A(2) and the NaïveIP-B(2) models and more importantly may impact which of the two table mix models yields the best results for the table sizes under study.

Further research related to how the physical size and space proportionality of tables used affects the best use of space would also expand the refine the findings of this study as they relate to the field of Environmental Psychology. Just as atmospheric lighting and sound influence customer responses in a restaurant (Robson, 1999), certain table sizes, table assignment rules, and the amount of space allotted to each customer at a table may impact customer reactions in terms of spend and satisfaction. Therefore, determining the optimal table sizes and table space proportions would be a highly beneficial augmentation to this research since more accurate space requirements per table type would be input into either of the modified NaïveIP heuristics.

One other facet of Environmental Psychology not addressed in this study but likely to have an impact on the amount and mix of table inventory that should be used is how tables are situated in the given space. Research has shown that the placement and configuration of tables on a dining room floor influences both duration and spend (Kimes and Robson, 2004). Since service facilities have been finding new and innovative ways to fit in more revenue-producing supply units and subsequently serve more customers; for example, urban hotels offer sleeping pods and some restaurants use communal tables, understanding customer perceptions of these practices is imperative. Determining whether or not customers are willing to pay for more personal space would impact the supply profile of a restaurant.

Summary

In a service operation, the level and mix of physical inventory units put into use to serve customers is crucial to maximizing revenue. Since businesses operate within a fixed area, a factor associated with diverse physical inventory units is the amount of space each type occupies and how these potentially non-homogeneous spatial requirements impact the physical capacity profile. This study tested two ways in which space could be incorporated into the revenue management problem faced by a typical casual, full-service restaurant and established that the size of tables used in an operation was the determining factor for which method recommended the number and mix of tables that produced the highest revenues. Existing heuristics were modified to provide practitioners with the actual means to apply these findings; they also afford restaurateurs with options in terms of choosing the physical capacity profile that best serves customers, aligns with strategic objectives, and uses available space.

Although this study was grounded in Service Operations Management and Revenue Management literature and conducted based on conventional research and statistical methods, it had several limitations that warrant future research. Augmenting the structure of the simulation model used to incorporate table combinability, kitchen operations, and staffing requirements would provide a more holistic approach to overall service capacity. Additionally, testing more table sizes would expand the application of this research to a wider variety of restaurants since not every facility uses the table sizes and table space proportions used in this study. Further, connecting these findings to Environmental Psychology research would give a more accurate picture of how design and layout of a dining room impacts the physical capacity tools recommended by this research.

Appendix A: Summary of Simulation Scenarios

Scenario	Number of Table Mixes Run	Input Factor			
		Method of Inventory Allocation (2 Levels)	Table Space Proportion (3 Levels)	Demand Level (2 Levels)	Demand Mix (3 Levels)
1	1200	Seats	Standard	100%	Current
2	1200	Seats	Standard	100%	Skewed Small
3	1200	Seats	Standard	100%	Skewed Large
4	1200	Seats	Standard	115%	Current
5	1200	Seats	Standard	115%	Skewed Small
6	1200	Seats	Standard	115%	Skewed Large
7	1620	Seats	Far from proportional	100%	Current
8	1620	Seats	Far from proportional	100%	Skewed Small
9	1620	Seats	Far from proportional	100%	Skewed Large
10	1620	Seats	Far from proportional	115%	Current
11	1620	Seats	Far from proportional	115%	Skewed Small
12	1620	Seats	Far from proportional	115%	Skewed Large
13	509	Seats	Close to proportional	100%	Current
14	509	Seats	Close to proportional	100%	Skewed Small
15	509	Seats	Close to proportional	100%	Skewed Large
16	509	Seats	Close to proportional	115%	Current
17	509	Seats	Close to proportional	115%	Skewed Small
18	509	Seats	Close to proportional	115%	Skewed Large
19	2115	Space	Standard	100%	Current
20	2115	Space	Standard	100%	Skewed Small
21	2115	Space	Standard	100%	Skewed Large
22	2115	Space	Standard	115%	Current
23	2115	Space	Standard	115%	Skewed Small
24	2115	Space	Standard	115%	Skewed Large
25	3764	Space	Far from proportional	100%	Current
26	3764	Space	Far from proportional	100%	Skewed Small
27	3764	Space	Far from proportional	100%	Skewed Large
28	3764	Space	Far from proportional	115%	Current
29	3764	Space	Far from proportional	115%	Skewed Small
30	3764	Space	Far from proportional	115%	Skewed Large
31	1133	Space	Close to proportional	100%	Current
32	1133	Space	Close to proportional	100%	Skewed Small
33	1133	Space	Close to proportional	100%	Skewed Large
34	1133	Space	Close to proportional	115%	Current
35	1133	Space	Close to proportional	115%	Skewed Small
36	1133	Space	Close to proportional	115%	Skewed Large

