Revenue Management in Airline Operations: Booking Systems and Aircraft Maintenance Services

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ABSTRACT

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Although the principles of Revenue Management (RM) have vaguely been used in business for a long time, an increasing number of organizations are implementing well structured RM systems in the last few decades due to the developments in science and technology, especially in economics, statistics, operations research and computer science. The improvements in information and telecommunication technologies, wide use of Internet, rise of e-commerce and successful supply chain management strategies have enabled organizations to model and solve complex RM problems.

This dissertation research concentrates on airlines, the earliest and leading user of RM. Today, airlines face serious financial problems due to the increasing costs and competition. They continuously explore new opportunities especially in terms of RM to make profit and survive. In this study, two problems are analyzed within this scope; airline booking process with adapted options approach and aircraft maintenance order control through RM.

First; a new approach, financial options approach, is proposed to sell tickets in airline reservation systems. The options are used to overcome the uncertainty in air travel demand and competitors' actions. The seat inventory control problem is formulated with overbooking and embedded options respectively. Then a simulation study is conducted the potential of using options in airlines booking process. Accordingly, empirical results show that they present an opportunity both to utilize capacity more efficiently and to value seats more precisely compared to overbooking approach.

Secondly; a peak load pricing concept is applied for aircraft maintenance order control problem. Aircraft maintenance centers face with peak loads in some seasons and the capacity is underutilized in other seasons. A peak load pricing model is proposed to shift some of the price elastic demand from peak seasons to off-peak seasons to balance demand and supply around the year. A dynamic programming algorithm is developed to solve the model and a code is written in C++. Results show that the model improves both annual capacity loading factors and revenues without causing a discomfort from the perspective of the customers. The details of both studies are presented in this dissertation research.

To my father, Süreyya Türkmen

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Chapter 1

1. Introduction

In the market place, organizations often use some limited resources to satisfy different classes of demands. There has been increasing awareness towards management of resources and selling process in the last few decades since organizations would like to survive in today's callously competitive environment. High competition has forced airlines to seek opportunities to increase their revenues from limited resources. Today most airline companies use some form of revenue management (RM) methodologies developed after 1980's. RM is a process of managing perishable inventories to maximize the total revenue from these inventories. Addressing this issue, RM deals with modeling and optimization of pricing, demand management and capacity allocation decisions. It is a systems management philosophy of business management that links variety of operations such as planning, marketing, and finance. Since RM implementation requires strategic stability between functional areas, it enhances strategic linkages too.

1.1 Revenue Management

1.1.1 RM Definition

RM deals with managing demand and supply by the decision making process about selling method, pricing and quantity (how to allocate capacity, accept or deny decisions). RM is a practice of maximizing revenue by selling the right seats to the right customers at the right price and at the right time according to American Airlines mentioned in Weatherford and Bodily (1992). Subramanian et al. (1999) define RM as a commodity or service that is priced at differently depending on various restrictions on booking or cancellation. Gorin and Belobaba (2004) define RM for airline industry as "the combination of forecasting and optimization algorithms which enable the airlines to maximize revenues, given a set of fares by determining how much seat inventory to make available to specific fare products based on forecasts of expected demand for each fare product". In the editorial introduction of Yeoman, Ingold and Kimes (1999), they define yield management as the process of allocating the right capacity or inventory unit to the right customer at the right price so as to maximize revenue or yield. There are various definitions of RM over years changing with the perspective, focus and discipline of the researcher.

Another issue is the distinction between inventory management (IM), yield management (YM) and RM terms. IM is a rather broad spectrum term. YM is assumed to develop into RM by Li (1998). He analyzes the focus in these 3 approaches. In IM, he claims focus is on the high load factors on individual flights resulting in high average load factors and low yields per passenger mile since the number of low fare class passengers is high. In YM the objective is to get high average fare by limiting the number of low fare class seats available for sale and low load factors might occur. RM approach focuses on the average increase in yield per available seat and the overall load factor at the same time. Belobaba and Wilson (1997) compare these 3 approaches in terms of effectiveness in load factor, average fare and total revenue. Today YM and RM are used interchangeably and in this study RM is preferred to be used.

1.1.2 Historical Background

The basics of RM has been known and applied in practice for a long time, as long as commerce itself. Yet the developments in science especially in economics, statistics and operations research (OR) and the developments in information technology in the last few decades has enabled to model real world complex decision problems and compute optimal solutions. RM approach aims to manage supply and demand by bringing people and systems together to understand the market, to anticipate customer behaviour and to take advantage of opportunities by responding quickly. Availability of demand data from customer relationship management (CRM) software, the rise of e-commerce, widespread use of enterprise resource planning (ERP), the interest in automated supply chain management systems such as SAP and inspiration by the great success of RM applications in airlines has caused acceleration in RM research and implementations. Phillips (2005) determines 4 factors that will increase the importance of pricing: RM, the rise of Internet, the new wealth of information and the success of supply chain management.

Since RM applications come from airline industry, the history of airlines in this scope is reviewed. The need to improve airline seat inventory control is a result of the U.S. Airline Deregulation Act of 1978. The United States government gave up authority over domestic fares and routes and so allowed airlines to enter and leave domestic markets freely. This act caused increased competition and pricing freedom, allowing airlines to charge whatever fare the market would bear. Deregulation policy expanded to Canada and Europe and throughout the world by 1992. The beginning of application of RM techniques dates back the initiate of American Airlines' Super Saver fares in 1977. Kimes (1989) states that during deregulation years many airlines reported 5% revenue increases or more due to RM applications.

The airline overbooking problem is studied first through a dynamic model by Rothstein (1971). The booking process in divided into T time units, demand in each time unit is random and independent of those in other periods. The booked customers have a certain probability of cancellations and the control used in this study is a set of booking limits. The optimal policy is obtained by using the standard dynamic programming (DP) technique. Research in RM started with Littlewood (1972) which proposed a simple two-fare allocation rule. Given average high fare (f_1), average discount fare (f_2), random full fare demand Y, and s seats remaining, Littlewood's rule stipulates that a discount seat should be sold as long as the discount fare equals or exceeds the expected marginal return from a full fare booking of the last remaining seat; that is discount demand should be satisfied as long as $f_2 \geq f_1 \Pr(Y > s)$.

Although RM applications first emerged from airline industry, it is applied in many industries.

1.1.3 Practices of RM in Different Industries

There is a vast research about RM applications in the industries other than airline industry. Bitran and Mondschein (1995) study a hotel RM problem where there are multiple classes of customers and multiple types of rooms. They find out a monotone threshold policy is an optimal policy. Bitran and Mondschein (1997) study pricing policies for retail industry. Ciancimino et al. (1999) consider a deterministic linear programming model and a probabilistic nonlinear programming model for the network problem with non-nested seat allocation for railway passenger transportation. Kasilingam (1997) suggest a cost model to optimize overbooking level for air cargo with variable capacity. Slager and Kapteijns (2004) study a case of RM implementation in KLM, as an organization in cargo industry, and present insights and critical success factors during implementation. Edgar (2000) focuses on the economic theory underlining the concept of RM within the context of the hospitality and tourism industry. Nair and Bapna (2001) study the RM application for Internet service providers. Their service is continuous, the request and the service happen simultaneously and overbooking is impossible. They model a continuous time Markov Decision Process to maximize revenue and to improve service performance for high class customers. Chiang, Chen and Xu (2007) analyze the price discrimination method of various industries. The following table is taken from their study summarizes some RM practices in different industries:

Table 1.1: RM practices in different industries

Industries	**Example of Practices**
Hospitality organizations	
Hotels	Provide special rate packages for period of low occupancy; use overbooking policy to compensate for cancellations, no-shows.
Restaurants	Move customers to off-peak periods by offering discount coupons, or charging reservation fees and higher meal prices on Friday and Saturday nights.
Attractions	Set different admission charge levels, provide joint entry tickets, group discounts, coupons, membership rates.
Cruise and ferry lines	Provide luxury class, economy class; change prices frequently according to demand; sell more tickets than seats to avoid cancellation and no-show.
Casinos	Customize offers such as complimentary room, tickets, gifts, and discounts etc., based on customers' profitability.
Saunas	Determine price based upon factors such as room type, duration and service type.
Resort	Provide different resort packages to attract different customers.
Golf	Use different prices to reflect the value of different times of the golf course.
Sports and entertainment events	Determine ticket price for an event based on factors such as customer tastes and area of seating; determine the price of season tickets; determine the number of tickets sold for each seat segment.
Conference	Provide different packages and rates to satisfy different customers' requirements.
Transportation industries	
Airlines	Provide business class, economy class; adjust prices frequently

	according to demand; provide more tickets than seats to avoid cancellation and no-shows.
Rental cars	Adjust prices frequently according to demand; serve high-valued fleet utilization with priority; accept or reject booking requests based on length-of-rent controls.
Boat	Provide discount to stimulate demand.
Railways	Divide customers into standard class and first class; provide different prices based on the day of travel and the time of the day.
Cargo and Freight	Determine price based on cabin space, location and comfort; determine the optimal ship size and capacity for each class.
Subscription services	
IT and Internet Services	Allocate resources such as human resource, computing capacity, storage and network capacity among segments of customers and determine appropriate price for each segment, high class customers will be served with priority.
Cellular network services	Control call admission based on customer priority, higher class customers will be served with priority.
Miscellaneous	
Retailing	Use early discount pricing to maximize the revenue from sales of a 'seasonal' product.
Manufacturing	Determine the right price for every product to every customer segment through every channel in response to changing market conditions.
Natural gas, petroleum storage and transmission	Make the right price for the transportation services so that the pipelines stay full.
Project management	Use capacity planning and scheduling to reserve specific capacity for customers willing to pay higher prices to have critical activities.
Apartment renting	Establish optimal rates for individual units, adjust prices based on competitors' price, supply and demand, optimal renew price adjustment.
Inclusive holiday industry	Provide early booking discount, child discounts, and late sales reductions to stimulate demand.

1.1.4 The Core Concepts of Revenue Management

According to Cross (1997) the seven underlying principles of RM are as follows:

- Focus on price rather than costs when balancing supply and demand.
- Replace cost-based pricing with market-based pricing.
- Sell to segmented micro markets, not to mass markets.
- Save your products for your most valuable customers.
- Make decisions based on knowledge, not supposition.
- Exploit each product's value cycle.
- Continually re-evaluate your revenue opportunities.

For instance, hotels are very busy with business travelers during the week and empty on weekends. The traditional approach to this problem is to cut stuff on weekends to reduce labour costs while they continue to bear high overhead costs. The RM approach is to offer low rates to attract customers at weekends. Cross (1997) claims that although most airlines use capacity adjustments to account for demand fluctuations, such adjustments are made only if price discounts do not sufficiently balance the demand and supply. He highlights a RM tactic to address short term fluctuations first with price, then with capacity. He states that cat food industry is a good example to visualize the necessity to price the products at customer value. In the mid 1980s, in response to competition from Quaker, Nestle etc., Heinz cut the price of its cat food 24%. More discounts followed due to competition until the discounted prices do not cover for production costs. So they decided to go back to the cost plus profit margin pricing scheme. However the customers resisted the prices and its market share dropped from 23% to 15%. They had to change from cost-based pricing to price-based costing by changing the manufacturing process to meet the target price. Afterwards, their revenue increased from $41 million to $55 million and market share increased to 25% in 1994. He concludes that organizations have to be sensitive to customers' perception of value. In his study, he underlines that different market segments demand different prices and to maximize revenue, prices must vary to meet the price sensitivity of each market. As opposed to traditional approach of 'first come first served', he emphasizes to reserve capacity for the customers who are willing to pay rather than the customers who come early or make advance bookings. He argues the importance of forecasting to predict customer behaviour to make the best rational decisions. Another issue is the understanding the value cycle of the product. He suggests that the timing for moving the product throughout its life cycle is established to achieve optimal revenues. The final core point is the significance of reacting quickly to the changes in the market by making dynamic decisions at the micro market level.

1.1.5 Common Characteristics of Revenue Management

The common characteristics of RM are stated as perishable inventory, fixed capacity and market segmentation by Weatherford and Bodily (1992).

Perishable Inventory:

There is a horizon end of which the product or service is unavailable or useless. It cannot be stored or associated inventory cost is too high. For airlines, an empty seat after departure is useless and it has value only before the departure. A concert ticket is perishable as its value deteriorates after the concert is over.

Fixed capacity or high cost of incremental capacity:

There is relatively high fixed cost and low variable cost associated with the product or service so that offering the product or service with discounted price is more favourable than letting it waste. Yet airlines offering price discounts at the last minute might condition the customers to refuse to buy in advance. So they sell discounted seats early and as capacity fills up, the price gets higher until all seats are filled up. Although fixed capacity is a common characteristic in RM applications, its presence is not necessary for RM practices. For instance in hotel industry there is uncertainty about the time of check-out of a customer and capacity is a forecast and is fluctuated.

Market segmentation:

Price elasticity of customer groups enables to segment the market. For example, in retail industry, some customers are more price sensitive than others. The least price sensitive passengers wait until the end of season to buy products to benefit from price discounts. Thus time of purchase is a way to segment the customer groups.

1.1.6 The Revenue Management Attitude

A plan that focuses on the customer behaviour, market and competition rather than internal processes is a must for the companies to survive. Cost cutting or downsizing strategies might yield short term benefits but they lower the productivity and growth potential of the company. Traditional approaches focus on grasping productivity out of people and processes whereas RM concentrate on the revenue productivity coming from the products and their presentation in the market. Cross (1997) remarks the traditional attitude as negatively mannered and RM attitude as positive, uplifting endeavours and enhancing growth potential. For example price management allows companies to improve profitability the most with the least investments. In the work of Marn and Rosiello (1992), a study by McKinsey and Associates is analyzed. Accordingly, a 1% improvement in profit, on average, would result in an 11.1% improvement in operating profit. On the other hand 1% improvement in variable cost, volume and fixed cost would result in operating improvements of 7.8%, 3.3% and 2.3% respectively. A. T. Kearney analysis of 500 companies produced similar results in 1999. Thus pricing decisions has the highest impact on the profitability of the company among fixed cost, variable cost and sales volume. In the light of these studies and many others, the focus of management has turned from internal operations to cut costs which limits the marketing, to the RM tools to understand the market, respond to its needs fast and explore the revenue opportunities continuously. RM attitude is towards producing decision making tools to seize the complexities and uncertainties of today's highly competitive world.

1.2 Quantity vs. Price Based RM

Quantity based RM concerns with the product and availability control; accept or deny decisions for product requests, booking limits, seat inventory allocation etc. On the other hand, price based RM concerns with the prices; setting mix fares, variation of prices over time, market segmentation, auctions etc. This classification is highly studied in RM literature.

There are static and dynamic versions of RM problems. Static models assume that demand for different classes arrives in different time intervals in the order of increasing prices. Arrivals of classes are independent and random while demand for a specific class does not depend on the availability of other classes. Furthermore, static models ignore the way that demand arrives; in groups, sequentially over time etc. They assume an aggregate quantity of demand arrives in a single stage and the focus is whether to accept and how much of it to accept. On the other hand dynamic models assume arbitrary demand arrivals across from all fare classes. The main distinction between dynamic and static models is the arrival pattern of demand and the selection is based on the data available for a specific application. OR centered RM studies which dominate RM literature, deal with overbooking, capacity allocation and demand forecasting.

1.2.1 Single Resource Capacity Control

It is assumed that demand for different fare classes arrives sequentially; all booking requests for the lowest class come first in the static problem. Littlewood (1972), Belobaba (1987 a, b, 1989), Curry (1990), Wollmer (1992), Brumelle and Mcgill (1993), Robinson (1995) study the static problem.

Littlewood (1972) proposes a simple two-fare allocation rule. Given average high fare (f_1), average discount fare (f_2), random full fare demand Y, and s seats remaining, Littlewood's rule stipulates that a discount seat should be sold as long as the discount fare equals or exceeds the expected marginal return from a full fare booking of the last remaining seat; that is discount demand should be satisfied as long as $f_2 \geq f_1 \Pr(Y > s)$. This is essentially equivalent to the classic optimal stocking rule for single period stochastic inventory problems.

Belobaba (1987 a, b, 1989) develops an expected marginal seat revenue (EMSR) approach to find an approximation to an optimal policy for the single leg, multi-fare problem. He develops the idea of Littlewood (1972) as that was for two fare classes only. In order to determine when to turn away class i booking requests, he solves the two-fare problem for fares 1 and i, 2 and i,..., $i-1$ and i to obtain $S_1, S_2, ..., S_{i-1}$. Class i booking requests are rejected if the number of empty seats is $S_1 + S_2 + ... + S_{i-1}$ or less, and they are accepted otherwise. He finds that while the optimal policy often differs significantly from that of the EMSR model, the expected revenue from the optimal policy is extremely close to that of the EMSR policy. EMSR heuristic uses pair wise fare comparisons to quickly arrive at approximate booking limits. Because of its computational ease, his EMSR heuristic provides a natural alternative to the optimal policy.

Van Ryzin and McGill (2000) introduce a simple adaptive approach for finding protection levels for multiple nested fare classes, which has the distinctive advantage that it does not require any demand forecasting. Instead, the method uses historical observations to guide adjustments of the protection levels. They suggest adjusting the protection level upwards after each flight if all the fare classes reached their protection levels, and downwards if this has not occurred. They prove that the algorithm converges to the optimal nested protection levels under reasonable regularity conditions. This scheme of continuously adjusting the protection levels has the advantage that it does not need demand forecasting and therefore it is a way to get around all difficulties related with forecasting. On the other hand, the updating process needs a sufficiently large sequence of flights to converge to a good set of protection levels. In practice, such a start-up period cannot always be granted when there are profits to be made.

In the dynamic problem, demand for each class is modeled as a stochastic process. The decision to accept or to deny a request is based on the number of unsold seats and the remaining time to departure. Kleywegt and Papastavrou (1998) show that airline RM problem can be formulated as a dynamic and stochastic knapsack problem. Their work is aimed at a broader class of problems than only the single leg seat inventory control problem and includes the possibility of stopping the process before time 0 with a given terminal value for the remaining capacity, waiting costs for capacity unused and a penalty for rejecting an item. Their model is a continuous-time model but only considers homogeneous arrival processes for the booking requests. In a later study, Kleywegt and Papastavrou (2001) extend their model to allow for batch arrivals.

Lee and Hersh (1993), Chatwin (1996, 1998), Subramanian et al. (1999), Launtenbacher and Stidham (1999) and Liang (1999) study this dynamic type of seat inventory control. Gosavi et al. (2002) develop a model for a single leg of a flight that counters the factors such as; multiple fare classes, overbooking, concurrent demand arrivals across different fare classes, and class dependent random cancellations. They design a semi-Markov Decision Problem (SMDP) and solve it with reinforcement learning technique which is an approximation method to solve stochastic dynamic programming problems.

Zhang and Cooper (2005) present the simultaneous seat inventory control of a set of parallel flights between a common origin and destination with dynamic customer choice among the flights. They use simulation techniques to solve this stochastic problem.

1.2.2 Network Capacity Control

Optimizing the bookings over its network as a whole rather than on each flight leg in isolation can bring an airline more profit. Williamson (1992) shows that focusing on network aspect of RM problem leads to a significant increase of expected revenue over leg based methods. Gallego and van Ryzin (1997) capture this network aspect in a dynamic programming problem but in practice it is infeasible.