Appendix B: Pairwise Comparisons of Means

For the TableSpaceProportion-DemandLevel interaction, a comparison of treatment means estimates how the mean revenue of the test restaurant fluctuates when the top-performing table mix is determined by the SEATS method and the SPACE method when the table sizes used have either the standard, far from/narrower, or close to/wider space proportion per person. A total of three confidence intervals for differences in mean revenue generated under the two levels of inventory allocation and the three table space proportions provide these estimations. The factor level means used in the calculation of these three pairwise mean comparisons are found in Table B1.

Likewise, a comparison of treatment means for the TableSpaceProportion-DemandLevel interaction estimates how the mean revenue of the test restaurant differs between current and high demand situations when its table mix is comprised of tables with either standard, narrower, or wider space proportion per person. A total of three confidence intervals for differences in mean revenue generated under the table space proportions and demand levels provide these estimations. The factor level means used in the calculation of these three pairwise mean comparisons are found in Table B2.

Table B3 provides the confidence intervals for the six comparisons made to test the nature of the two separate interactions. Differences 1-3 evaluate the relationship between the MethodofAllocation and TableSpaceProportion factors, while Differences 4-6 do so for the relationship between the TableSpaceProportion and DemandLevel factors.

Table B1: Estimated Factor Level Means for MethodofAllocation and TableSpaceProportion Factors

	Method of Allocation	
Table Space Proportion	Level 1 (SEATS)	Level 2 (SPACE)
Level 1 (Standard Proportion)	$\bar{Y}_{11\cdot\cdot} = 15820$	$\bar{Y}_{21\cdot\cdot} = 15831$
Level 2 (Narrower Tables)	$\bar{Y}_{12\cdot\cdot} = 18182$	$\bar{Y}_{22\cdot\cdot} = 18714$
Level 3 (Wider Tables)	$\bar{Y}_{13\cdot\cdot} = 15314$	$\bar{Y}_{23\cdot\cdot} = 15361$

Table B2: Estimated Factor Level Means for TableSpaceProportion and DemandLevel Factors

	Demand Level	
Table Space Proportion	Level 1 (100%)	Level 2 (115%)
Level 1 (Standard Proportion)	$\bar{Y}_{\cdot 11\cdot} = 14671$	$\bar{Y}_{\cdot 12\cdot} = 16979$
Level 2 (Narrower Tables)	$\bar{Y}_{\cdot 21\cdot} = 17162$	$\bar{Y}_{\cdot 22\cdot} = 19734$
Level 3 (Wider Tables)	$\bar{Y}_{\cdot 31\cdot} = 14396$	$\bar{Y}_{\cdot 32\cdot} = 16279$

Table B3: 95% Confidence Interval Calculations for Multiple Comparisons of Treatment Means

Point Estimate	Variance	Scheffé's S	95% Confidence Interval $[\hat{D} \pm Ss\{\hat{D}\}]$
$\hat{D}_1 = \overline{Y}_{11..} - \overline{Y}_{21..} = -11$	$s^2\{\hat{D}_1\} = s^2\{\hat{D}_2\} = s^2\{\hat{D}_3\} = \frac{MSE}{ncd}[(1)^2 + (-1)^2] = 3893.63$	$S_1 = S_2 = S_3 = \sqrt{(ab-1)F[1-\alpha; ab-1, (n-1)abcd]}$ = 3.32905	$-219 \le \mu_{11..} - \mu_{21..} \le 197$
$\hat{D}_2 = \overline{Y}_{12..} - \overline{Y}_{22..} = -532$	3893.63	3.32905	$-740 \le \mu_{12..} - \mu_{22..} \le -324$
$\hat{D}_6 = \overline{Y}_{13..} - \overline{Y}_{23..} = -47$	3893.63	3.32905	$-255 \le \mu_{13..} - \mu_{23..} \le 161$
$\hat{D}_4 = \overline{Y}_{.11.} - \overline{Y}_{.12.} = -2308$	$s^2\{\hat{D}_4\} = s^2\{\hat{D}_5\} = s^2\{\hat{D}_6\} = \frac{MSE}{nad}[(1)^2 + (-1)^2] = 3893.63$	$S_4 = S_5 = S_6 = \sqrt{(bc-1)F[1-\alpha; bc-1, (n-1)abcd]}$ = 3.32905	$-2516 \le \mu_{.11.} - \mu_{.12.} \le -2100$
$\hat{D}_5 = \overline{Y}_{.21.} - \overline{Y}_{.22.} = -2573$	3893.63	3.32905	$-2780 \le \mu_{.21.} - \mu_{.22.} \le -2365$
$\hat{D}_6 = \overline{Y}_{.31.} - \overline{Y}_{.32.} = -1882$	3893.63	3.32905	$-2090 \le \mu_{.31.} - \mu_{.32.} \le -1675$

Appendix C: Calculation of Linear Contrasts

Table C1: Description of Contrasts of Treatment Means

Contrast	Explanation	Point Estimate
$\hat{L}_1 = (\overline{Y}_{\cdot 22\cdot} - \overline{Y}_{\cdot 21\cdot}) - (\overline{Y}_{\cdot 12\cdot} - \overline{Y}_{\cdot 11\cdot})$	Gain in revenue based on higher demand for narrower vs. standard tables	2573 – 2308 = 265
$\hat{L}_2 = (\overline{Y}_{\cdot 12\cdot} - \overline{Y}_{\cdot 11\cdot}) - (\overline{Y}_{\cdot 32\cdot} - \overline{Y}_{\cdot 31\cdot})$	Gain in revenue based on higher demand between standard vs. wider tables	2308 – 1882 = 426
$\hat{L}_3 = (\overline{Y}_{\cdot 22\cdot} - \overline{Y}_{\cdot 21\cdot}) - (\overline{Y}_{\cdot 32\cdot} - \overline{Y}_{\cdot 31\cdot})$	Gain in revenue based on higher demand between narrower vs. wider tables	2573 – 1882 = 691

Table C2: Joint 95% Confidence Intervals for Family of Three Contrasts of Treatment Means

Point Estimate	Variance	Scheffé's S	95% Confidence Interval $[\hat{L} \pm Ss\{\hat{L}\}]$
$\hat{L}_1 = 265$	$s^2\{\hat{L}_1\} = s^2\{\hat{L}_2\} = s^2\{\hat{L}_3\} =$ $\frac{MSE}{nad}[(1)^2 + (-1)^2 + (1)^2 + (-1)^2] = 7787.26$	$S_7 = S_8 = S_9 =$ $\sqrt{(bc-1)F[1-\alpha; bc-1, (n-1)abcd]} =$ 3.32905	$-129 \le L_1 \le 559$
$\hat{L}_2 = 426$	7787.26	3.32905	$132 \le L_2 \le 720$
$\hat{L}_3 = 691$	7787.26	3.32905	$397 \le L_3 \le 985$