Wollmer (1986), Williamson (1992), Talluri and van Ryzin (1999 a, b) use mathematical programming for network RM while Curry (1990), Bertsimas and Popescu (2000) use alternative methods. Weatherford et. al. (1993) examine dynamic booking limits for two classes of passengers with sell-ups and overlapping dynamic arrival rates based on Belobaba's (1987, a, b) work. Independently, McGill (1988) and Curry (1990) develop models for the case where lower classes are booked first. They use continuous demand distributions. McGill's expressions for optimal booking limits are probability statements that require integration. Curry's optimal booking limits are expressed in terms of a convolution integral. He examines booking limits for a network of flights. He divides each origin-destination itinerary into one or more fare class-nests each of which contains at least one fare class. Curry shows that the revenue received from each nest is a concave function of the space allotted to it. By approximating the nest revenues by piecewise linear functions, he uses linear programming to allocate seats to the individual fare class-nests. His formulation does not allow seats to be swapped among the various nests. Wollmer (1992), Brumell and McGill (1993), and Robinson (1995) investigate the single-leg problem with multiple fare classes. They showed that Belobaba's heuristic is sub optimal. They develop procedures to find the optimal booking policy under the assumption that the probability of filling the plane is known. Liang (1999) proposes a continuous-time dynamic yield management model and shows that a threshold control policy is optimal. The control policy is for an arbitrary number of fare classes and arbitrary booking curves. Zhao and Zheng (1998) prove that a similar threshold control policy is optimal for a more general airline seat allocation model that allows diversion/upgrade and no-shows. Lee and Hersh (1993) present a general model of booking limits for multiple fare classes and multi seat booking requests by subdividing time into sufficiently small intervals. On the other hand, van Slyke and Young (2000) study a time dependent finite horizon stochastic knapsack model. They characterize the optimal return function and the optimal acceptance strategy for this problem. Feng and Xiao (2000) investigate a yield management model with multiple prices. They find an exact solution for the continuous time model and their value function is piecewise concave with respect to time and inventory. They claim that the implementation of optimal policies is fairly simple because of the existence of threshold points embedded in the value function. Feng and Xiao (2001) analyze an airline seat inventory control problem with multiple origins, one hub and one destination. They present a stochastic control model and develop optimal control rules. The basic model is subsequently distended to consider multiple fares on each route, time-dependent demands and booking control on an extended network. You (1999) considers a multiple booking class airline seat inventory control problem that relates to either a single flight leg or to multiple flight legs. He develops a dynamic pricing model in which the demand for tickets is modeled as a discrete time stochastic process. An important result of his work is that the strategy for the ticket booking policy can be reduced to sets of critical decision periods, which eliminates the need for large amounts of data storage. Bertsimas and de Boer (2000) introduce a simulation based solution method for the network seat inventory control problem. They design a method to get bid prices from the booking limits by use of simulation. The bid price is defined as the average of the opportunity costs over the simulations. El-Haber and El-Taha (2004) model a discrete time, finite horizon Markov decision process to solve the two-leg airline seat inventory control problem with multiple fare classes, cancellations, no-shows and overbooking. They analyze a formulation for the multi-leg airline seat inventory control problem. They conclude that their model provides solutions that are within a few percentage points of the optimal solution. For a comprehensive list of revenue management work, one can refer the survey paper of McGill and van Ryzin (1999).

1.2.3 Overbooking

Overbooking is the practice of ticketing seats beyond the capacity of an aircraft to allow for the probability of no-shows. Booked passengers who fail to show up at the time of flight departure, thus allowing no time for their seat to be booked through normal reservations process are no-shows. The characteristics of an airline seat such as perishability, advanced bookings and high fixed cost vs. low variable cost enable overbooking which is an essential opportunity to improve revenues. The overbooking decisions are based on two metrics; spoilage rate, the number of empty seats at departure expressed as a fraction of total seat and denied boarding rate, the number of denied boardings, as a fraction of total seats.

Research in this field can be divided into static models and dynamic ones too. Littlewood (1972) and Belobaba (1987 a, b) are examples of static version. Chatwin (1996, 1998) uses dynamic models to explain overbooking. Chatwin (1999) analyze a model of airline overbooking in which customer cancellations and no-shows are explicitly considered. He models the reservations process as a continuous-time birth-and-death process with rewards representing the fares received and refunds paid and a terminal value function representing the penalty. In particular, Subramanian et. al. (1999) present a model permitting cancellations, overbooking and discounting. They develop a discrete time, finite horizon Markov Decision Process (MDP), and solve by backward induction on the number of periods remaining before departure. Gallego (1996), Lee and Hersh (1993), Rothstein (1985) and Talluri and van Ryzin (1999 a, b) can be referred for overbooking policy and bid-price control. Bertsimas and de Boer (2005) combine a stochastic gradient algorithm and approximate dynamic programming to improve the quality of overbooking limits.

1.2.4 Dynamic Pricing

Dynamic pricing refers to prices updated in real time responding a change in market. Recent developments like Internet, mobile phones, e-commerce and decision support tools made dynamic pricing possible. Ng (2008) analyses dynamic pricing in two perspectives; demand-based dynamic pricing such as, auctions, bundle pricing/quantity discounts, e-coupons etc. and capacity-based dynamic pricing such as PROS which is a dynamic pricing optimization solution provider. Capacity-based optimization, in other terms optimization of capacity allocation and mix fares where capacity is perishable and fixed in the short term is a typical subject of RM field. Research in pricing can roughly be divided into static, dynamic pricing models and resource allocation-pricing models. Static models are based on the aggregate demand distributions while dynamic models represent demand as a controllable stochastic process. Zhao and Zheng (2000), Zhao (1999), Chatwin (2000), Feng and Xiao (2000), Feng and Gallego (2000), Gallego and van Ryzin (1997) and Paschalidis and Tsitsiklis (2000) study dynamic pricing models. The dynamic multi-class model of Zhao (1999) captures additional revenue from discount fare customers who accept the upgrading offer. This model assumes that demand for both classes arrive concurrently according to independent, non-homogenous Poisson processes. The approaches to find the optimal or approximate optimal solution for pricing problems have been proposed by Feng and Xiao (2000). Gallego and van Ryzin (1997) consider a finite horizon joint pricing and resource allocation problem. The continuous-time pricing problem can not be solved exactly, but the authors propose two heuristics based on a deterministic version of the problem that are asymptotically optimal as the scale of the problem increases. Paschalidis and Tsitsiklis (2000) address the pricing of network services as a finite-state, continuous-time, and infinite-horizon average reward problem. They also show that a static, deterministic model can be used to determine an asymptotically optimal pricing policy. Elmaghraby and Keskinocak (2003) present an overview of the literature and current practices in dynamic pricing in the presence of inventory considerations.

1.2.5 Auctions

Auctions offer a means of selling with dynamic prices reflecting market conditions. They are applicable in many industries such as; used cars, flowers, oil sales, bonds, real estate, art collectibles etc. They have become popular in daily life too by the emergence of e-commerce auction sites like eBay. EBay allows the seller to establish a reserve price for their products and the highest bidder buys the item above the reserve price. Besides, the seller may allow immediate purchase by setting a "buy now" price. Priceline.com provides a different auction mechanism that customers declare their prices to buy commodities and suppliers accept or reject these offers. It is called "buyer driven conditional purchase offer".

Cooper and Menich (1998) study the case where customers bid on products and firms allocate resource based on these bids. Klemperer's (1999) survey provides a broad source of literature on auction theory. Talluri and van Ryzin (1999 a, b) analyze a randomized version of the deterministic linear programming method for computing network bid prices. Their method consists of simulating a sequence of realizations of itinerary demand and solving deterministic linear programs to allocate capacity to itineraries for each realization. The dual prices from this sequence are then averaged to form a bid price approximation. Valkov and Secomandi (2000) study capacity auctions to allocate pipeline capacity in the natural gas transmission industry. Vulcano et al. (2002) present a specific dynamic auction model for RM. A seller with c units to sell faces a sequence of buyers in t time periods. They prove that dynamic variants of the first-price and second-price auction mechanisms can maximize the expected revenue and provide a model to compute and implement these optimal auctions. Van Ryzin and Vulcano (2002) study the optimal auction and replenishment policy for dynamic infinite-horizon auction problem. Baker and Murthy (2005) analyse auctions in RM in the presence of forecast errors where two market segments book in sequence and auctions are considered in neither, one, or both segments.

1.3 Other Topics in RM

Dynamic capacity is one of the topics covered in this study. Most of the researches mentioned assume the capacity available is deterministic while the demand is uncertain. Wang and Regan (2002) propose a solution for the continuous stochastic dynamic yield management problem in which flight capacities are subject to change. They suggest aircraft assignments accordingly. The problem is divided into two periods. The result from the second stage is used to derive the salvage function for the first period for determination of the optimal policy. They also claim that though only the simple case of changing capacity is considered, the method developed can be extended to a more general case where the capacity can be changed at multiple times and to multiple levels. Pak et. al. (2003) show how to incorporate the shifting capacity opportunity into a dynamic, network-based RM model. They use convertible seats for shifting business and economy class capacities. A row of these seats can be converted from economy class to business class seats and vice versa. When a row is converted from business to economy class, the number of seats in the row is increased and the width of each seat is decreased. It can be analyzed under dynamic capacity management.

Next, the analysis of business models of *no-frills and network carriers* is popular in RM literature. Franke (2004) makes a comparison of low cost carriers and network carriers in terms of market share and cost figures. He also discusses reasons why at least some network carriers should be able to restructure their business and return to a profitable growth.

Congestion pricing is significant for broadcasting and internet services. Paschalidis and Tsitsiklis (2000) study a dynamic programming formulation of the problems of revenue and welfare maximization for communication network industry. They develop congestion-dependent pricing of network services. This industry has similar characteristics with airline industry in terms of RM strategies.

They claim that a service provider charges a fee per call, which can depend on the current congestion level and which affects user's demand for calls. For airline industry, again, fares are higher in some seasons and total demand affects those fares. Besides, one similarity between two industries is that the marginal cost of serving an additional customer is negligible once a flight has been scheduled or a communications infrastructure is in place. They also consider that Internet relies on technical means to prevent congestion (the TCP - transmission control protocol), but includes no mechanisms for ensuring quality of service guarantees or for delivering service to those users who need it most. Pricing mechanisms can overcome these shortcomings, resulting in more efficient resource allocation, by charging users on the basis of the congestion that they cause. In their study, a pricing policy is a rule that determines the current vector u as a function of the current state $N(t)$. The process $N(t)$ is a continuous-time Markov chain. This Markov chain is uniformized, leading to a Bellman equation. Once Bellman's equation is solved, an optimal policy is readily obtained by choosing at each state N, a price vector u that maximizes revenue. They explore a number of alternatives such as the computation of the exact optimum and several approximations, and provide a comparison with congestion-independent pricing. One of the strongest results of their work shows that in the case of many small users, (users requiring less than 5% of the total bandwidth) static pricing is nearly optimal (within the 2% of the optimal static pricing policy) within the class of dynamic pricing policies.

RM models have been applied in a wide variety of industries where suppliers offer *flexible products*. Gallego and Phillips (2004) introduce the concept of flexible products for revenue management. They define a flexible product as a 'menu' of two or more alternative products offered by a supplier using a sale or booking process.

Managerial aspects of RM are essential both in terms of how RM is related to the other functions in the company and how to organize the right RM plan. RM has a great impact especially for sales, marketing, customer service, airport operations etc. It may have a positive influence on the performance of a department like marketing and a limiting influence on the performance of another department like customer service. Gaffey (1995) suggests airlines to coordinate the roles of RM with other functions for effective RM implementation. Besides, management needs to make a series of business decisions fast for the implementation of RM. Yeoman and Ingold (2000) discuss this decision-making processes using examples from airlines and hotels.

Another issue about revenue management is the *fairness perception* of customers. Customers who pay more for a similar product and could not perceive a difference of a higher fare possibly will view the situation unfair. They may perceive RM practices, especially overbooking or demand-based pricing, as unfair. If the tactics of RM is considered as unfair, revenue improvements will be short term. Thus, airlines need to make sure that customers are able to perceive the value of different fare products by justifying the price differences and changes. Kimes and Wirtz (2003) did a study on the perceived fairness of five demand based pricing methods for restaurants. They suggest that demand-based pricing in the form of coupon, time-of-day pricing, and lunch/dinner pricing are perceived as fair. Choi and Mattila (2005) conduct a scenario-based survey to study how much and what type of information hotels should provide customers to enhance their perception of fairness.

Solution methodologies of RM problems are another well studied topic in RM literature. In various researches mentioned in this study, some of the widely used solution techniques and approaches are as follows: linear or nonlinear programming, integer programming, dynamic programming, stochastic programming, heuristic methods, bid-price methods, reinforcement learning technique, greedy algorithms, adaptive algorithms, Markov Decision Processes, scenario trees, simulation, game theory and graph theory. Moving average methods, exponential smoothing methods, linear regression and time series methods are used for forecasting. Pak and Piersma (2002) present an overview of operations research techniques used in solving airline RM problems.

The *performance measurement of RM* applications is another topic that has gained interest in the literature. Although it is widely accepted that RM practices in airline, hotel management, car rental companies etc. are helping companies to improve their revenues, the exact contribution of these practices is very difficult to measure. Smith et al. (1992) show that American Airlines estimates that RM techniques improved the revenues by $500 million annually from 1989 to 1992. They use demand forecasts to determine the right number of seats that should be offered at the discount rate to maximize the revenue of each flight. Other companies such as United Airlines or the car rental company Budget reported similar contributions of RM practices in their businesses. Another example is Passenger Origin-Destination Simulator (PODS) which is a simulator developed and applied by airlines to examine the impact of revenue management methods. Eguchi and Belobaba (2004) use a modified-PODS to investigate the impact of revenue management on Japan's airline market. Anderson and Blair (2004) analyze an approach called *Performance Monitor* to measure the impact of RM through the lost revenue opportunities of historic decisions. Their approach is designed and implemented at Dollar Thrifty Automotive Group.

1.4 Competition and RM

Deregulation opened the airline business to newcomers just as Congress intended. According to Air Transport Association (ATA) Airline Handbook, in 1978, there were 43 carriers certified for scheduled service with aircrafts. By contrast, in 2005, there were 139 certificated U.S. air carriers. The number has fluctuated over the years with changing market conditions. Since 1990, there has been a wave of new airlines operating different business models ranging from low-cost hub-and-spoke and point-to-point network operators to regional carriers operating smaller aircraft for their mainline network partners. The appearance of new airlines, combined with the rapid expansion into new markets by many of the established airlines, resulted in unprecedented competition in the industry. The advent of overlapping national aviation networks resulted in increasing competition in hundreds of small markets that would not normally support competitive service with a linear route system. Proportionally, the biggest increase in competition occurred in the small and medium-sized markets.

Belobaba and Wilson (1997) analyze the impact of RM applications under competitive market conditions. They design a simulation model concerning passenger choice behaviour and the fluctuations of airline RM systems and use this model to assess the impact on market shares, traffic and revenues of each competitor in a hypothetical market. The results show that effective RM causes revenue increases for the users and there is a significant "first mover" advantage for the airline who implements RM before its competitors. The most common techniques to include competition within RM are the techniques introduced by game theory. The theory models the interaction between agents, who behave rationally and generate an action in response to competitors' actions. Yet, empirical testing of such models is almost impossible due to existence of a lot of confounding factors and there is not a clear solution to these too theoretic models to give feasible solutions.

1.4.1 Discount Fares

Increased competition generated discount fares, which travelers found to be the most important benefit of airline deregulation. Fares have declined more than 50 percent in real terms since deregulation in 1978. They have become so low, in fact, that interstate bus and rail services have been hard-pressed to compete with the airlines, which today provide the primary means of long-distance transportation between cities in the United States.

1.4.2 Growth in Air Travel

With greater competition on the vast majority of routes, extensive discounting and more available flights, air travel has grown rapidly since deregulation. In 1977, the last full year of government economic regulation of the airline industry, U.S. airlines carried 240 million passengers in scheduled service. In 2005 they carried 739 million. In a 2006 survey, the Travel Industry Association of America (TIA) found that 38 percent of Americans took a trip by air in 2005.

1.4.3 Frequent Flyer Loyalty Programs

Competition also enhanced marketing innovations, like frequent flyer loyalty programs, which reward customer loyalty with tickets, cabin upgrades, priority check-in, priority boarding, lounge access and other benefits. Most airlines have such a program. Once customers enrol, they can earn points for the number of miles flown or the number of trips taken on the sponsoring carrier or its partners. These points are then redeemed for rewards that include tickets and upgrades. A more recent development has been the growth of partnership marketing arrangements tied to frequent flyer loyalty programs. Because of their extensive membership rolls, frequent flyer programs are very attractive to non-airline companies who are willing to pay for the privilege of participating in them as marketing partners. In addition, the airline benefits as its loyalty program becomes more attractive through its relationship with partners: it is now possible to earn frequent flyer points by purchasing non-airline goods and services and redeem points for non-airline products. Frequent flyer programs are now integral to an airline's product offering, complementing convenient schedules, price, safety and customer service. Alliances have increased the popularity of such loyalty programs by extending reciprocal benefits to customers of member airlines.

1.4.4 Global Distribution Systems (GDS)

Another important result of competition is the initiation of computer reservation systems (CRS). These systems helped airlines and travel agents keep track of fare and service changes, and more efficiently process hundreds of millions of passengers worldwide. Several major airlines developed their own systems and later sold partnerships in them to other airlines. The systems listed not only the schedules and fares of their airline owners, but also those of any other airline willing to pay a fee to have their flights listed. Travel agents also paid fees to access the systems. In the 1990s, airlines began to separate from their computer reservation systems, allowing the systems to become independent businesses. The systems became known as global distribution systems (GDS) because of their increased functionality. Airlines do not reveal their complete availability information to the GDSs, not to reveal their inventory decisions to competing airlines for competitive purposes. For example, individual travelers access a GDS when booking a trip online. In addition, a GDS can be used to purchase hotel stays, rental cars and other travel services.

1.5 Air Travel Demand

Airlines face uncertainty in demand distribution over time. Accurate demand forecasting has always been an issue for airlines and it is a crucial side of RM studies. The researchers mostly dealt with stochastic heterogeneous and aggregated demand. They assumed demand is random in nature and the customer choice behaviour is probabilistic.

1.5.1 Forecasting and Customer Behaviour

Lee (1990) develops the necessary statistical framework to produce accurate forecasts of bookings in a particular fare class on a specific flight number departing on a given date at various points before departure. The booking process is modeled as a stochastic process with requests, reservations and cancellations interspersed in the time before a flight departs. Ng (2008) determines the reasons for ineffective demand forecasting. First, the past data may not be a good indicator of future since why customers purchase the way they do is just as important as how they purchase and demand characteristics should be based on the concepts of customer behaviour. Second, past demand profiles are subject to many factors such as; pricing strategies of competitors, the airline's reaction to them etc. Besides demand could be influenced by the customer attributes.