Appendix D: Simulation Output for Eight Performance Measures

Table D1: Customers Served, Customers Lost, RevPASH, and RevPAST for Top Revenue-Producing Table Mixes Generated by Each Scenario

Scenarios	**Total Number of Customers Served**		**Total Number of Customers Lost**		**Overall RevPASH for Friday-Saturday Dinner Service**		**Overall RevPAST for Friday-Saturday Dinner Service *(calculated using square feet available)***		**Overall RevPAST for Friday-Saturday Dinner Service *(calculated using square feet used)***	
	SEATS	*SPACE*	*SEATS*	*SPACE*	*SEATS*	*SPACE*	*SEATS*	*SPACE*	*SEATS*	*SPACE*
1 vs. 19	627	626	2	3	$9.20	$8.77	$0.74	$0.74	$0.75	$0.74
2 vs. 20	584	584	2	2	$8.65	$8.65	$0.69	$0.69	$0.70	$0.70
3 vs. 21	658	658	2	2	$9.88	$9.88	$0.78	$0.78	$0.78	$0.78
4 vs. 22	725	725	14	14	$10.68	$10.68	$0.86	$0.86	$0.86	$0.86
5 vs. 23	678	678	2	2	$10.43	$10.43	$0.81	$0.81	$0.81	$0.81
6 vs. 24	758	756	21	16	$11.16	$10.80	$0.89	$0.90	$0.91	$0.90
7 vs. 25	727	739	10	4	$10.53	$7.96	$0.86	$0.87	$0.93	$0.87
8 vs. 26	681	688	3	1	$9.94	$9.34	$0.81	$0.81	$0.84	$0.82
9 vs. 27	760	778	16	4	$11.00	$8.16	$0.90	$0.92	$1.01	$0.93
10 vs. 28	824	857	45	12	$11.89	$9.11	$0.97	$1.01	$1.05	$1.02
11 vs. 29	787	803	17	5	$11.47	$9.57	$0.94	$0.96	$0.99	$0.96
12 vs. 30	852	901	54	17	$12.34	$9.98	$1.01	$1.07	$1.12	$1.08
13 vs. 31	614	614	10	10	$10.52	$10.52	$0.72	$0.72	$0.73	$0.73
14 vs. 32	576	580	2	2	$9.90	$9.99	$0.68	$0.69	$0.69	$0.70
15 vs. 33	644	644	16	16	$10.78	$11.03	$0.76	$0.76	$0.76	$0.77
16 vs. 34	698	696	40	40	$11.89	$11.91	$0.82	$0.82	$0.82	$0.83
17 vs. 35	664	668	12	17	$11.41	$11.45	$0.79	$0.79	$0.79	$0.80
18 vs. 36	717	718	57	57	$12.25	$12.28	$0.84	$0.85	$0.85	$0.86

Table D2: Peak Operating Hour Table Utilization for Top Revenue-Producing Table Mixes for Each Scenario