Consumer behaviour is widely studied in RM area too. Belobaba and Wilson (1997) use a simulation model including both passenger choice behaviour and the actual functions of airline RM systems. Their major finding is that there are important interactions between the impacts of yield management (YM) and airline frequency and flight schedule in a market, and also YM cannot overcome major schedule disadvantages. Headley and Bowen (1997) outline the efforts of the consumer researchers to develop a weighted, consumer oriented rating scale for the U.S.A. domestic airline industry as an alternative to survey based rating scales. Belobaba and Parkas (1999) introduce the recursive fare class spill model, which can be used to obtain more accurate estimates of spill for each specific flight demand scenario. They demonstrate that both the fare class-mix and the magnitude of spill can be affected by YM systems. Van Ryzin and Vulcano (2004), is helpful in terms of its approach to customer choice behaviour. They formulate a continuous demand and capacity approximation of optimization of the protection levels for airline virtual classes accounting for the choice behaviour of its customers, which also allows for the partial acceptance of requests for products. They calculate the simple path gradient of the network revenue function and then use it to construct a stochastic steepest ascent algorithm. In the model, they use a general demand function based on a path description of the number of customers and their preferences. They also assume that each customer requires a random quantity of plane tickets. So each sample path includes the preference vector and quantity vector for each individual. They describe the revenues on a sample path basis by using some extra notation. $X_i^j(t)$; the capacity available to a customer t in product j's virtual class on resource i, which is the remaining capacity minus the protection level for virtual classes higher than the virtual class of j on resource i, less the amount of capacity already purchased of products with higher preference that also use resource i. Capacity allocated to a product j is u_j, a function of remaining capacity, protection level, preference vector and quantity vector. So they describe revenue of a state as fare times capacity allocated to products plus revenue that can be obtained from next states and so on. Afterwards they maximize the expected revenue function over the set of feasible protection levels. They find out sample path gradients of the revenue function to obtain an efficient recursion. They also show that the revenue function is Lipschitz continuous in terms of its parameters and justify the interchange of differentiation and expectation. The stochastic gradient can then be used in place of the actual gradient in a steepest ascent type algorithm to search for an optimal vector of protection levels. In summary, they propose a model and a method to find locally optimal nested protection levels for network capacity control under a general model of customer choice behaviour.

1.5.2 Effect of Socio-Economic and Technological Changes on Air Travel Demand

Air travel decisions have been affected by socio-economic changes and technological changes in the last few decades. Air travel demand could be unpredicted by exogenous factors such as terrorist acts involving commercial aircrafts, the spread of the severe acute respiratory syndrome (SARS) virus, rising unemployment rates, etc. Rubin and Joy (2005) examine the airline structure and change for customers. The growth of low fare airlines motivated competitive change in the industry. The cost structure of these airlines allows lower cost per seat-mile and profitability at lower fares and load factors. For instance, Southwest Airlines breaks even at 60% load factor whereas network airlines might need 90% load factors to break even according to Federal Reserve Bank of Atlanta (2003). Economic market factors have increased elasticity of demand and studying the state of demand elasticity is more crucial than ever. In Chapter 4, demand elasticity has been considered profoundly in the proposed modeling too. On the other hand, technological changes such as; the rise in online purchases, more knowledge about substitutable flights, and developments in telecommunication technologies influenced air travel decisions. Online purchases allow cost savings of distribution and selling costs from the perspective of airlines. According to Travel Industry Association of America (2002), 39 million people purchased air travel through Internet in 2002, a 25% increase from 2001. Customers, on the other hand, have more transparency on prices and availabilities of the products, increasing demand elasticity and the pressure to decrease the prices. Mackinac Center for Public Policy (1997) states that leisure travellers are the majority, (85%) of all travellers and their demand elasticity is about 2.4, that is a 10% fare reduction increases sales by 24% and the demand elasticity of business travellers is 0.1; highly inelastic. Widespread of videoconferencing and webcasting decreases the number of travellers. For example; college students take online courses at distant locations and business people have group meetings or job interviews via audio/video streaming as discussed in Cope (2002).

1.5.3 Demand Elasticity

Demand is elastic because of customers' sensitivity to price. The elasticity is influenced by several factors. Ng (2008) examines these factors in her book.

- Availability of substitutes: If there are substitutes in the market, demand will be more elastic, as in the case of airlines.
- The degree of necessity: If the product is considered as necessary as opposed to luxury, its demand will be less elastic such as dentists vs. cosmetic surgery.
- Habitual: If the customer gets used to buy/use a specific product, s/he becomes less elastic with respect to its price such as beauty spas.
- Proportion of the income spent on the service: When the proportion of the income spent is high; the demand is highly elastic as in the case of tour package for a family holiday.
- Time span in the purchase/consumption of the service: Over the long run, customers adjust themselves and demand becomes more elastic such as price changes in utilities.
- Price points: A reduction in the price of a product/service has different effect on elasticity with respect to the original price.
- Short term price changes: Offering a one week promotion in a restaurant does not have the same effect on elasticity if the promotion was effective continuously.

1.6 Airlines

As the earliest and leading user of RM, airlines deserve special attention. Airlines with respect to industry, corporate structure, business, RM organization, and the booking process are discussed in detail to inform the readers about airlines and prepare them to comprehend the thesis presented. Since the issues examined in this research are airline related problems, the following topics are explored thoroughly:

1.6.1 Airline Industry

The airline industry is characterised by an oligopoly market structure, a form of imperfect competition where several carriers dominate the industry. There are network carriers, regional carriers and cargo carriers etc. They all have to meet strict standards and regulations to fly an aircraft; both at international and national level. Rubin and Joy (2005) explore customer impact of airline industry change. The standard measure of oligopoly market power is the industry concentration ratio. It shows the ratio of market share of the biggest companies to the entire market. ATA (2002) states that 6 major airlines had 70% market share of U.S. passengers in 2001. A critical oligopoly characteristic is the high fixed cost coming from the high capital investment. ATA (2002) reports that two-thirds of the costs are fixed costs for airlines. Airlines may achieve economies of scale by route optimization and alliances. Airline industry like other industries with high capital costs is unstable in terms of price determination, product differentiation, economies of scale and contestability with low-cost carriers.

1.6.2 Airline Corporate Structure

There are operations, sales and marketing, reservations and ticketing, management and administrative staff departments in a typical airline corporate. *Operations* include flight, ramp, customer service and technical operators. Operations personnel are responsible for operating an airline's fleet of aircraft safely and efficiently. They schedule the aircraft and flight crews and develop and administer all policies and procedures necessary to maintain safety and to meet operating requirements. Operations is in charge of all flight-crew training and it establishes the procedures crews are to follow before, during and after each flight to ensure safety. Dispatchers release flights for takeoff, following a review of all factors affecting a flight. These include weather, routes the flight may follow, fuel requirements, and both the amount and distribution of weight onboard the aircraft. Weight must be distributed evenly aboard an aircraft for it to fly safely. By keeping planes in excellent condition, maintenance programs keep aircraft in safe, working order; ensure passenger comfort; preserve the airline's valuable physical assets (its aircraft); and ensure maximum utilization of those assets. An airplane costs its owner money every minute of every day, but generates revenue only when it is flying with freight and/or passengers aboard. It is vital to an airline's financial success that aircraft are properly maintained. In addition to large maintenance facilities, airlines typically have inspection and repair capabilities at hub or focus-city airports.

Sales and Marketing division encompasses such activities as pricing, scheduling, advertising, ticket and cargo sales, reservations and customer service, including food service. While all are important, pricing and scheduling, in particular, can make or break an airline, and both have become more complex and a source of competitive advantage since deregulation. Airline prices change frequently in response to supply and demand and to changes in the prices of competitors' fares. Schedules change less often than fares, but far more often than when the government regulated the industry. Airlines use sophisticated global distribution systems (GDS) and their own Web sites to market and distribute their schedules and fares directly to consumers and to intermediaries such as travel agents. Travel agents, who sell approximately 70 percent of all airline tickets, use GDS systems to research flight schedules and available fares, book reservations, and issue electronic tickets for travelers.

Reservations and Ticketing division adapts the changes in recent years. Major changes in air transportation have simplified the process for airline passengers to make a reservation and to purchase a ticket. Electronic commerce is playing a rapidly growing part in today's airline industry. In addition to the paper tickets issued in the past, all of the major airlines now offer electronic ticketing for domestic and international air travel. Today's e-tickets allow an airline to document the sale and track the usage of transportation. Passengers worry less today about carrying flight coupons or losing their tickets. They have the ability to shop for the lowest priced transportation, make or change a reservation, select a seat assignment, request refunds, and perform other functions, not only through their travel agent but also from a personal computer or telephone. The number of air travelers shopping, making reservations and purchasing electronic tickets using the Internet is increasing daily. Airlines continue to adapt new technologies to automate check-in procedures. Customers now have the ability to verify their itineraries, select seat assignments, obtain cabin class upgrades and print their own boarding passes, at their own discretion. Electronic self-service check-in kiosks are now prevalent at all major airports for use by passengers holding e-tickets. Internet check-in functionality is now available on many carriers' own Web sites.

Management and Administrative Staff includes specialists in such fields as law, accounting, finance, corporate real estate, network planning, revenue management, governmental affairs, employee relations, corporate communications and public relations. Their function is to plan, manage and support the firm's operations and employees, so that the airline runs efficiently and profitably. Staff personnel typically work out of corporate headquarters and fall into several broad corporate job categories: finance and property, purchases, information technology, personnel, medical, legal, communications, public relations and planning. Finance and corporate real estate divisions handle company revenues, finances and assets. They oversee all company property and the purchase of food, fuel, aircraft parts and other supplies needed to run an airline. Information technology designs and maintains the company's internal computer systems used to store and analyze data needed for operations and planning.

1.6.3 Airline Business

Airline Revenue: According to Air Transport Association (ATA) Airline Handbook, on average, 80 percent of a U.S. passenger airline's revenue comes from passengers purchasing tickets. Of the balance, the majority comes from cargo and other transport-related services. For the all-cargo sector, of course, freight, express and mail is the sole source of transport carriage revenue. The majority of tickets are processed by travel agents, most of who rely on global distribution systems (GDS) to keep track of schedules and fares, to book reservations and to print tickets for customers. Similarly, freight forwarders book the majority of air-cargo space. Like travel agents, freight forwarders are independent intermediaries that match shippers with cargo suppliers.

Airline Costs: According to reports filed with the Department of Transportation in 2005, airline costs were as follows:

- Flying Operations: essentially any cost associated with the operation of aircraft, such as fuel and pilot salaries; 37 percent
- Maintenance: parts and labour; 10 percent
- Aircraft and Traffic Service: basically the cost of handling passengers, cargo and aircraft on the ground and including such things as the salaries of baggage handlers, dispatchers and airline gate representatives;14 percent
- Promotion/Sales: including advertising, reservations and travel agent commissions; 6 percent
- Passenger Service: in-flight service, including such things as food and flight attendant salaries; 6 percent

- Transport Related: outsourced regional capacity providers, in-flight sales; 17 percent
- Administrative: 6 percent
- Depreciation/Amortization: equipment and plants; 5 percent.

Labour costs are common to nearly all of these categories. When looked at as a whole, labour accounts for a fourth of the airlines' operating expenses and three fourths of controllable costs. Fuel recently overtook labour as the airlines' largest cost (about 25 to 30 percent of total expenses), and transport-related costs are third (about 17 percent). Transport-related costs, in particular, have grown sharply in recent years, and many airlines have outsourced a substantial portion of their flying needs to smaller regional carriers to align supply and costs more closely with demand.

Scheduling: Since deregulation, airlines have been free to enter and exit any domestic market at their own discretion and have adjusted their schedules often, in response to market opportunities and competitive pressures. Along with price, schedule is an important consideration for air travelers. For business travelers, who typically are time sensitive and value convenience, schedule is often more important than price. A carrier that has several flights a day between two cities has a competitive advantage over carriers that serve the market less frequently, or less directly. Airlines establish their schedules in accordance with demand for their services and their marketing objectives. Scheduling, however, can be extraordinarily complex and must take into account aircraft and crew availability, maintenance needs and local airport operating restrictions. Airlines do not cancel flights because they have too few passengers for the flight. The nature of scheduled service is such that aircraft move throughout an airline's system during the course of each day. A flight cancellation at one airport, therefore, means the airline will be short an aircraft someplace else later in the day, and another flight will have to be cancelled, rippling costs and foregone revenue across the network. If an airline must cancel a flight because of a mechanical problem, it may choose to cancel the flight with the fewest number of passengers and utilize that aircraft for a flight with more passengers. While it may appear to be a cancellation for economic reasons, it is not. The substitution was made in order to inconvenience the fewest number of passengers.

Fleet Planning: Selecting the right aircraft for the markets is vitally important to its financial success. As a result, the selection and purchase of new aircraft is usually directed by an airline's top officials, although it involves personnel from many other divisions such as maintenance and engineering, finance, marketing and flight operations. There are numerous factors to consider when planning new aircraft purchases, beginning with the composition of an airline's existing fleet. For example; some potential aircraft purchases are related to replacement of existing aircraft and some are intended to drive service growth. The potential cost impacts on a carrier's fuel and maintenance programs, its crew resources and its training requirements are important too. In general, newer aircraft are more efficient and cost less to operate than older aircraft, as a result of new airframe and engine technologies. A Boeing 737-200, for example, is less fuel efficient than the 737-700 that Boeing designed to replace it. As planes get older, maintenance costs can also rise appreciably. However, such productivity gains must be weighed against the cost of acquiring a new aircraft. the airlines ability to afford to take on more debt is crucial. The effects on profits, the company's credit rating, and the borrowing cost of money need to be considered carefully. A company's finances, like those of an individual considering the purchase of a house or a new car, play a key role in the aircraft acquisition process. Marketing strategies are important, too. An airline considering expansion into international markets, for example, typically cannot pursue that goal without long-range, wide-body aircraft. If it has principally been a domestic carrier, it may not have that type of aircraft in its fleet. Besides, changes in markets already served may require an airline to reconfigure its fleet. Having the right-sized aircraft for the market is vitally important. Too large aircraft can mean that a large number of unsold seats will be moved back and forth within a market each day. Too small aircraft can mean lost revenue opportunities. Since aircraft purchases take time (often two to four years if there is a production backlog), airlines also must do some economic forecasting before placing new aircraft orders. This is perhaps the most difficult part of the planning process, because no one knows for certain what economic conditions will be like many months, or even years, into the future. An economic downturn coinciding with the delivery of a large number of expensive new aircraft can lead to deep financial losses. Conversely, an unanticipated boom in the travel market can mean lost market share or operating-cost disadvantages for an airline that held back on aircraft purchases while competitors were moving ahead. Sometimes airline planners may determine that their company needs an aircraft that is not yet in production or even in design. In such cases, they approach the aircraft manufacturers about developing a new model, if the manufacturers have not already anticipated their needs. Typically, new aircraft reflect the needs of several airlines because start-up costs for the production of a new aircraft are enormous and, consequently, manufacturers must sell substantial numbers of a new model just to break even. They usually will not proceed with a new aircraft unless they have a launch customer, meaning an airline willing to step forward with a large order for the plane, plus smaller purchase commitments from several other airlines. There have been several important trends in aircraft acquisition since deregulation. One is the increased popularity of leasing versus ownership. Leasing reduces some of the risks involved in purchasing new technology. It also can be a less expensive way to acquire aircraft, since high-income leasing companies can take advantage of tax credits. In such cases, the tax savings to a lessor can be reflected in the lessor's price. Some carriers also use the leasing option to safeguard against hostile takeovers. Leasing leaves a carrier with fewer tangible assets that a corporate raider can sell to reduce debt incurred in the takeover. A second trend in fleet planning, relates to the size of the aircraft ordered. The development of hub-and-spoke networks resulted in airlines adding flights to small cities around their hubs. In addition, deregulation enabled airlines to respond more effectively to consumer demand. In larger markets, this often means more frequent service. These considerations increased the demand for small and medium size aircraft to feed the hubs. Larger aircraft remain important for the more heavily traveled and capacity-constrained routes, but the ordering trend is toward smaller jet aircraft. The third trend is toward increased fuel efficiency. As the price of fuel rose rapidly in the 1970s and early 1980s, the airlines gave top priority to increasing the fuel efficiency of their fleets. The most recent run-up in fuel prices in the 21st century has renewed focus on this issue by both airlines and airplane manufacturers, leading to numerous design innovations on the part of manufacturers. Today, airline fuel efficiency compares, on a per passenger basis, favourably with even the most efficient autos. Similarly, the fourth trend has been in response to airline and public concerns about aircraft noise and engine emissions. Technological developments have produced quieter and cleaner-burning jets, and Congress produced timetables for the airlines to retire or update their older jets.

1.6.4 Airline RM Organization

Airlines need to establish RM organization to implement RM system and to achieve sustainable revenue improvements.

According to Weatherford and Bodily (1992), the objective of airline management is maximizing revenues without sacrificing customer satisfaction. There are operational, marketing and strategic constraints in airline operations. As operational constraint, there is a fixed capacity of seats to offer. Aircrafts with different cabin capacities could be used for a given flight. Scheduled routes, the number of aircrafts and the frequency of flights are other operational constraints. As marketing constraints, there are minimum tolerable customer service levels such as number of denied customers or number of customer complaints etc.

Strategic constraints are determined by the long term vision of the top management which could be affected by the competitors' actions, their prices, routes, and flight schedules. The costs relevant to RM studies are variable costs for the seat and the cost associated with the denied boarding event. Denied boarding cost is hard to measure as it includes loss of customer good will besides denied boarding compensation, possible overnight hotel stay or complimentary things.

1.6.5 Airline Booking Process

The objective in airline seat inventory control is to maximize revenue by optimally allocating the seats in the aircraft among the various fare classes. Most airlines offer price discount based on restrictions such as; advanced purchase restrictions (of 7, 14, 21 and 30 days), Saturday night stay, non-refundability, and fees for request of changes in itineraries. The low cost carriers especially focus on advanced purchase discounts and change fees. Airlines are able to change their pricing structures taking into account the fundamental differences between leisure travelers and business travelers. In general, business travelers are time sensitive and tend to make reservations closer to the departure date. On the other hand, leisure travelers are price sensitive and book well before the departure date. In order to protect seats for high fare passengers, airlines need to limit seats available to early booking low fare passengers. In other words, seats that are available for sale to a particular booking class are also available to bookings in any higher fare booking class, but not the reverse. This process is called nesting.