	Table Utilization - Peak Operating Period (8:00PM - 9:15PM)									
Scenarios	***SEATS***					***SPACE***				
	Total	**2-tops**	**4-tops**	**6-tops**	**8-tops**	**Total**	**2-tops**	**4-tops**	**6-tops**	**8-tops**
1 vs. 19	93.0%	91.3%	97.5%	N/A	91.1%	93.2%	92.2%	94.7%	N/A	91.2%
2 vs. 20	92.6%	90.7%	98.1%	96.5%	90.2%	92.6%	90.7%	98.1%	96.5%	90.2%
3 vs. 21	93.0%	89.9%	97.3%	94.6%	92.7%	93.0%	89.9%	97.3%	94.6%	92.7%
4 vs. 22	94.7%	94.2%	94.5%	98.1%	94.9%	94.7%	94.2%	94.5%	98.1%	94.9%
5 vs. 23	94.0%	92.8%	97.3%	93.8%	91.3%	94.0%	92.8%	97.3%	93.8%	91.3%
6 vs. 24	94.8%	91.5%	97.6%	99.1%	96.8%	93.5%	90.3%	96.1%	N/A	98.8%
7 vs. 25	92.3%	89.6%	95.9%	96.9%	96.1%	93.8%	98.1%	95.1%	88.2%	94.1%
8 vs. 26	92.2%	91.8%	95.3%	92.9%	84.8%	91.4%	91.2%	94.8%	N/A	83.0%
9 vs. 27	94.2%	91.4%	96.9%	99.1%	97.6%	95.3%	99.7%	96.0%	93.2%	91.9%
10 vs. 28	94.9%	92.6%	97.7%	99.7%	98.5%	95.0%	97.0%	95.2%	93.9%	91.9%
11 vs. 29	94.2%	91.9%	98.6%	99.4%	95.1%	95.2%	94.8%	96.7%	91.0%	89.3%
12 vs. 30	95.5%	93.3%	97.5%	99.7%	99.4%	96.3%	95.6%	96.7%	97.7%	93.5%
13 vs. 31	94.6%	91.9%	98.8%	98.8%	96.3%	94.6%	91.9%	98.8%	98.8%	96.3%
14 vs. 32	90.6%	89.8%	92.0%	92.2%	88.2%	94.8%	94.2%	97.4%	96.7%	86.0%
15 vs. 33	94.8%	93.0%	97.0%	N/A	95.7%	95.8%	93.6%	98.4%	99.4%	95.6%
16 vs. 34	94.3%	91.5%	97.6%	99.5%	97.6%	96.3%	94.9%	97.4%	99.9%	97.4%
17 vs. 35	93.6%	91.4%	97.7%	95.9%	96.8%	95.0%	92.9%	98.3%	99.4%	95.2%
18 vs. 36	94.8%	91.8%	98.5%	99.4%	99.6%	97.2%	96.0%	97.9%	99.9%	98.4%

Table D3: Peak Operating Hour Seat Utilization for Top Revenue-Producing Table Mixes for Each Scenario

	Seat Utilization - Peak Operating Period (8:00PM - 9:15PM)									
	SEATS					***SPACE***				
Scenarios	**Total**	**2-tops**	**4-tops**	**6-tops**	**8-tops**	**Total**	**2-tops**	**4-tops**	**6-tops**	**8-tops**
1 vs. 19	73.6%	83.0%	78.2%	N/A	61.2%	72.6%	84.2%	71.7%	N/A	63.8%
2 vs. 20	71.7%	82.2%	64.5%	68.4%	68.4%	71.7%	82.2%	64.5%	68.4%	68.4%
3 vs. 21	78.1%	83.9%	79.8%	72.8%	74.6%	78.1%	83.9%	79.8%	72.8%	74.6%
4 vs. 22	74.4%	85.7%	69.9%	72.8%	72.6%	74.4%	85.7%	69.9%	72.8%	72.6%
5 vs. 23	77.0%	84.1%	76.3%	68.0%	67.9%	77.0%	84.1%	76.3%	68.0%	67.9%
6 vs. 24	77.1%	85.3%	77.2%	74.8%	71.8%	74.9%	84.4%	77.3%	N/A	67.5%
7 vs. 25	75.6%	81.6%	77.0%	71.7%	68.0%	71.4%	89.6%	74.3%	62.1%	67.9%
8 vs. 26	74.4%	83.1%	69.0%	68.4%	65.2%	72.9%	82.7%	67.5%	N/A	62.4%
9 vs. 27	78.2%	85.4%	78.6%	74.7%	72.9%	75.2%	93.1%	77.2%	69.5%	70.4%
10 vs. 28	77.8%	84.4%	75.3%	75.0%	76.9%	72.1%	88.4%	71.6%	69.9%	69.1%
11 vs. 29	78.0%	83.4%	78.1%	72.6%	71.7%	74.9%	86.1%	74.7%	65.6%	64.5%
12 vs. 30	80.4%	87.2%	79.5%	76.3%	77.3%	76.0%	89.3%	76.6%	73.7%	67.1%
13 vs. 31	76.2%	83.8%	79.5%	68.7%	71.6%	76.2%	83.8%	79.5%	68.7%	71.6%
14 vs. 32	75.2%	81.2%	72.7%	70.4%	68.7%	76.1%	85.4%	74.7%	67.5%	64.1%
15 vs. 33	76.1%	87.0%	77.7%	N/A	65.9%	77.0%	87.4%	77.5%	71.7%	69.4%
16 vs. 34	78.7%	83.6%	78.2%	75.8%	77.8%	77.4%	86.7%	74.5%	74.6%	71.9%
17 vs. 35	78.2%	83.0%	78.1%	70.6%	73.8%	76.3%	84.4%	74.8%	71.2%	66.8%
18 vs. 36	81.6%	85.9%	82.8%	77.2%	81.1%	79.0%	89.6%	76.5%	75.1%	74.0%