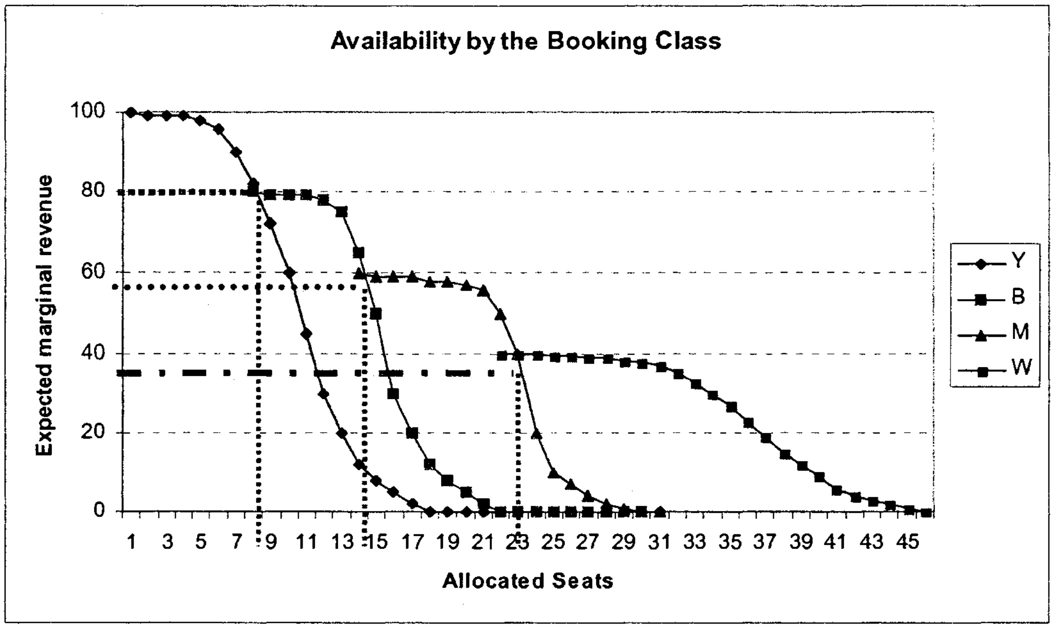

Figure 1.1: Nesting Process

Airlines offer different compartments of service; first, business and coach. Each compartment has a number of fare classes; 8 or more for coach, one or two for business and one or two for first. These classes are represented by letters; F for first class, J and C for business, Y for full fare coach and M, B, W and others for discounted fare classes in coach. As seen in Figure 1.1, in practice, there are different fare classes like Y, B, M and W and for a higher fare class expected marginal revenue obtained is higher and low fares are not available always because of nesting strategy. For instance the fare class W is not available for sale once the available capacity is less than 23 and the fare class M is not available once the available capacity drops below 14.

There are many researches done in seat inventory control but none of them suggests a perfect modeling of revenue maximization, in terms of being realistic and at the same time being practical. There are a lot of variables to model and execution time of these models are long and they are not convenient to use in a reservation process of an airline. In other words, there is a trade of between being optimal and being practical in terms of modeling. As a result, there are studies concerning near optimal solutions by using some heuristic methods in literature.

The crucial decision in RM problem is whether to accept a request or deny it with available data in the system. A booking policy is a set of rules that specify at any point during the booking process whether a booking class should be open. Figure 1.2 illustrates the entire booking process clearly:

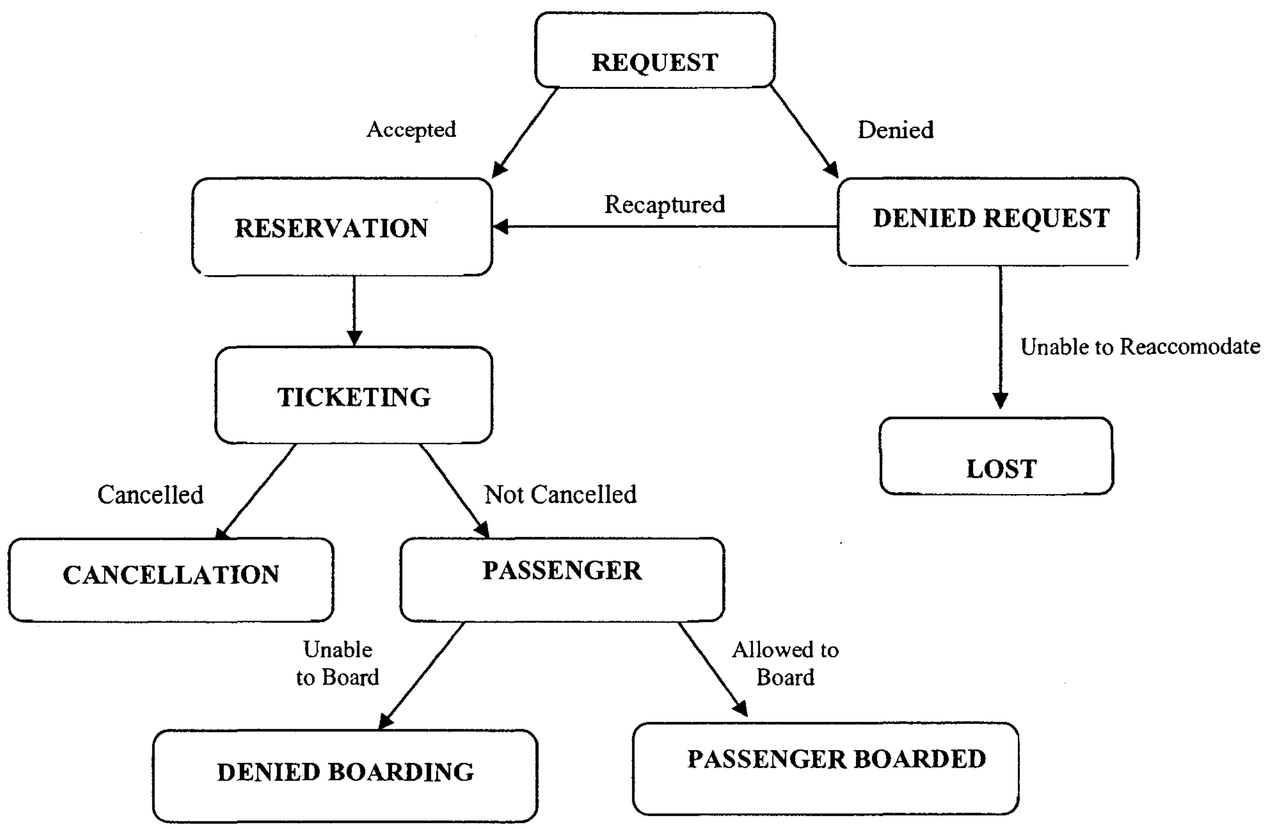

Figure 1.2: Booking Process

RM systems require an information system that identifies the booking patterns resulting from continuous demand forecasts, estimates price elasticity of demand and suggests optimal booking policies. Furthermore, a company which wants to implement RM has to be able to reasonably forecast the demand of its different customer segments and in addition to that the company has to develop sophisticated capacity allocation techniques in order to reserve enough capacity for high-value customers. If frequent ticket cancellations do occur, the company might also use the technique of overbooking by selling more of its capacity than it actually has. While this might lead to some unsatisfied customers in the case that the final demand was underestimated, the benefit of overbooking is that the company's capacities are better used.

1.7 Alliances

Airlines are seeking various ways to increase their strength in the market through mergers, purchase of equity from other carriers and a variety of joint marketing agreements and cooperative ventures. An alliance is a strategy either to enter new markets or to enhance advantages collectively and to improve service quality and profitability. International Air Transport Association (IATA) defines airline alliance as three or more airlines participating in commercial relationship or joint venture, where (i) a joint and commonly identifiable product is marketed under a single commercial name or brand; and (ii) this commercial name or brand is promoted to the public through the airlines participating in the alliance and its agents; and (iii) the commercial name or brand is used to identify the alliance services at airports and other service delivery points in situations where bilateral agreements exist, e.g. code share agreement. According to Iatrou and Alamdari (2005), the majority of airlines want to extend their network but they have been pushed towards forming alliances instead of acquisitions and mergers due to the regulatory restrictions on market access, ownership and control. For example, a non-US airline can only have up to a maximum of 25% of share in any US carrier. A non-EU carrier can purchase up to a maximum of 49% of a EU carrier. Thus alliances have occurred to expand networks, to reduce costs, and to improve service, customer satisfaction and revenues. Iatrou and Alamdari (2005) conclude that alliances, regardless of the type of cooperation (FFP - frequent flyer program-, Code Share, Strategic Alliance with and without antitrust immunity) bring an increase in passenger traffic with a parallel increase in load factors and some reduction in costs. The greatest benefits come from alliances with the more advanced and integrated forms of cooperation, as Wings alliance, which is characterized by the existence of antitrust immunity and the establishment of a joint venture.

Another innovation has been the development of code-sharing agreements. In code sharing agreements, passengers fly a segment of their journey on an airline other than the airline that sold the ticket for that particular flight. Code-sharing agreements allow two (or more) airlines to offer a broader array of services to their customers than they could individually. These marketing arrangements enable an airline to issue tickets on a flight operated by another airline as if it were its own, including the use of its own two-letter code for that flight. These arrangements allow airlines to market expanded networks for their passengers at minimal expense. Code-sharing agreements can be between a larger airline and a regional airline or between a U.S. airline and a foreign airline or any combination thereof. Code-sharing agreements often link each airline's marketing and frequent flyer programs and facilitate convenient connections between the code-sharing partner carriers. Code sharing with foreign carriers allows U.S. airlines to expand their global network reach through the services operated by their partners.

In addition to code sharing, several groups of airlines have formed global alliances, such as *Wings*, *oneworld*, *Star* and *SkyTeam*, that compete against each other for international passengers. Each alliance consists of several carriers, including some that may fly under the same flag, which not only share codes on one another's flights and link frequent flyer programs, but also offer consumers benefits such as common airport terminal and lounge facilities and coordinated flight schedules. In addition to expanded networks, participating airlines benefit from reduced costs through the sharing of staff, facilities, sales offices and ancillary services. Groenewege (2003) states that, the alliances provide a wider choice of routings and schedules for the customers as well as simplification of travel; allowing passengers to fly to many areas in the world on a single ticket. FFPs between participating airlines might bring additional benefit for the customers too.

1.8 Scope, Contributions and Objectives of the Dissertation Research

1.8.1 Scope and Contributions

There is a vast literature about RM theory and applications covered in this thesis. Our review shows that many aspects of RM are inspected thoroughly in these studies. Most studies deal with either quantity-based RM where the control is on seat capacity allocations and the booking limits or price-based RM where pricing strategy of airline determines its RM system. All models aim to obtain higher revenues and/or higher loading factors. Incremental revenue opportunities searched through various models, theories, algorithms, and solution methodologies. We fill some voids in the literature and explore new revenue opportunities through the proposed approaches. The issues covered in this research are options approach in airline booking systems and peak load pricing strategy to make accept/deny decisions for aircraft maintenance service.

The contributions of this research are:

- We propose a new approach for selling airline tickets which compensates fluctuation in demand and allows pricing of seat value from customers view. A mathematical model is introduced and a simulation study is conducted to explore the effectiveness and the potentials of the financial options in airline reservation systems. Simulation analysis is conducted to show revenue and load factor improvements via options. An option is defined as the right to buy or sell an asset at a fixed price before a predetermined date. Financial options are used as a tool for changing the firm's risk exposure. We develop an "option" based seat management strategy, which would potentially serve as a more revenue generating alternative to the existing "overbooking" based RM. Efficient capacity utilization brings operational efficiency with higher load-factors and presents a profit opportunity. To this date, there is no theoretical study or a practical application investigating the utilization and potentials of financial options in the booking process of airlines.

- A peak load pricing model is designed to maximize revenue of an aircraft maintenance company by shifting demand through pricing. We model our problem only allowing discounts to attract customers at off-peak periods and leaving regular prices as they are at peak periods. The algorithm requires the solution of m single knapsack problems, which can be solved in pseudo-polynomial time by dynamic programming. To our knowledge, this peak load pricing problem has not been studied before with a comprehensive approach for maintenance services but the dynamic programming knapsack algorithm is used in various contexts in the literature.

1.8.2 Objective

The overall objective in this research is to propose a new way of selling tickets to utilize capacity more efficiently and to propose a pricing strategy which takes into account the service time, the price elasticity and the price discount leverages for aircraft maintenance service. The options approach is justified with a simulation study showing revenue and load factor improvements over traditional overbooking approach. On the other hand, the peak load pricing approach is analytically solved with a dynamic programming algorithm which has been used to solve the longest common subsequence (LCS) problem in the literature. C++ programming is used to execute the algorithm and the program is computationally feasible for realistically sized problems.

The specific objectives of the proposed research are as follows:

- To position financial options in airline booking process
- To stabilize the adverse effect of the uncontrollable factors such as; demand and fuel prices via options.
- To attempt to quantify the impact of options approach on airline revenues and load factors by a simulation study.
- To conduct sensitivity analysis for options approach assessing numerical results for various scenarios.
- To characterize aircraft maintenance demand and supply
- To segment the market based on the characteristics of maintenance demand and the demand elasticity of customers to explore potential RM application opportunities
- To design a peak load pricing model for job selection of maintenance companies.
- To solve the proposed pricing model by dynamic programming algorithm, coded in C++.
- To analyze results to confirm revenue improvements and to see the impacts of price discounts, demand elasticity and service time on revenue improvements.

- To provide flexibility for the program users, enabling them to decide on decision variables for their case.

1.9 Thesis Organization

The rest of this thesis is organized in the following manner:

Chapter 2, the literature directly related to the contributions of this thesis is reviewed. This literature is about financial options based RM and peak load pricing RM in aircraft maintenance business. The connection between these studied topics of RM is presented in Chapter 3. Chapter 4 entitled *RM with Options Approach* introduces the financial options and their potential place in airline booking process. A RM model with options approach replacing a traditional RM model with overbooking is designed. A simulation analysis is conducted to see the impacts of options and numerical results are used to compare two models.

Chapter 5 is devoted to explain aircraft maintenance service and to explore a RM opportunity for the industry. Based on the maintenance demand characteristics, peak load pricing is modeled to make accept/deny decisions for maintenance orders. A dynamic programming algorithm is used to solve the model. Numerical results are illustrated to show the effect of demand elasticity, price discounts and service time on load factors and revenues.

Conclusions and the directions of future work are given In Chapter 6. This chapter begins with summary and conclusions of the thesis and then major contributions are given. Then extensions of the proposed models are discussed. Finally the practical issues surrounding the RM applications are examined.

Chapter 2

2. Literature Review

A broader literature related to the general RM concepts is reviewed earlier in Chapter 1. It is our guideline to explore new expansions and opportunities related to the field most of which is analysed in the rest of this study. In this chapter, the literature directly related to the contributions of this thesis which are; the RM applications in the financial options-based airline booking and peak load pricing of aircraft maintenance business is summarized. First, literature about options approach is given then peak load pricing literature is discussed.

Research in options mostly focuses on financial markets. In recent years a new theory of pricing and operating assets has been developed when uncertainty and managerial flexibility in operating strategies are involved. This is the theory of real options (Dixit and Pindyck, 1994). Analytical approaches applying real options are studied by Amram and Kulatilaka (1999). Merton (1990), Hull (2003) and Wilmott (2000) develop mathematical models on option pricing. It is known that options are used for aircraft purchases and fuel hedging in airline industries but not in the booking process. Anderson, Davison and Rasmussen (2004) present a real options approach related to the swing options used in the power industries, specifically suited to the car rental business. They illustrate the concept with actual car rental data.

However, to the best of our knowledge, utilization of financial options in the airline booking systems has not been studied to this day. So the direct literature in this field is almost none.

On the other hand, literature about peak load pricing and aircraft maintenance is vast. We attempt to apply peak load pricing in aircraft maintenance industry which has not been explored before, to the best of our knowledge. The literature reviewed here analyses the theory and the practice of peak load pricing and the characteristics of aircraft maintenance business separately. Studying both literatures allows us to apply peak load principles for aircraft maintenance industry.

Until recently, aircraft maintenance centers (AMCs) were considered as cost centers within airlines. As a result, the literature on Aircraft Maintenance focused on effective and efficient maintenance operations. On the other hand, the business structure of AMC's has changed drastically in the last decade. Especially small airlines dispatched their AMCs and started outsourcing their maintenance needs. Even large airlines incline to outsource their heavy maintenance work to private contractors (third party vendors) in order to cut costs. According to Seidenman and Spanovich (2005), it is only practical for carriers to outsource their maintenance works since maintenance, repair and overhaul (MRO) industry is able to provide the maintenance service at lower cost; offering competitive advantage to airlines. Adams (2005) highlights the increasing percentage of outsourcing maintenance of major airlines which is outlined in Table 2.1. She informs that Delta Airlines outsourced scheduled maintenance for 344 jetliners to Air Canada Technical Services (ACTS) saving $240 million over five years.

Table 2.1: Outsourcing Maintenance (Adams, 2005)

Carrier	1990	2003	2004 (through Sept. 30)
Alaska	76%	75%	80%
American	27%	38%	42%
America West	45%	75%	72%
Continental	44%	65%	65%
Delta	13%	37%	35%
JetBlue	NA	51%	63%
Northwest	20%	56%	51%
Southwest	72%	65%	64%
United	21%	41%	54%
US Airways	50%	58%	60%

ACTS is subsidiary of Air Canada responsible from maintenance operations which was originally built as in-house maintenance division of Air Canada in 1937. Influenced by the mentioned recent developments in the maintenance industry, Air Canada announced the formation of ACTS, a new organization within ACE Aviation Holdings, the parent company of Air Canada, which operates as a global maintenance, repair and overhaul profit centre (Canadian Corporate News, 2000).

Obviously the changing nature of the maintenance industry pushes the researchers to canalize on revenue aspect of AMCs as well as the cost aspects. Hence firstly, the literature discussing the cost aspects of AMCs is reviewed. Secondly, various RM studies are analyzed to motivate the proposed RM model on for aircraft maintenance business.

Literature on aircraft maintenance mainly focuses on scheduling, maintenance operations, and operational efficiency. Dijkstra et al (1994) study a scheduling problem for aircraft maintenance of KLM Royal Dutch Airlines. First, they use workforce and workload estimates as inputs to find out the teams with minimum number of engineers while satisfying service level constraints. Then this output is used as input to maximize service level given the maintenance teams. Later, Ahire et al. (2000) tackle the scheduling problem with an objective to minimize the turnaround time for the maintenance operations using evolution strategy algorithm. While Dijikstra et al (1994) attempt to maximize service levels, Ahire et. al. (2000)'s objective is to minimize the service time.

A large body of works in maintenance system models and operations is available in literature. Duffuaa et al. (2001) highlight the importance of maintenance operations in an organizations structure and develop a generic conceptual model for maintenance systems. Their study is helpful to understand the details of maintenance operations. The aircraft maintenance is the set of actions necessary to sustain or restore the integrity and performance of an airplane. The criterion used to measure a safe flight is airworthiness. Airworthiness shows whether an aircraft is worthy of safe flight. It includes aircraft inspections; routine inspection, minor services and tests performed at prescribed intervals, scheduled maintenance; replacement of life-limited items, periodic overhauls and special inspection; and unscheduled maintenance; which is generated by inspections, pilot reports and failure analysis. Lopez and Centeno (2006) design an integrated maintenance information system to supply efficient bus transportation maintenance service focusing on forecasting of maintenance demand, time standardization of maintenance jobs and work scheduling model. They claim better planning of repairs will result in cost savings, timely maintenance and reduction of road calls, and more efficient and cost effective transit service. Duffuaa and Andijani (1999) outline the elements of an integrated simulation model for the maintenance system at Saudia Airlines. Their model is composed of several modules; planning and scheduling, maintenance organization, supply, quality control and performance measures that represent the maintenance activities and the interaction of the maintenance activities. Gatland, Yang and Buxton (1997) give an overview of an engine maintenance system, develop a capacity planning problem and apply a simulation analysis. They analyze the available capacity of the engine maintenance facility versus the current realized capacity and find out loading of engines into the repair cycle has a great effect on the capacity of the facility. According to Valeika (2007), the Aircraft Maintenance, Repair and Overhaul (MRO) business today is very fragmented and runs on a job shop basis. It is a system that is lacking direction and currently is organized and operated on a strictly functional level, that is; there are engine repair facilities, component repair facilities, line and hangar maintenance support groups, etc. The aircraft business does not run well on a functional basis because it is too complex. It is ultimately the most effective when there is a summation of information, labour, operations, inventory, supply chain and other skills integrated into a single whole. Today among major airlines in the United States, there is an across-the-board migration of airframe maintenance to third-party providers. A great deal of the engine and component capability already has been outsourced, and many of the line and other support functions also are slowly migrating away from in-house airline accomplishment. Valeika's (2007) observations further support the work presented in this study. The trend shows that the aircraft maintenance operations will soon become independent from airlines and serve to larger customer groups resulting with higher competition.