Table D4: Average Wait Time by Party Size for Top Revenue-Producing Table Mixes Generated for Each Scenario

	Average Wait (in minutes) by Party Size															
Scenarios	***SEATS***								***SPACE***							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1 vs. 19	3.84	3.76	3.89	3.74	3.89	3.62	3.23	2.65	3.93	3.79	3.76	3.89	3.60	3.67	3.50	3.05
2 vs. 20	4.97	5.12	5.12	5.12	5.09	4.07	3.23	3.03	4.97	5.12	5.12	5.12	5.09	4.07	3.23	3.03
3 vs. 21	4.66	4.76	4.65	4.80	4.21	5.05	4.74	4.71	4.66	4.76	4.65	4.80	4.21	5.05	4.74	4.71
4 vs. 22	11.45	11.39	11.81	12.00	11.76	10.78	11.41	10.28	11.45	11.39	11.81	12.00	11.76	10.78	11.41	10.28
5 vs. 23	5.73	5.88	6.14	5.87	6.00	6.92	4.66	3.89	5.73	5.88	6.14	5.87	6.00	6.92	4.66	3.89
6 vs. 24	13.42	12.71	13.20	13.01	12.49	13.69	13.30	12.06	11.45	11.26	11.37	11.34	11.45	11.47	12.72	10.67
7 vs. 25	7.23	7.37	7.30	7.44	8.04	7.24	8.42	6.26	5.38	5.31	5.35	5.28	5.39	5.10	5.48	4.14
8 vs. 26	5.02	5.30	5.33	5.29	5.49	5.08	4.33	3.74	2.83	2.83	2.78	2.57	2.99	1.88	2.42	1.93
9 vs. 27	10.51	10.62	10.62	11.03	10.65	10.81	10.00	10.41	6.40	6.49	6.63	6.70	7.20	6.32	5.59	5.17
10 vs. 28	15.82	16.64	16.97	16.68	17.33	15.84	18.37	14.29	11.45	12.11	12.17	11.94	12.08	11.48	12.60	9.45
11 vs. 29	11.00	11.13	11.12	11.55	11.78	10.77	9.74	9.66	7.97	8.24	8.34	8.13	7.70	8.56	5.95	5.88
12 vs. 30	17.95	18.28	18.76	18.78	18.73	20.04	19.25	20.75	12.10	12.36	12.38	12.42	12.62	12.69	13.87	13.17
13 vs. 31	9.43	9.58	9.60	9.35	9.87	10.15	8.83	5.89	9.43	9.58	9.60	9.35	9.87	10.15	8.83	5.89
14 vs. 32	3.26	3.24	3.29	3.10	3.08	3.50	3.19	2.00	5.44	5.76	5.66	6.03	5.59	6.00	4.55	2.57
15 vs. 33	11.09	10.60	11.33	10.70	11.21	11.47	11.07	11.95	11.57	12.60	12.48	12.53	12.64	13.35	11.19	13.81
16 vs. 34	15.77	15.87	16.08	16.55	16.38	16.65	13.61	11.73	16.41	17.46	17.42	17.68	18.64	18.22	17.85	15.16
17 vs. 35	9.57	9.67	9.92	9.57	9.46	9.54	7.30	7.01	12.45	12.96	13.44	13.63	12.35	12.80	11.00	8.36
18 vs. 36	17.53	18.38	18.80	18.77	18.51	19.22	21.93	18.45	18.51	19.77	19.13	19.95	20.20	20.95	19.32	20.92