The analysis of the aircraft maintenance business and the review of the airline RM literature reveal several similarities between two areas. First of all, both businesses work with the fixed capacity and the fluctuated demand. They both accept orders more than their capacity resulting in overbooking for airlines and backorders for maintenance centers. Besides, nesting is another crucial tactic for all kind of capacity management problems as well as overbooking. Since capacity is stable, responding to fluctuated demand is a challenge for both industries. In the literature, peak load pricing strategy, an early version of RM, is frequently applied to deal with such problems in service industries particularly in utility companies. Peak load pricing is an approach to price perishable commodities which has variable demand by means of price discrimination. Crew et. al. (1995) survey the literature on the theory and applications of peak-load pricing. Borenstein and Rose (1994) study the price dispersion of airline seats in the U.S. airline industry due to competition and peak load pricing by an empirical model. Koschat, Srinagesh and Uhler (1995) analyze the peak load problem of a local telephone service through a comprehensive statistical model. Braid (1996) applies the peak load pricing on two transportation routes which are perfect substitutes. Readers shall refer to the research overview of Elmaghraby and Keskinocak (2003) for further understanding of peak load pricing within the scope of dynamic pricing. Airports and postal services are two businesses where peak load pricing could be applied too. Main characteristics of these industries are; the significance of service reliability, capital intensive structure of business, non-storable services, high impact of price sensitivity of customers. In that way, it is safe to claim that the aircraft maintenance operations have these characteristics. Thus the literature on the peak load pricing motivates us to implement the peak load pricing strategy, as a form of RM for AMC operations.

The reviewed literature enables us to conclude that the literate on aircraft maintenance service is dominated by scheduling, workforce capacity planning, case studies of maintenance systems simulation etc. whose main objectives are cutting costs, reaching higher productivity and obtaining higher human resource performances. Their focus is on how to provide more efficient and more reliable service. The basic distinction between their work and ours is that we manipulate price of the service in order to control varying demand throughout the year and achieve higher cumulative capacity utilization and revenues. We do not attempt to improve elements of maintenance operations themselves but provide a marketing strategy to change the supply and demand interaction existing within the maintenance business altogether. As a result, we introduce a revenue management strategy to be used as a capacity management tool in aircraft maintenance services since the recent tendencies in the market drives our attention to revenue aspect rather than cost aspect of maintenance centers.

Chapter 3

3. Revenue Management on Airline Booking Process and Maintenance Center Management

Revenue management deals with modeling and optimization of pricing, demand management and capacity allocation decisions. It also covers the issues of competition and consumer behaviour. Revenue management systems require an information system that identifies the booking patterns resulting from continuous demand forecasts, estimates price elasticity of demand and suggests optimal booking policies. Furthermore, a company which wants to implement RM has to be able to reasonably forecast the demand of its different customer segments and in addition to that the company has to develop sophisticated capacity allocation techniques in order to reserve enough capacity for high-value customers. When we analyse airline operations, nesting strategy is used commonly to protect capacity for high value customers. Market is segmented by advance bookings to differentiate high value customers, i.e. business passengers from low value customers, i.e. leisure passengers in airline business. Overbooking, a technique of selling more than its capacity, is used when frequent ticket cancellations do occur. While it leads to some unsatisfied customers when the final demand was underestimated, the company's capacities are still better used.

Today, the economic conditions in effect show that airlines are not able to sustain their profitability with the existing RM techniques. The highly competitive air-traveling market pushes firms to operate more efficiently; firms are incumbent to focus on inventory and risk management. High competition in the airline market, obliges airlines to seek opportunities to increase their revenues from the limited resources. The challenging situations faced in the airline RM applications are: empty seats in a departing flight, high overbooking costs, imprecise pricing of seats, slow response to the competitors' actions, slow response to the changes in the air travel market etc.

In this dissertation, first we focus on how to utilize capacity more effectively and how to value seats more precisely in airline booking process. We suggest an adoption of financial options approach to value seats which also improves capacity utilization. In general, options help to value the underlying asset in financial markets and in our case, they are considered to expose the correct market price of aircraft seats. They reflect the market response fast as expected and facilitate the price changes according to the demand. So we analyze the booking process with financial options to see their effect on capacity utilization and revenues of airlines. The proposed method is compared to the overbooking approach which is assumed to be the most popular approach in airline booking practice. Accordingly, we change the way of selling tickets by introducing call and put options. We sell a number of tickets with call options which can be recalled for high value customers when demand is higher than expected. So we remove the tangible and intangible costs of overbooking; denied boarding costs and loss of goodwill respectively. We also sell a number of put options to the agents to be used in the case of low demand which allows selling a number of low fare tickets by agents at the end of booking period. So we decrease number of empty seats before departure to some extent by allowing the exercise of put options. As a result; the options let airlines to arrange the capacity and price decisions to the unexpected change in the air travel environment. They could be used as a tool to respond fast in the fast changing competitive markets. The detailed analysis is presented in Chapter 4.

Secondly, our research in airline RM reveals that another segment in airlines; maintenance industry has certain difficulties in utilizing capacity and satisfying customers. The maintenance industry has RM characteristics such as; it is almost impossible to change the capacity, unused capacity is gone forever, market can be segmented by customer valuation etc. We see that the maintenance demand is seasonal; in the peak seasons, demand is greater than capacity and most orders are backlogged; in the off-peak seasons, capacity is underutilized due to low demand. So, we study a form of RM, peak load pricing, to bring a rational solution to the capacity utilization problems of the industry. Accordingly; we offer price incentives to shift some price sensitive demand from peak periods to the off-peak periods. So, a more balanced demand supply relationship by controlling the demand through pricing strategies causes higher capacity utilization and higher revenues. The main challenge in this topic is to determine the discount prices which will lead to better capacity utilization. The details of this work are discussed in Chapter 5.

Chapter 4

4. Revenue Management with Options Approach

This chapter investigates the potential of using financial options as a means of managing the ticket sales in an airline booking process. Call options are used to recall the tickets already sold to customers, whereas put options are exercised to sell low-fare tickets in the last booking period whichever is favourable to the airline. By utilizing the proposed approach, airlines can prevent the inherent drawback of overbooking, customer dissatisfaction due to denied boarding that occurs when the demand is higher than the flight capacity. Moreover, the proposed options approach can decrease the probability of a flight departing with vacant seats when the demand is lower than the capacity with consequent improvements in revenue for an airline company. First, a mathematical model is introduced and then, a simulation study is conducted to explore the effectiveness and the potentials of the financial options in airline reservation systems for revenue improvement. Results obtained from the simulation study suggest that adoption of financial options creates significantly higher revenues in comparison to those by the traditional overbooking based RM approach. It can be further conjectured that adoption and utilization of the financial options in an airline booking process will reveal a seats' true economic value in the long term. One potential and immediate application area of the suggested RM approach is the Internet based booking and bidding systems.

4.1 Introduction

The objective of this chapter is to propose a novel idea through the potential use of financial options in the booking process of an airline company as well as to investigate the consequent revenue improvement opportunities. Furthermore, in this work, the decision making process when financial options are used is presented mathematically. In order to demonstrate the effectiveness of the proposed financial options based RM approach, a simulation study was conducted. For a given itinerary, we simulated 100 flights for various denied boarding (DB) cost, option premium, and demand scenarios. Booking process is conducted and compared in two ways: through the traditional "*overbooking*" approach; and through the proposed "*options*" approach. Revenues obtained using the two approaches are calculated. The simulation results indicate that the revenue can be improved against the traditional "*overbooking*" approach within a particular percentage range as a function of demand when an option-based RM policy is implemented. For example, revenue improvements of 2.4% and 22.37% are attained when the demand is over 110% and 80% of the capacity respectively. Sensitivity analysis further shows that as the mean demand changes, the percentage improvements in revenue are always attainable, however vary in different magnitudes. These results suggest a more efficient seat inventory control and a better RM policy with the "options" approach in place.

4.2 Motivation

Profit margins for the large airline companies have been decreasing due to high competition and increasing operation costs in the recent years. There are several RM methodologies developed and reported in the literature contributing little or none to revenues attained. In the present market situation, airlines are increasingly looking for additional opportunities for revenue improvements to stay competitive. Observing that the current RM practices in the airline industry are not sufficient to give airlines a comfortable profit margin; both the industry and researchers are seeking additional strategies to boost the revenue generated from each departing plane. Financial options have already been used in many different industries for many years. Thus, using them in the airline booking process can be a new way of revenue improvement for airlines. This chapter presents a new approach, use of financial options, to manage the booking processes in the airline industry. An option is defined as the right to buy or sell an asset at a fixed price before a predetermined date. While the call option gives its owner the right to buy, the put option gives the owner the right to sell. To this date, there is no theoretical study or a practical application investigating the utilization and potentials of financial options in the booking process of airlines. We developed a novel "option" based seat management strategy, which would potentially serve as a more revenue generating alternative to the existing "overbooking" based RM.

4.3 Financial Options

Options are contingent claims on the value of an underlying asset and are frequently embedded or hidden in the everyday activities of corporations. An option is a contract giving its owner the right to buy or sell an asset at a fixed price on or before a given date. Options are a unique type of financial contracts because they give the buyer the right, but not the obligation, to do something.

The special vocabulary associated with options is as follows:

- Exercising the option: The act of buying or selling the underlying asset via the option contract is referred to as exercising the option.
- Striking or exercise price: The fixed price in the option contract at which the holder can buy or sell the underlying asset.
- Expiration date: the maturity of the option after which the option is dead.
- Agent: A person or persons who can benefit trading airline tickets by buying options. His/her profit is either the option's premium or the difference between the face value and the market value of the option.
- Call Option: A call option gives the owner the right to buy an asset at a fixed price during a particular time period.
- Put Option: A put option gives the holder the right to sell the asset.

There are two kinds of options: American and European options. An American option may be exercised at any time up to and including the expiration date. A European option differs from an American option in that it can be exercised only on the expiration date. Ross et al. (2003) suggest that a call option on an underlying asset that pays no dividend should never be exercised before the expiration date for the case of Europeans options. Even though the proposed option-based approach pays no dividends, no restrictions on the options type has been posed since the selection of the most appropriate option type is out of the scope of this study. In general, financial options are used as a tool for changing the firm's risk exposure. They are used in many areas, such as agriculture, manufacturing, real estate, gas, electricity, metals, petroleum, etc. to manage risk and inventory. The intention is to decrease the adverse effect of the uncontrollable factors of the firm like climate, demand, price of raw materials, price of energy, etc.

4.4 RM and Options Approach

In "*overbooking*" based RM, airlines accept more reservations than they have available seats on the presumption that a certain number of people will not show-up. Airlines offer compensation for those who are denied from boarding a flight when number of show-ups is greater than the flight capacity. The compensation is called denied boarding (DB) cost. DB may occur in two ways: i) voluntary DB; and ii) involuntary DB. The true cost of involuntary DB, although difficult to quantify, could actually be much higher than the compensation paid by airlines.

On the other hand, when "*options*" approach is employed in an airline booking process, customers purchase a ticket with a call option due to the associated low-fare, knowing that their ticket can be recalled later in the booking process with a compensation of exercise price appointed by the options contract. Thus, there is no dissatisfaction from customer perspective and potential future economic loss, an inevitable result of "*overbooking*" approach, is avoided.

In the proposed "options" based RM, we suggest that financial options, calls and puts, are used to sell tickets in an airline booking process. Accordingly, we propose that, an airline sells some of the lowest fare tickets with call options, so that they can be recalled whenever needed. On the other hand, a number of puts are sold to an agent, claiming that, if the airline wants to exercise some puts, the agent accepts to buy the associated tickets. Exercise price and maturity date are noted on the contract. We assume that both type of options are purchased during the first time period and can be exercised during the last time period of the booking process. If the demand is higher than expected, airlines exercise the call options. On the other hand, when the demand is lower than expected, puts are exercised. Capacity is an important constraint in the seat inventory control. Using the capacity in a more flexible way can bring operational efficiency with higher load-factors that is defined as the ratio of passengers over total capacity for a flight leg. Furthermore the proposed approach presents a profit opportunity to both airlines and agents/customers by managing seat inventory more efficiently.

Since option prices are related to the prices of the underlying spot market goods, in the case of flight tickets, they can also be used to reduce or increase the risk of investing in the spot items. On the other hand, the ease and low cost of transacting in financial markets facilitate the arbitrage trading and rapid price adjustments that quickly eradicate these profit opportunities. Society benefits because the prices of tickets more accurately reflect the goods' true economic values.

Suppose, there is an agreement between an airline and an agent claiming that agent will buy a ticket at a specified fare on a given date. When the departure time gets closer, the airline determines whether the market price is higher than the offered price to an agent. If such condition exists, airline sells the ticket in the market, otherwise airline exercise its option to sell the ticket to the agent from the agreed fare. By selling to the agent, the airline will exercise a put option. If the airfare is less than the exercise price, then the put is said to be in the money. If the airfare is more than the exercise price, then the put is out-of-the-money. An out-of-the-money put should never be exercised.

By having call options for a number of tickets, the airline can prevent DB cost as well as some intangible costs, like goodwill cost, which represents future economic losses. Whenever, the demand is higher than expected, higher class passengers can be accommodated by using the flexibility coming from those call options. Likewise, whenever the demand is less than expected, the airline can use those puts to sell seats at specified prices, most likely lower than the current fare, to an agent, in order not to fly with vacant seats. Hence, the potential loss is limited to the premium paid. The airline pays the price of puts and calls. While the airline can create capacity for the high-fare customers, it can also sell excess capacity to the low-fare customers. This flexibility brings less DB costs, less good will costs, less probability of departing with vacant seats, and a high probability of satisfying the high-fare customers whenever the demand exists. In this research, we study the effects of this flexible capacity resulting from the adaption of financial options to the booking process. As our initial results suggest, more flexible capacity means higher revenues or at worst no difference.

4.5 Mathematical Modeling of Options-based RM

In this section, a model depicting the overbooking policy and the financial options approach is introduced. Whereas introduction of an analytical proof that the revenue obtained using "options" in a booking process is higher than that obtained by the overbooking process (i.e. the model of Coughlan, 1999) is beyond the scope of this particular study, the proposed model serves as a platform on which a simulation model is built. The simulation analysis based on the proposed model and the subsequent discussions of the results render preliminary intuitive expectations on revenue improvement potentials.

Assumptions of the Proposed Model:

- The booking process is composed of discrete time periods, the beginning of the process is time period 1 and the last time period before the plane departs is time period t.
- There is a finite number of fares $\{f_1 < f_2 < f_3 < .... < f_n\}$.
- There is a limit defined by the airline, on the number of puts and calls purchased.
- Premiums for puts and calls are paid by the airline. (Exercising rights for both put and call options is owned by the airline)
- Options are purchased in the first time period and they can be exercised only in the last time period.
- When put options are exercised, the lowest fare is received by the airline.
- Call options are exercised at the exercise price of call option and the recalled seats are resold at the current market fare.

Notations

i = index for fare class, $i = 1, 2, ..., n$

j = index for time period, $j = 1, 2, ..., t$

f_i = fare of class i

C = cabin capacity

$E(d_{ij})$ = expected demand for class i, during period j

n_p = number of puts purchased

n_c = number of calls purchased

n_p^e = number of puts exercised

n_c^e = number of calls exercised

$A_{\max}^p$ = maximum allowed number of puts purchased; company policy

$A_{\max}^c$ = maximum allowed number of calls purchased; company policy

p_p = premium paid for one put option

p_c = premium paid for one call option

π_c = exercise price of call option

π_p = exercise price of put option which is equal to f_1, the lowest fare

a_{ij} = authorization level for class i for time period j

b_{ij} = booking level of class i for time period j

n_{db} = number of DB

c_{db} = average DB cost

r = Probability of no-show

Model:

Number of puts and calls to be purchased is determined in the first time period of booking process and the number is affected by expected demand, capacity and maximum allowed number of options purchased as shown in Equation (4.1) and (4.2).

$$n_p = \max \left\{ 0, \min \left\{ C - \sum_{j=1}^{t} \sum_{i=1}^{n} \mathrm{E}\left[d_{ij}\right], A_{\max}^{p} \right\} \right\} \tag{4.1}$$

$$n_c = \max \left\{ 0, \min \left\{ \sum_{j=1}^{t} \sum_{i=1}^{n} \mathrm{E}\left[d_{ij}\right] - C, A_{\max}^{c} \right\} \right\} \tag{4.2}$$

Number of puts and calls to be exercised is determined in the last time period before the plane departs according to following equations.

$$n_p^e = \max \left\{ 0, \min \left\{ C - \left(\sum_{j=1}^{t-1} \sum_{i=1}^{n} b_{ij} + \sum_{j=t-1}^{t} \sum_{i=1}^{n} \mathrm{E}\left[d_{ij}\right] \right), n_p \right\} \right\} \tag{4.3}$$

$$n_c^e = \max \left\{ 0, \min \left\{ \left(\sum_{j=1}^{t-1} \sum_{i=1}^{n} b_{ij} + \sum_{j=t-1}^{t} \sum_{i=1}^{n} E\left[d_{ij}\right] \right) - C, \; n_c \right\} \right\} \tag{4.4}$$

Authorization levels are calculated as follows:

$$a_{ij}=\begin{cases}\mathrm{E}[d_{i1}](1+r)+n_p+n_c & \text{if } i=1,\cdots,n;\ \text{and } j=1\\ \mathrm{E}[d_{ij}](1+r) & \text{if } i=1,\cdots,n;\ \text{and } j=2,\cdots,t-1\\ \mathrm{E}[d_{ij}](1+r)+n_p^e+n_c^e & \text{if } i=1,\cdots,n;\ \text{and } j=t\end{cases} \tag{4.5}$$

$$0 \le n_p \le A_{\max}^{p} \tag{4.6}$$

$$0 \le n_c \le A_{\max}^{c} \tag{4.7}$$

Equation (4.1) and (4.2) can be modified in such that when the total expected demand and the aircraft capacity are equal or differ by a small margin some put and call could be sold to deal with the unexpected variations on bookings. The booking limits are limited by the authorization levels as shown in Equation (4.8).

$$b_{ij}=\begin{cases}d_{ij} & \text{if } 0\le d_{ij}\le a_{ij}\\ a_{ij} & \text{if } \mathrm{d}_{ij}>a_{ij}\end{cases} \tag{4.8}$$

Number of DB is calculated by Equation (4.9).

$$n_{db}=\begin{cases}\sum_{j=1}^{t}\sum_{i=1}^{n}E\left[b_{ij}\right](1-r)-C & \text{if } \sum_{j=1}^{t}\sum_{i=1}^{n}E\left[b_{ij}\right](1-r)>C\\ 0 & \textit{otherwise}\end{cases} \tag{4.9}$$

Hence, the Expected Revenue $E\left[R\right]$ is:

$$\mathrm{E}\left[R\right]=\sum_{j=1}^{t}\sum_{i=1}^{n}b_{ij}f_i-n_c^e\pi_c-n_{db}c_{db}-n_pp_p-n_cp_c \tag{4.10}$$

The expected revenue is calculated by Equation (4.10) as the product of the number of seats sold by fares for each seat minus the cost of exercising call options, the DB cost and the premiums paid for calls and puts.