Table D5: 85th Percentile of Wait Times for Top Revenue-Producing Table Mixes Generated for Each Scenario

Scenarios	85th percentile of Wait Times (in minutes) by Party Size															
	SEATS								*SPACE*							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1 vs. 19	10.02	9.46	9.94	9.72	10.51	0	0	0	9.76	9.64	9.59	9.83	9.49	0	0	0
2 vs. 20	14.38	14.90	14.98	14.21	13.54	0	0	0	14.38	14.9	14.98	14.21	13.54	0	0	0
3 vs. 21	12.53	13.56	13.11	13.31	11.70	14.82	0	0	12.53	13.56	13.11	13.31	11.70	14.82	0	0
4 vs. 22	29.58	29.61	30.87	31.26	32.73	29.98	0	0	29.58	29.61	30.87	31.26	32.73	29.98	0	0
5 vs. 23	16.62	16.88	17.50	16.80	0	0	0	0	16.62	16.88	17.50	16.80	0.00	0	0	0
6 vs. 24	34.34	33.26	34.47	34.50	32.23	36.94	0	0	29.89	30.05	30.80	30.83	31.81	0	0	0
7 vs. 25	20.04	20.58	20.76	20.58	23.63	0	0	0	14.74	14.02	14.61	14.10	14.45	15.25	0	0
8 vs. 26	14.29	15.09	15.34	15.58	16.64	0	0	0	6.60	6.59	6.90	5.08	8.43	0	0	0
9 vs. 27	28.73	29.20	29.11	31.11	29.31	0	0	0	17.85	18.45	18.40	19.32	19.31	17.87	0	0
10 vs. 28	38.04	40.12	41.07	41.26	41.23	41.36	0	0	29.66	30.76	30.64	30.61	31.25	31.41	0	0
11 vs. 29	29.65	30.21	30.71	31.41	32.07	0	0	0	22.18	23.07	23.32	22.48	21.90	25.85	0	0
12 vs. 30	40.57	41.40	42.60	43.47	44.79	45.10	0	0	31.00	31.83	31.65	31.85	33.05	32.66	0	0
13 vs. 31	25.41	26.47	27.52	26.33	27.05	0	0	0	25.41	26.47	27.52	26.33	27.05	0	0	0
14 vs. 32	8.14	7.73	7.71	7.50	0	0	0	0	15.27	16.62	17.05	17.11	18.36	0	0	0
15 vs. 33	29.43	29.07	30.19	30.07	29.79	31.37	0	0	31.69	32.97	33.44	32.46	33.17	37.82	0	0
16 vs. 34	37.72	38.15	38.70	40.10	41.23	41.29	0	0	38.89	40.81	40.6	41.85	42.9	42.91	0	0
17 vs. 35	32.11	32.47	33.91	34.95	31.44	0	0	0	32.11	32.47	33.91	34.95	31.44	0	0	0
18 vs. 36	41.55	42.64	44.80	44.43	44.34	45.86	0	0	42.44	44.61	44.59	46.11	45.21	0	0	0