4.6 Simulation Analysis and Numerical Results

In this section, a simulation study conducted to explore the effects of the financial options in the booking process is discussed. Numerical results show that between 2.4% and 22.37% revenue improvements is possible by utilizing financial options in RM. The flow chart in Figure 4.1 displays the booking process when financial options are used as a means of ticket sales. First, the procedure of obtaining threshold values in each booking class is explained. The decision on the quantity of options to be purchased and exercised is analyzed. Next, the decision making procedure in the reservation system is showed according to incoming requests. In Figure 4.1, $\mathrm{E}[d]$is the total expected demand at$t=0$, $\mathrm{E}[d_t]$ is the total expected demand during the t^{th}period and $b$is the total realized bookings up to t^{th}period.

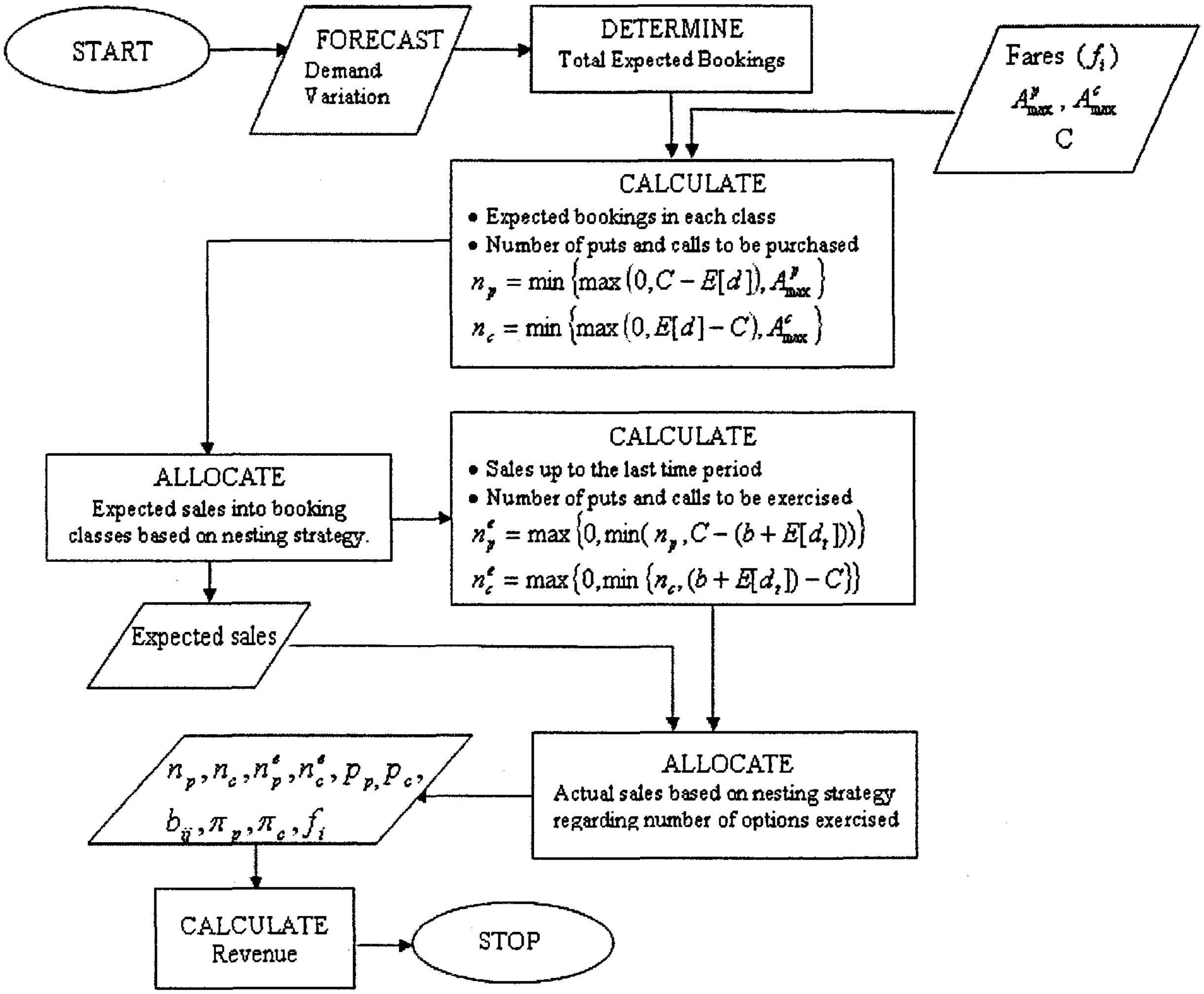

Figure 4.1: Simulation of Airline Booking Process with "*Options*" Implementation

Finally, the booking process with options approach is illustrated in Figure 4.2.

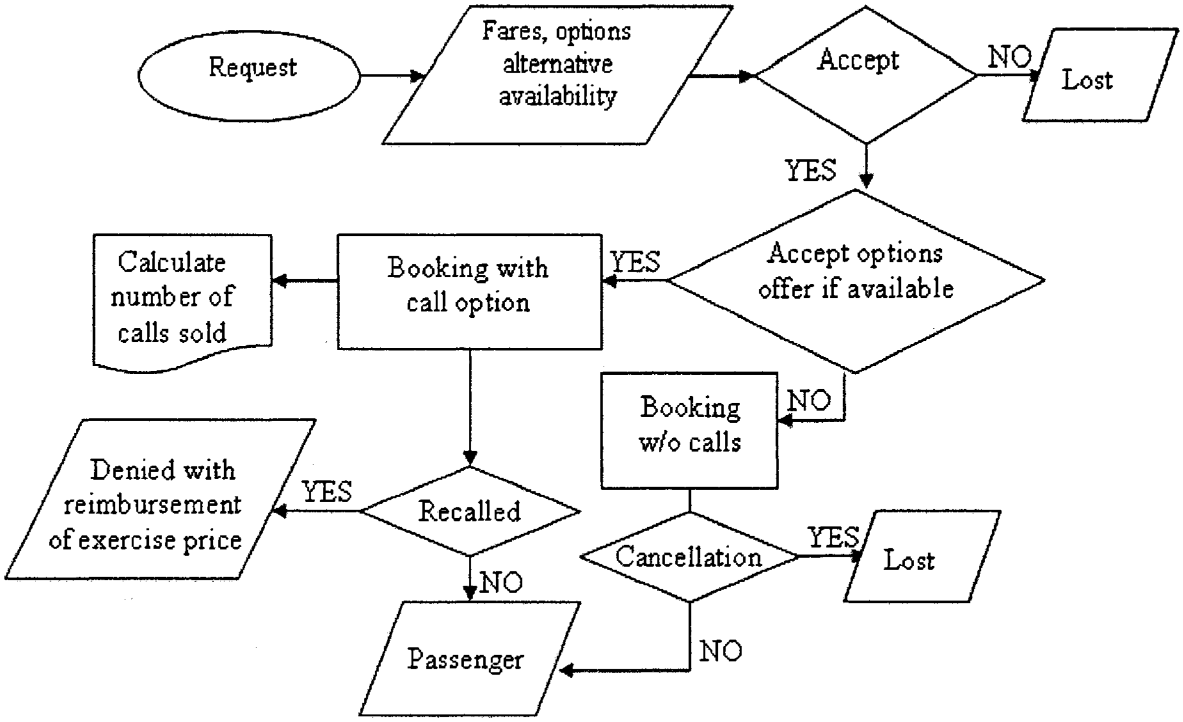

Figure 4.2: Booking process with options approach

After determining booking limits for each fare class and number of options to be purchased, the request is assessed by those booking limits and it is either accepted or denied. In the final booking period, a number of options are exercised to fill the seats in a profitable way. So basically the procedure is as follows:

1. Determine reservation choices that can be made by the customer.
2. Request comes.
3. Fares are introduced.
4. If capacity is reached, high-fare request arrives and there is a call option to be exercised, go to 8.
5. If capacity is reached STOP.
6. Else accept either booking with calls or accept booking without calls.

7. Make reservation.

8. If it is last time period, exercise puts according to decision made as a result of Figure 4.1.

9. If booking limit for the current fare class is reached, move to a higher booking class.

10. Go to Step 2.

Development of the Simulation Study:

In this study, total booking period will be 3 months before the departure and is divided into 7 time periods. Airline uses some time buckets to decide fares. First, expected demands for a specific flight are determined by a random number generator having a mean of 100 bookings, which is the assumed aircraft capacity, with a standard deviation of 6 for 100 flights. A random discrepancy is subsequently allowed by a random percentage (ranging between -6% and + 6%) to obtain the expected number of bookings. The booking process is divided into 7 booking time periods, such that at the end of the 7^{th} period departure takes place. It is assumed that the low-fare class customers arrive before the high-fare class customers. The percentage of customers arrive in each period accordingly are presented in Table 4.1.

Table 4.1: Percentage of requests arriving in each time period

Booking periods	1	2	3	4	5	6	7
Arrivals in each period (%)	15	20	15	20	15	10	5

In the model, three different booking approaches are employed, namely "without-overbooking", "overbooking" and "options" approaches. In the "without-overbooking" approach, an average no-show rate of 10% is randomly applied for each run of flight to realize the actual sales. Projected bookings for each time period based on expected bookings are calculated according to Table 4.1. Next, actual booking limits are determined for each time period as long as those requests are less than the projected bookings of the associated time period. If the actual demand is greater than the projected booking for each period, only as many as the projected bookings are allowed for each booking period. The sales revenues are calculated for the actual bookings using fares provided in Table 4.2.

Table 4.2: Fare classes for a specific itinerary.

Classes	1	2	3	4	5	6	7
Fares ($)	180	200	230	250	270	275	300

In the "overbooking" approach, authorization levels are calculated considering no-show rates and expected demand figures as long as the demand is less than the flight capacity. If the demand is over the capacity, the authorization is the product of capacity and no-show rate. The number of no-shows is binomially distributed (Coughlan, 1999) and the probability of x 'no-shows' out of b bookings is:

$$P(X=x)=\binom{b}{x}r^{x}(1-r)^{b-x} \tag{4.11}$$

and the expected number of no-shows is:

$$E[x] = \sum_{x=0}^{b} \binom{b}{x} r^{x} (1-r)^{b-x} \tag{4.12}$$

where r is the probability of a booking to be a 'no-show' or the no-show rate of an individual booking. After determining the authorization levels, a random no-show rate distributed with a mean of 10% is applied for each experimental run. The number of no-shows is then reflected on the expected booking figures to find out show-ups. Naturally, if the show-ups are higher than the capacity of the flight, there exist DBs. Again the percentages in Table 4.1 and the principles of the nesting strategy are used to calculate bookings for each period. The final revenue gain, determined considering the DB cost (3 different DB costs), is used to measure the revenue improvement for different cases and the number of DB occurrences.

In the "options" approach, bookings are determined according to the nesting principle. For the first booking-period, the number of calls exercised is also considered as part of the percentages given in Table 4.1 to find out the bookings for the first booking-period. All the call and put options are purchased during the first period and exercised during the 7th period provided that doing so is favourable to the airline. The termination date for options is in the last booking period. It is assumed that there are no taxes and transaction costs as well as no dividend payments. The number of calls and puts purchased is determined based on the expected demand, the flight capacity as well as the maximum number of options purchased to be used to sell tickets as a company policy. The number of calls and puts exercised is determined during the last booking period based on the actual bookings, the flight capacity and the number of options purchased in the first booking period. The number of calls exercised should be less than the total number of tickets sold during the 7^{th} period since tickets are recalled only to be resold at a higher fare while there is a limit on the number of tickets that can be sold during the last period. Since there is no practice of using "options" as a way of selling tickets, 3 different option premiums based on the average fare, are used to see different results on revenue improvement potentials. Profit of an agent is calculated based on the number of options purchased and exercised, the premiums paid and the fact that selling price of an agent can be anywhere in the range from $180 (the lowest possible fare) and the current market price in the 7^{th} period for that specific flight. Finally, the total revenue is calculated as the number of tickets sold for each fare class, fares, number of options purchased and exercised, the premiums paid, and the exercise price of options.

Simulation Results:

The revenue obtained through the three approaches employed, "without-overbooking", "overbooking" and the "options" approaches, are determined and the percentage revenue improvements are calculated as "overbooking" approach over "without-overbooking" approach and "options" approach over "overbooking" approach. The percentage improvements in the revenue for 100 flights are between -5.90% and 9.52% for "overbooking" approach over "without-overbooking" approach, is between 2.40% and 22.37% for "options" approach over “overbooking” approach and is between 0.97% and 32.47% for “options” approach over “without-overbooking” approach. Detailed numerical results under different scenarios can be seen in Figures 4.3, 4.4 and 4.5.

The three unknown parameters are set to different values to assess how sensitive the simulation analysis is.

c_{db} = average DB cost (one value for DB cost is average fare for the flight and two more different values are set)

π = exercise price of a call option (based on three highest fares)

p = premiums paid for puts and calls (three different values are set including 10% of average fare for the flight))

Scenario 1. (c_{db}=100, π=270, p=10):

According to Figure 4.3 (c_{db}=100, π=270 and p=10), percentage improvement in revenue is between 21.94% (if expected demand is 80 with 6% variance) and 3.07% (if expected demand is 110 with 6% variance) when the “options” approach is applied as opposed to the “overbooking” approach. In a similar way, percentage improvement in revenue is between 30.53% (if expected demand is 80 with 6% variance) and 1.89% (if expected demand is 110 with 6% variance) when the “options” approach is applied instead of the “without-overbooking” approach.

Table 4.3: Percentage improvements in revenue when Scenario 1 is considered.

(Mean expected demand, demand variation)	**Improvement (%) "*Overbooking*" vs. "*Without-overbooking*"**	**Improvement (%) "*Options*" vs. "*Overbooking*"**	**Improvement (%) "*Options*" vs. "*Without-overbooking*"**
(80,6)	7.05	21.94	30.53
(85,6)	6.38	14.89	22.21
(90,6)	0.84	14.18	15.14
(95,6)	3.13	11.53	15.02
(100,6)	1.99	5.91	8.02
(105,6)	-0.75	4.26	3.48
(110,6)	-1.14	3.07	1.89

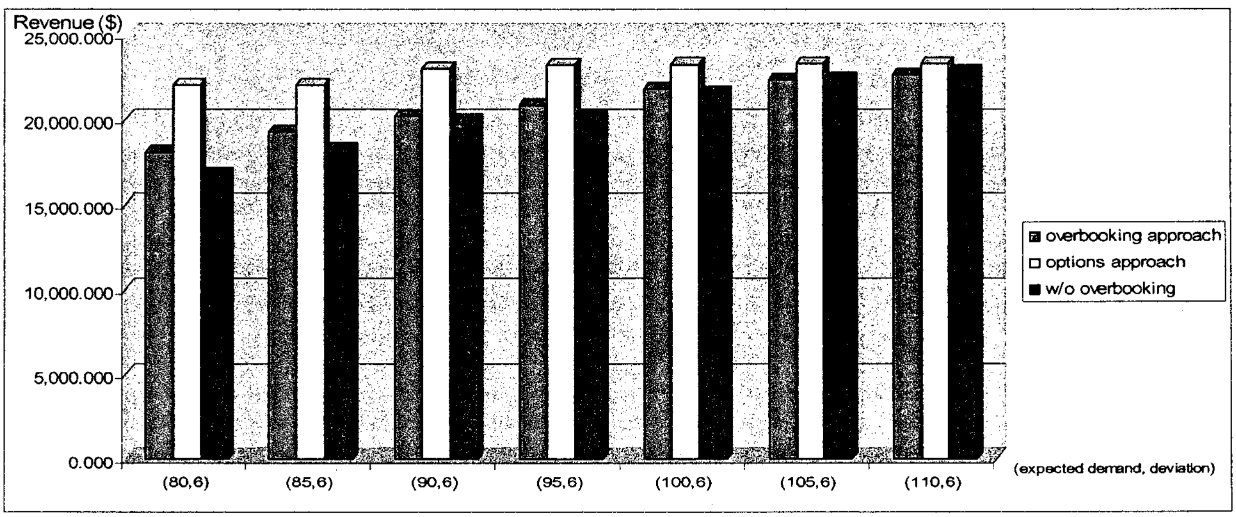

Figure 4.3: Revenue values ($) when c_{db}=100, π=270, p=10.

Scenario 2. (c_{db}=100, π=270, p=30):

When we analyze Figure 4.4 (c_{db}=100, π=270, p=30), percentage improvement in revenue is between 20.33% (if expected demand is 80 with 6% variance) and 2.31% (if expected demand is 110 with 6% variance) when the "options" approach is applied instead of the "overbooking" approach. In a similar way, percentage improvement in revenue is between 29.71% (if expected demand is 80 with 6% variance) and 1.07% (if expected demand is 110 with 6% variance) when "options" approach is applied instead of the "without-overbooking" approach.

Table 4.4: Percentage improvements in revenue when Scenario 2 is considered.

(Mean expected demand, demand variation)	**Improvement (%) "*Overbooking*" vs. "*Without-overbooking*"**	**Improvement (%) "*Options*" vs. "*Overbooking*"**	**Improvement (%) "*Options*" vs. "*Without-overbooking*"**
(80,6)	7.80	20.33	29.71
(85,6)	5.42	13.30	19.44
(90,6)	0.58	14.47	15.14
(95,6)	3.05	10.77	14.15
(100,6)	1.88	5.81	7.80
(105,6)	-0.30	3.75	3.44
(110,6)	-1.21	2.31	1.07

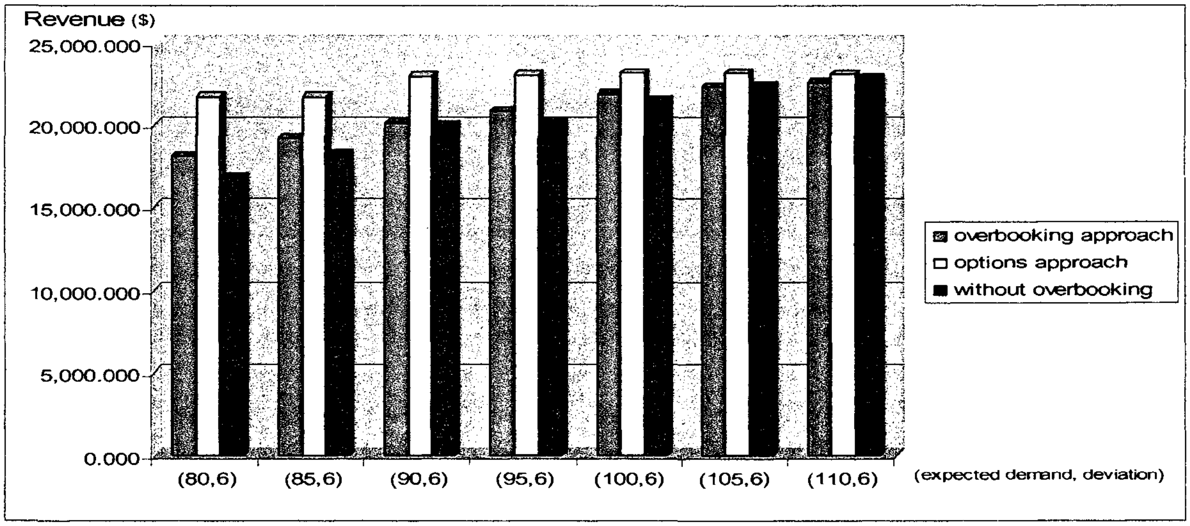

Figure 4.4: Revenue values ($) when c_{db}=100, π=270, p=30

If we look at the revenue improvement values when the "options" approach is used over the "overbooking" approach, Scenario 2 gives lower values than Scenario 1. This seems reasonable since in Scenario 2, the premiums paid for the call and put options are increased from $10 to $30 ceteris paribus. Thus, there is a less revenue improvement potential with "options" application in Table 4.4 than in Table 4.3 resulting from higher cost figures.