Appendix E: Comparisons of NaïveIP Model Variations and Complete Enumeration Results

Table E1: Complete Enumeration vs. NaïveIP-A(2)

Difference between NaïveIP-A(2) and Complete Enumeration Results

Scenario	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	NaïveIP-A(2) Revenue as a % of Maximum
1	+9	-5	+2	-3	-14	+3	-21.04	-$1,226.64	96.9%
2	+10	+2	0	-5	-12	+7	-2.47	-$1,534.34	92.3%
3	+6	+1	-2	-1	-4	+4	-5.49	-$1,397.04	96.0%
4	+9	-3	-1	-1	-8	+4	-7.34	-$1,561.14	95.0%
5	+7	0	-1	-2	-8	+4	-20.17	-$1,830.68	90.4%
6	+5	0	+2	-4	-10	+3	-9.29	-$1,661.55	93.9%
7	+23	-11	-6	0	-34	+6	+1.00	-$883.45	94.7%
8	+7	0	+1	-4	-12	+4	-39.00	-$1,518.43	90.6%
9	+24	-13	-3	-2	-38	+6	-10.00	-$1,432.57	92.7%
10	+23	-14	-3	-1	-36	+5	+6.00	-$1,638.65	92.4%
11	+17	-9	-2	-2	-30	+4	-39.00	-$2,389.43	87.4%
12	+18	-11	-1	-2	-30	+4	-12.00	-$2,163.12	90.5%
13	+5	+4	-2	-2	-2	+5	-20.00	-$2,390.28	92.7%
14	+9	0	-1	-2	-4	+6	-37.00	-$1,778.53	90.9%
15	+7	+2	0	-3	-2	+6	-8.00	-$2,595.75	92.2%
16	+7	0	0	-2	-2	+5	-10.00	-$2,219.51	93.1%
17	+8	-1	0	-2	-4	+5	-36.00	-$1,790.21	90.9%
18	+7	0	0	-2	-2	+5	-10.00	-$2,999.83	94.7%
									Overall Average: 92.6%

Table E2: Complete Enumeration vs. NaïveIP-B(2)

Difference between NaïveIP-B(2) and Complete Enumeration Results

Scenario	2-tops	4-tops	6-tops	8-tops	Seats	Tables	Total SF	Revenue	NaïveIP-B(2) Revenue as a % of Maximum
1	+8	-4	+2	-3	-12	+3	-8.79	-$515	96.5%
2	+8	+2	+1	-5	-10	+6	+13.16	-$686	95.0%
3	+4	+2	-2	-1	-4	+3	-24.74	-$531	96.6%
4	+8	-2	-1	-1	-6	+4	+4.91	-$642	96.2%
5	+5	0	0	-2	-6	+3	-4.54	-$600	96.3%
6	+3	+1	+2	-4	-10	+2	-28.54	-$989	94.5%
7	+21	-11	-5	0	-32	+5	-1.00	-$544	96.9%
8	+5	0	+2	-4	-10	+3	-41.00	-$1,027	93.7%
9	+22	-12	-2	-2	-32	+6	+20.00	-$656	96.4%
10	+21	-14	-2	-1	-34	+4	+4.00	-$954	95.3%
11	+15	-9	-1	-2	-28	+3	-41.00	-$1,028	94.6%
12	+16	-10	0	-2	-24	+4	+18.00	-$1,036	95.1%
13	+3	+3	-2	-1	-2	+3	-26.00	-$404	97.2%
14	+7	0	0	-2	-2	+5	-10.00	-$626	95.4%
15	+5	+1	0	-2	-2	+4	-14.00	-$469	96.9%
16	+5	-1	0	-1	-2	+3	-16.00	-$603	96.3%
17	+6	-1	+1	-2	-2	+4	-9.00	-$418	97.3%
18	+5	-1	0	-1	-2	+3	-16.00	-$450	97.3%
									Overall Average: 96.0%

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