Scenario 3. (c_{db}=300, π=270, p=20):

In Figure 5 (c_{db}=300, π=270, p=20), percentage improvement in revenue is between 20.66% (if expected demand is 80 with 6% variance) and 6.29% (if expected demand is 100 with 6% variance) when "options" approach is applied instead of "overbooking" approach. In a similar way, percentage improvement in revenue is between 30.04% (if expected demand is 80 with 6% variance) and 1.21% (if expected demand is 110 with 6% variance) when the "options" approach is applied over the "without-overbooking" approach

Table 4.5: Percentage improvements in revenue when Scenario 3 is considered

(Mean expected demand, demand variation)	Improvement (%) "*Overbooking*" vs. "*Without-overbooking*"	Improvement (%) "*Options*" vs. "*Overbooking*"	Improvement (%) "*Options*" vs. "*Without-overbooking*"
(80,6)	7.77	20.66	30.04
(85,6)	5.79	13.72	20.30
(90,6)	0.18	14.94	15.14
(95,6)	2.68	10.45	13.41
(100,6)	0.25	6.29	6.56
(105,6)	-3.22	6.64	3.21
(110,6)	-5.65	7.27	1.21

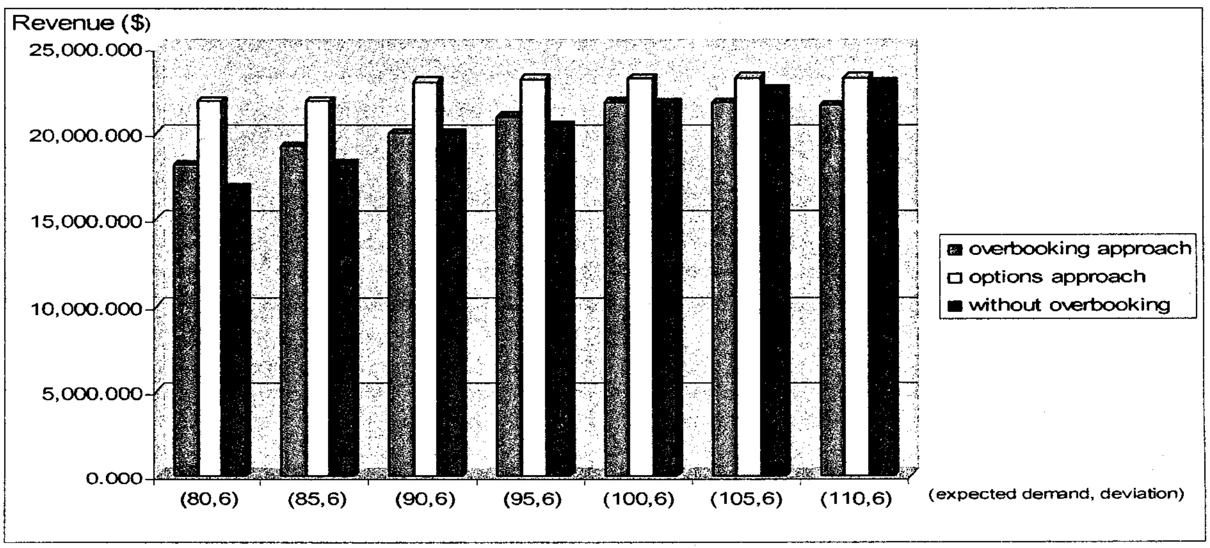

Figure 4.5: Revenue values ($) when c_{db}=300, π=270, p=20

Whenever the expected demand is less than 100, the revenue improvement percentages with the application of the financial options do not change significantly in Tables 4.4 and 4.5. However when the demand is high enough to result in DB, the revenue improvement percentage increase in Table 4.5 in comparison to those in Table 4.4 due to high DB costs which are $300 in Scenario 3 rather than $100 in Scenario 2.

In fact, in the literature it can be seen that "overbooking" approach is superior to "without-overbooking". As a result, for a few decades, "overbooking" policy is used in most airline companies as a revenue management tool. Hence, for the remainder of this chapter the focus will be on the comparisons between the "options" and "overbooking" approaches.

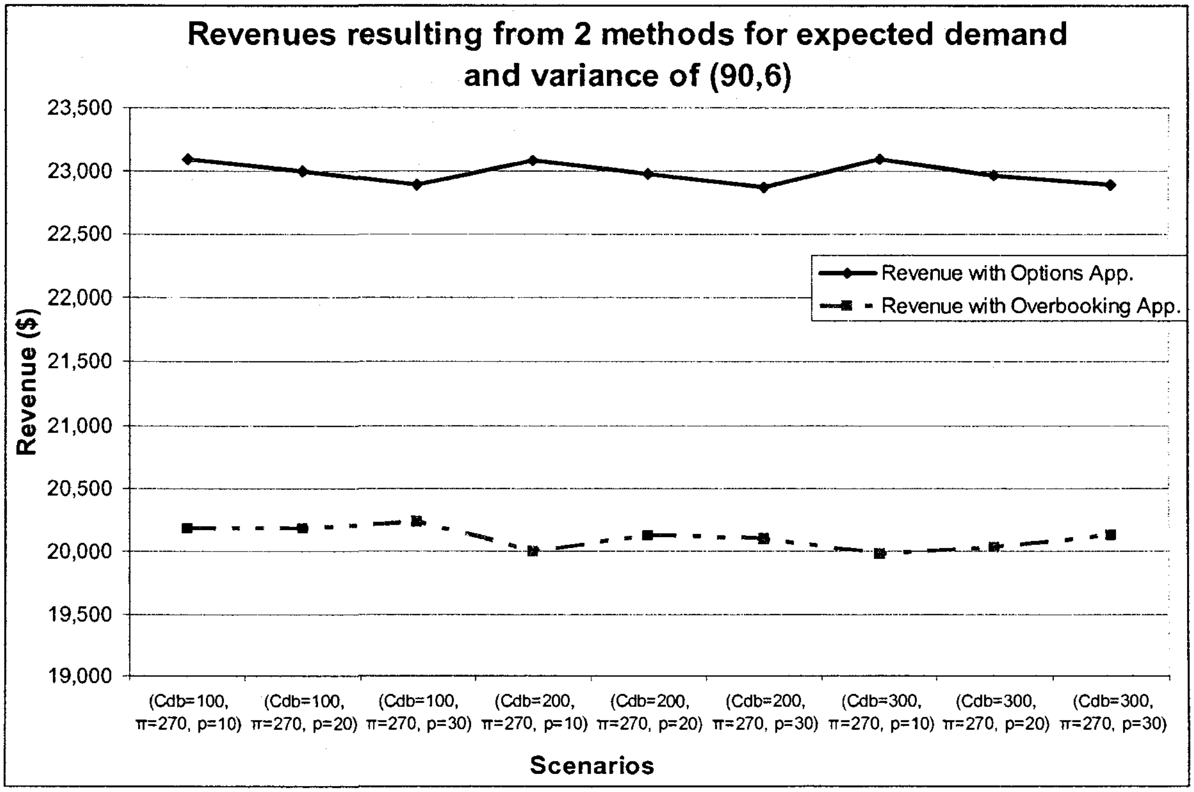

Figure 4.6: Sensitivity analysis of the expected revenue under 9 different market conditions

The revenue obtained either with “options” approach or with “overbooking” approach with the expected demand of 90 passengers for 9 different scenarios is given in Figure 4.6. As seen in all the scenarios, the “options” approach is superior to the “overbooking” approach by 2.40% to 22.37%. The results indicate a clear gap between the revenues obtained using the two approaches, so we decide to expand the range of premium values as $10, $50 and $100. Figure 4.7 shows the revenues obtained with the two approaches in this case. The first 9 points are the outcomes of the demand of 80, the second 9 points are the outcomes of the demand of 100 and the last 9 points are the outcomes of the demand of 110. As seen, whenever the load-factor is lower, the gap is wider and as the demand increases the gap narrows down. In other words, when the demand is greater than the capacity, both methods produce similar results. There is one point where the two methods produce the same revenue. That point is at the DB cost of $100 (minimum value) and the premium of $100 (maximum value) favouring the “overbooking” method as much as possible. In all other scenarios, “options” approach still produces higher revenues.

The results obtained from this experimental study are very encouraging, hence surely justifies the necessity of further studies to be conducted on the subject.

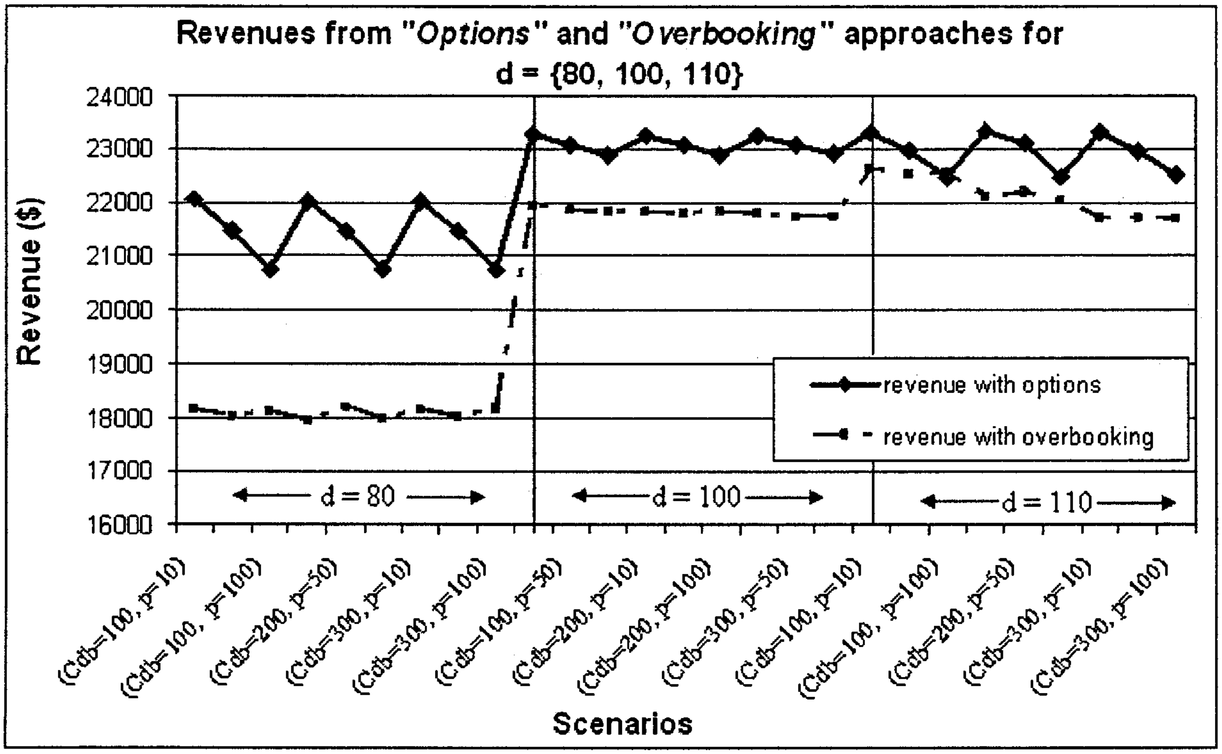

Figure 4.7: Sensitivity analysis of the expected revenue under 27 different market conditions.

4.7 Summary and Conclusion

We provide computational results that give insight into the revenue improvement potentials through financial options for different expected values of demand scenarios. In general the "*options*" approach gives superior revenues in comparison to those given by the other two approaches. Our results reveal that the revenue improvement is much higher when the load-factor at the departure is low when "*options*" approach is used. Increase on the premiums of options or the expected demand causes a decrease on the marginal profit with the "*options*" approach. Alternatively, whenever the expected demand and the DB cost increase, the revenue improvement decreases with the "*overbooking*" approach. In brief, simulation study presented demonstrates encouraging results in support of our claim that utilization of options in the booking process renders higher revenues for the airline companies.

The topic covered in this chapter was published in the Journal of Revenue and Pricing Management: Akgunduz A, Turkmen B, Bulgak A.A., "Using Financial Options in the Airline Booking Process", Journal of Revenue & Pricing Management, 6(2): 135-150, 2007.

Chapter 5

5. Aircraft Maintenance Order Control through Revenue Management: A Peak Load Pricing Strategy

This chapter discusses a demand shifting strategy for aircraft maintenance companies by employing price incentive options to customers. Penalties for not meeting the due-dates on aircraft maintenance operations have major implications for the companies. Moreover, the demand for aircraft maintenance services is observed to be seasonal. Meeting the due dates with the relatively constant capacity is a further challenge when the demand is seasonal. Hence the aircraft maintenance companies face a serious capacity management problem, while the peak seasons cause due-date penalties, low seasons lead to lower utilization.

In this study, we show that controlling the demand and maintenance operations through pricing strategies has a potential to achieve greater capacity utilization and higher revenues. We analyze the peak load maintenance problem by shifting demand to off-peak periods with price discounts and examine the results of the proposed mathematical model. We find the subset of demands that maximize the revenue within the capacity constraint by a design of knapsack problem.

5.1 Introduction

The Peak-Load Pricing is a tactic of varying the price of capacity to overcome the imbalances between supply and demand. It is often confused with the revenue management (RM), with which it shares a number of characteristics. However, unlike RM, the peak-load pricing is based on changing prices (not availabilities) and does not require advance bookings to be effective. Yet, the peak load pricing is considered a form of RM.

Our motivation in this study arises from the idea to find an appropriate pricing policy that leads to the correct amount of physical capacity and its efficient utilization. There are two situations to consider; either the case of decreasing costs or the case of peak loads. Obviously, they might also happen together in a combination. When prices are close to marginal costs or possibly below average costs, the strategy tends to decrease costs. When there are peak loads, total capacity available is underutilized. In this study, we focus on peak load pricing as it reflects the characteristics of aircraft maintenance service well. It is assumed that operating costs are linearly dependent to product quantities and capacity costs are linearly dependent to unit capacity usage in peak load problems. In general if inventory is perishable or inventory costs are very high, peak load problems are likely to occur such as in electricity production and transportation, in broadband network, in postal services etc.

Various industries use pricing as a means to manage the capacity. Market conditions and competition enable companies to dynamically adjust their prices. Airline industry is the major application area of RM. We study the characteristics of airlines and the aircraft maintenance industry to adapt the principles of airline RM for aircraft maintenance industry.

5.1.1 Airlines and Aircraft Maintenance Industry

A number of similarities and distinctions between airlines and aircraft maintenance centers (AMCs) are analyzed in terms of RM applicability. This analysis is based on the operational complexity, decision making process to accept or reject the orders, peak loads, product/service attributes, market characteristics, market segmentation, order arrivals, number of customers, customer behaviour.

- *The basic similarities observed are*:

Both industries are subject to high standards and strict operational procedures. They both make decisions to accept or reject the incoming request based on their remaining capacity, prices and the expected customer behaviour. Besides, both industries have peak loads; such as Thanksgiving Day for airlines and summer time for AMCs.

- *The basic distinctions are summarized as follows*:

It is straightforward to sell plane tickets, however it is a complex process to sign a contract between AMCs and the customer. The conditions of a maintenance contract are determined after a careful analysis of the required job and the customer profile with ongoing negotiation process. Moreover, the competition is perfect for airlines whereas there are a few competitors in aircraft maintenance industry. Thus, aircraft maintenance industry shows the characteristics in between the monopoly and the perfect competition when we analyze the market structure. In monopoly markets, market segmentation is achieved by the demand elasticity of customers and resulting price discrimination is sustainable. Whereas in perfectly competitive environments, price discrimination happens to decrease as the market saturates. Customer characteristics and product characteristics enhance the price discrimination. For example, private jet owners have greater price elasticity than the airline companies. Besides as the maintenance service requires high compatibility with the industry standards and regulations and performs complex test procedures, entry of market is relatively difficult and number of providers in the industry is limited.

Next, the methods to segment the market is different for each industry. Airlines use advance bookings to segment the market and implement price discrimination. Business customers tend to book closer to the departure and leisure customers book early to benefit from discounted prices. However AMCs have well studied customer profiles and each customer is treated exclusively. Arrival of orders is also quite different for airlines and AMCs. While the low fare customers arrive early in airline industry, the high profile orders are placed well before the low profile orders due to long operation times in aircraft maintenance industry. Major customers sign the contracts and the majority of the capacity is allocated to these certain orders while low fare customers compete for the remaining capacity in aircraft maintenance industry. Heavy maintenance or large airlines' orders are like business passengers of airlines and private jet owners' or small airlines' orders are like leisure passengers of airlines for aircraft maintenance industry. Another distinction between the two industries is the number of customers. AMCs have smaller number of customers and it is easier to understand and predict customer behaviour; allowing quick response time to the changes in the market. They could study and determine price elasticity of each individual customer via some research. Airlines have large number of customers and they study the whole society to explain the customer behaviour which is difficult to forecast for them.

After discussing some characteristics of both industries, let us analyze the operations of these businesses.

5.1.2 Bookings in Airlines and in Aircraft Maintenance Centers (AMCs)

The booking process of airlines and AMCs needs to be analyzed thoroughly since we attempt to design a model to decide the requests to be accepted or rejected.

In the case of airlines, varying fares are offered for an identical service. Airfares are dynamically updated based on the remaining capacity, expected future demand and market competition. The problem is to manage the airfares in such a way that customers are not lost to the competitors, all the seats are sold, and the maximum amount of revenue is achieved. However in practice, airlines reject several potential customers and they still end-up flying with empty seats. In this low profit margin, highly competitive business environment, airlines employ well researched RM tools to increase their revenues. As such in the airline industry, various other industries face similar problems in managing their perishable assets. For an airline, a departing flight with empty seats is the revenue lost forever. As such, unused capacity in a manufacturing system faces the same problem. However, when the demand is higher than the capacity, in most cases, airlines do not have the option to add additional capacity. On the other hand, manufacturing facilities may seek alternatives to satisfy the excess demand. Overtime and outsourcing are the popular methods to deal with the excess demand. Not all the industries have the options to reject a customer (airlines frequently deny customers with the valid tickets due to overbooking) or to outsource to compensate the capacity shortage. Aircraft maintenance companies (AMCs) are highly specialized and regulated businesses that all the accepted jobs have to be completed before the deadlines with the highest quality. Usually AMCs work in multiple shifts limiting the possibility of going overtimes. Hence, year-round, the capacity is near constant. On the other hand the demand shows seasonal trends (Fig. 5.1).

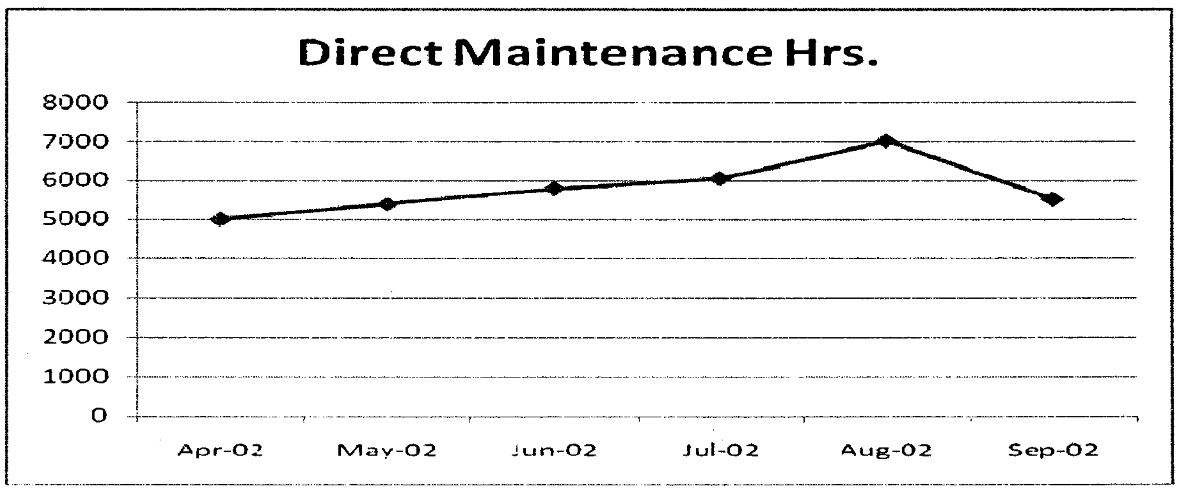

Figure 5.1: Monthly Man-Hours spent for direct maintenance in 2002 (Beabout, 2003)

Airlines sell more seats than their actual capacity with an expectation that some of their confirmed customers will not show-off (No-Show) for the flight due to varying reasons. Consequently, the fundamental question for an airline is to accept or reject a booking request. If the airline rejects the booking request, there is a chance that the customer may pay a higher fare for the same seat or decides to take a later/earlier flight from the same company. Rejecting a customer is described by the term "spill" and if the spilled customer is convinced to book at a higher booking class (pays more) or move to a later/earlier flight with the same company, the situation is described as "recapture" in the airline literature. Therefore, when airlines make decisions about booking request, consequences of spill, the possibility of recapturing the passenger should be well thought. Accepting a booking request may consume the capacity that can be sold with higher price later on. On the other hand, rejecting a booking may result with lost revenue and low loading factors. Both airlines and AMCs accept orders to fill their limited capacity. For both businesses, the capacity is a perishable asset. Similar to the airline booking systems, maintenance companies have options to accept more customers than their actual capacity, resulting with overbooking. Overbooking in an aircraft maintenance business results with delayed jobs (backorders). Financial consequences of delayed maintenance may be severe. Major AMCs have exclusive contracts with major carriers. As the business is structured, order comes without warning and rejecting an order is almost impossible. The current business structure leads to low utilization during the low seasons and backorders during the high seasons. Another similarity with the airline companies is that changing the capacity of AMCs to respond to the varying demand is not a straightforward option. Changing the aircraft type to respond to the demand is a rare option for airline companies. The capacity of an aircraft maintenance business mainly depends on the manpower. Aircraft maintenance technicians are well trained and very difficult to replace. Hence the capacity is almost stable. To overcome the capacity problem and still make the highest possible revenue from their flights, airlines use pricing strategies in order to shift the demand from flights with low remaining capacity to the flights with higher remaining capacity. The objective of increasing the fares is to keep the remaining seats for business customers and to encourage the leisure travelers to book on a flight with more empty seats. While the natures of the businesses have significant similarities, AMCs on the other hand, do not respond in the same way for the very similar problem.

In this study, we tackle the capacity management problem in AMCs and propose a pricing strategy to shift the demand from high demand seasons to low demand seasons. The proposed pricing strategy results in a balanced capacity management and higher revenues for AMCs. Changing prices frequently has an adverse effect on customers too. So the dynamic pricing or demand pricing should be analyzed carefully without losing the perspective of customer. Having considered this point, we will model our problem only allowing discounts to attract customers at off-peak periods and leaving regular prices as they are at peak periods.

5.2 Peak Load Pricing

When there are peak loads and the capacity utilization discrepancy is high, the opportunity cost of providing aircraft maintenance is significant depending on the season: peak or off-peak. Since the total capacity is fixed throughout the year, in peak seasons the shadow cost of incremental capacity is higher than that of the off-peak seasons which may be assumed as zero. In other terms, when there is an idle capacity, the corresponding shadow cost would be zero. Thus, the peak load pricing strategy offers lower prices in off-peak seasons reflecting the variation in shadow costs of the capacity. Maintenance companies have good information about their capacity utilization ratios. The effect of a change in the marginal capacity utilization is greater at the high levels of utilization periods than at low levels of utilization periods. The price levels are determined based on the capacity utilization rates, which differs according to the time of the year since the maintenance demand is observed as highly seasonal (Table 5.1).

The decision making regarding a maintenance request could be done by a traditional approach where price per unit capacity used is fixed and orders are accepted until the capacity is reached for each time period. In other terms, a mathematical model without any pricing strategy is designed to provide maximum annual revenue while staying within the capacity constraint in each period. The output for each order is to accept or deny the request.

On the other hand, we propose another model which abides by the principles of peak load pricing to find a pricing policy that maximizes the revenue. The proposed model gives price incentives to delay orders towards off-peak seasons. It aims to obtain maximum annual revenue while staying within monthly capacity constraint in each period. In this model, there are 3 possible assignments for each order as; accept, deny or delay the request. Deny or delay decisions are made based on the associated price elasticity of orders. The request is denied if the corresponding customer's probability of accepting a delay is less than a certain threshold value (0.5, in our case). Otherwise the order is delayed to be completed in other periods. Thus the proposed model supposedly fills the off-peak seasons with the delays coming from the peak seasons and results with higher revenue and capacity utilization rates.

The decision models analyzed are given in the next section.

5.3 Job Acceptance Decision Models

Two decision models have been developed to analyze the cases where a delay of an order is possible or not.

5.3.1 Traditional Model

Assumptions

1. The demand forecasts D_{ik} and the full-fares for the maintenance job f_{ik} for each order in each time period are known.
2. There are t planning periods.
3. Capacity (C_i) is fixed for each time period.

4. After an order arrives, there are 2 outcomes, accept the order (A_{ik} = 1) if the required capacity D_{ik} is less than or equal to available capacity or deny the order (A_{ik} = 0) if capacity is reached.
5. Demands are satisfied in each period with an objective to maximize the capacity utilization.
6. Revenue is calculated as a product of satisfied demand and price.

The Algorithm for Accept/Deny Decisions

We find the subset of demands that maximizes the revenue within the capacity constraint as a 0/1 knapsack problem. The orders are either accepted or denied fully (fractional orders are not possible) in each time period and the periods are independent of each other. The weights are defined as capacity requirements of orders. Then we start to pack our knapsack starting with the orders that has the greatest weight and continue to load until we reach the capacity constraint. If an order with the greatest weight requires capacity more than available one, we continue to check other orders until we reach the capacity constraint.

Formulation

i = time period index; 1, 2, 3... t

k = job order index; 1, 2, 3... m

D_{ik} = k^{th} demand arrived in time period i

f_{ik} = regular maintenance price for k^{th} demand arrived in time period i

C_i = available capacity in time period i

L_i = back orders in time period i

λ = average cost of one unit backorder

A_{ik} = binary variable depending on whether the order k in time period i is satisfied

Objective function:

Max

$$E[R] = \sum_{i=1}^{t} \sum_{k=1}^{m} (D_{ik} * f_{ik}) * A_{ik} - \sum_{i=1}^{t} \lambda L_i \tag{5.1}$$

Subject to:

$$\sum_{k=1}^{m} D_{ik} * A_{ik} \le C_i + L_i \qquad \forall i = \{1, \cdots t\} \tag{5.2}$$

$$A_{ik} = \{0,1\} \qquad \forall i = \{1, \cdots t\}; \forall k = \{1, \cdots m\} \tag{5.3}$$

$$\sum_{i=1}^{t} A_{ik} \le 1 \qquad \forall k = \{1, \cdots m\} \tag{5.4}$$

5.3.2 Peak Load Pricing Model

Assumptions

1. The demand forecasts D_{ijk} for each order k, arrived in time period i and delayed until time period j are available.
2. There are t planning periods.

3. Capacity (C_i) is constant for each time period.

4. After an order arrives, there are 3 outcomes: accept, delay or deny.

5. Customers are price sensitive and the probability of delaying an order from period i to period j, $p(f_{ijk})$, to be accepted by a customer is known $\left(0 \leq p(f_{ijk}) \leq 1\right)$. If this probability is higher than a pre-defined threshold $\left(p(f_{ijk}) > \eta\right)$, the corresponding order can be delayed to maximize the expected revenue.

6. Incoming orders have their unique weights $\left(\mathrm{w}_{\mathrm{ik}}\right)$ based on their importance to the company. Some privileged customer's orders are not delayed by assigning them low price sensitivity values, in other terms; low probability of accepting a delay from the customer point of view. If we assign a probability value less than the threshold value for a specific order, we protect that order from delays. For example, if the threshold value μ is 0.50 and a probability of accepting a delay for a specific order is assigned as 0.49, our model will not delay that order.

7. These probability values are known for each order in the arrival period and do not change in the following periods if the order is delayed more than once.

8. If the total demand is greater than the capacity in a specific period, the orders with high price elasticity are tend to be delayed among the other orders.

9. Demands are satisfied in each period regarding the principles that reaching maximum capacity utilization and gaining maximum revenue.
10. The percentage of price reduction depends on the number of delays and/or delay time, and an order is processed only if it helps maximizing revenue objective. If the order is delayed more than a certain time period, it is denied at the beginning of our planning horizon.
11. Revenue is calculated as a product of satisfied demand and price.

The Algorithm for Accept/Deny/Delay Decisions

We find the subset of demands that maximizes the revenue within the capacity constraint as a multiple 0/1 knapsack problem. The orders are accepted, denied or delayed fully (fractional orders are not possible) in each time period and the periods are dependent of each other as the delayed orders from the previous periods are coming to the current period and again the delayed orders of the current period are going to the following periods to be processed. The weights are defined as marginal revenue over demand for each order. Then we start to pack our knapsack starting with the orders that have the greatest weight and continue to load until we reach the capacity constraint. If an order with the greatest weight requires more capacity than available one, we continue to check other orders until we reach capacity constraint. The algorithm requires the solution of m single knapsack problems, which can be solved in pseudo-polynomial time by dynamic programming.

Formulation

i = time period index; i = {1, 2, …, t}

k = job order index; k = {1, 2,..., m}

D_{ijk} = k[th] demand arrived in time period i and delayed until the time period j;

$$E[MR_{ik}] = MR_{iik} + \sum_{j=i+1}^{i+h} P(f_{ijk}^{d})MR_{ijk} \tag{5.5}$$

where j={i, i+1, i+2 … i+h}; ($j = i$, when demand is satisfied regularly, i.e. in the same time period that it arrives, *h* is the maximum allowable delay.

${f^r}_k$ = regular price

${f^d}_{ijk} = {f^r}_k * (1-\gamma_{ijk})$, discounted price associated with the order k which is satisfied with $j-i$ periods delay where γ_{ijk} is the discount rate for period *j*.

C_i = fixed capacity for the given period i

L_i = back orders in period i

λ = average cost of one unit backorder

A_{ijk} = binary variable depending on whether the order k in time period i is satisfied in time period j.

$P({f^d}_{ijk})$ = probability of delaying demand k from the time period i to j , which is randomized for all orders and between 0 and 1. This value corresponds to price elasticity of each order.

$$MR_{ijk} = \begin{cases} D_{ijk} * f^{r}{}_{k} * A_{ijk} & j = i \\ D_{ijk} * f^{d}{}_{ijk} * A_{ijk} & j = i+1 \ldots i+h \end{cases} \tag{5.6}$$

$w_{ik} = E[MR_{ik}] / D_{ik}$, is the weight of D_{ik} where $E[MR_{ik}]$ is the expected marginal revenue for demand arriving in period i with an order number k. After sorting the weight data for each time period, priority is given for an order that has greater weight value until we reach the capacity constraint.

If we analyze demand with respect to the period in which the order arrives, the period in which the order is satisfied and the job number *k* in the arrival period, the revenue function will take the following form:

Objective function:

Max

$$E[R] = \sum_{i=1}^{t} \sum_{k=1}^{m} \left(D_{iik} * f_{k}^{r}\right) * A_{iik} + \sum_{i=1}^{t-1} \sum_{j=i+1}^{t} \sum_{k=1}^{m} P\left(f_{ijk}^{d}\right)\left(D_{ijk} * f_{ijk}^{d}\right) * A_{ijk} - \sum_{i=1}^{t} \lambda L_{i} \tag{5.7}$$

Subject to:

$$\sum_{j=1}^{i} \sum_{k=1}^{m} D_{ijk} * A_{ijk} \leq C_{i} + L_{i} \qquad \forall i = \{1, \cdots t\} \tag{5.8}$$

$$A_{ijk} = \{0,\ 1\} \qquad \forall i = \{1, \cdots, t\}; \forall j = \{j, \cdots, t\}; \forall k = \{1, \cdots, m\} \tag{5.9}$$

$$\sum_{j=i}^{t} A_{ijk} \leq 1 \qquad \forall i = \{1, \cdots t\}; \forall k = \{1, \cdots m\} \tag{5.10}$$

$$L_{i} = Max\left\{\left(\sum_{k=1}^{m} D_{ik} * A_{ik} + L_{i-1}\right) - C_{i}, 0\right\} \qquad \forall i = \{1, \cdots t\} \tag{5.11}$$

Thus an order k with arrival period i is satisfied only in one period, or denied.

We expect to have even more improvements with the update of the discounted price after each arrival since we have more accurate data to grasp higher revenues. Moreover, we have to consider the effects of weight of an order. The weight of order k which arrives in period i, w_{ik}, is defined according to the marginal revenue of that order. However in some special cases, customer priority is high even though the marginal revenue is not sufficiently high. In such cases, the weight of that order could be determined manually between 0 and 1; 1 means that the customer of that order has the top priority and should be served in the arriving period. Then, we have another constraint for the weight, to make sure that the orders with high values of w_{ik} are not delayed.

$$A_{ijk}(\mu - w_{ik}) \geq 0 \tag{5.12}$$

Furthermore, in the mathematical model, an additional constraint is needed to guarantee that all the orders with $w_{ik} = 1$ are accepted for the intended period. In other words, some weights are set to 1 artificially to guarantee that some customers are not delayed. If $w_{ik} = 1$, then $A_{iik} = 1$. This condition can be added to our mathematical model as:

$$\left(w_{ik} - 1\right) < MA_{iik} \tag{5.13}$$

where M is a big number.

The mathematical model with the new constraints becomes as:

Objective function:

Max

$$E[R]=\sum_{i=1}^{t}\sum_{k=1}^{m}\left(D_{iik}*f^{r}{}_{k}\right)*A_{iik}+\sum_{i=1}^{t-1}\sum_{j=i+1}^{t}\sum_{k=1}^{m}P\left(f_{ijk}^{d}\right)\left(D_{ijk}*f^{d}{}_{ijk}\right)*A_{ijk}-\sum_{i=1}^{t}\lambda L_{i}$$

Subject to:

$$\sum_{j=1}^{i}\sum_{k=1}^{m}D_{ijk}*A_{ijk}\le C_i+L_i \qquad \forall i=\{1,\cdots t\} \tag{5.14}$$

$$A_{ijk}=\{0,1\} \qquad \forall i=\{1,\cdots,t\};\forall j=\{i,\cdots,t\};\forall k=\{1,\cdots,m\} \tag{5.15}$$

$$\sum_{j=i}^{t}A_{ijk}\le 1 \qquad \forall i=\{1,\cdots t\};\forall k=\{1,\cdots m\} \tag{5.16}$$

$$L_i=Max\left\{\left(\sum_{j=1}^{i}\sum_{k=1}^{m}D_{ijk}A_{ijk}+L_{i-1}\right)-C_i,0\right\} \qquad \forall i=\{1,\cdots t\} \tag{5.17}$$

$$A_{ijk}(\mu-w_{ik})\ge 0 \qquad \forall j>i;i=\{1,\cdots,t\} \tag{5.18}$$

$$\left(w_{ik}-1\right)<MA_{iik} \qquad \forall i=\{1,\cdots t\};\forall k=\{1,\cdots m\} \tag{5.19}$$

5.3.3 Analysis of Discounted Price after Each Arrival

Our model could be modified to include the effect of the deviation of the demand forecasts. Accordingly; we adjust maintenance supply and demand data for each period after each order arrival. We also have control over discounted price to reflect the effect of the changes in orders and available capacity. For instance; if the demand for a specific period is greater than the expected value, the price discount needs to be lower than the predefined value for the orders that are expected to be delayed into that specific period. Likewise; if the realized demand is lower than the demand forecast for a specific period, the orders should not be delayed into the following periods with a discounted price. Thus we integrate a level of dynamism into our model. We define the lower and upper bounds for the discounted price of an order; depending on the price elasticity of that order and the available and remaining capacities of the arrival period and the period into which the order could be delayed.

Price elasticity of demand is the responsiveness of demand to the changes in price. Therefore, in our model the price elasticity depends on the customer's willingness to accept a delay in order-completion time based on the given discount. If an order is elastic to a price change, it could be delayed when a sufficient decrease in price is offered. Accordingly; price elasticity is defined as follows;

$$\varepsilon_{ijk} = \frac{\%\text{ delay in period}}{\%\text{ change in price}} = \frac{(j-i)/h}{\left(f_k^r - f_{ijk}^d\right)/f_k^r} \tag{5.20}$$

After rearranging the above equation, a protection level for the discount price can be determined as shown below:

$$f_{ijk}^d = f_k^r - \frac{f_k^r\,(j-i)}{h\varepsilon_{ijk}} \geq f_{ijk}^* \tag{5.21}$$

where f_k^r is the regular price for order k which arrives in the period i and completed in the same period and f_{ijk}^* is the minimum discounted price that can be offered to customer k to convince him/her to delay the order from period i to period j.

On the other hand, the optimal price should be greater than the marginal revenue that could be obtained from the expected remaining capacity of K_i of i^{th} period and/or from the expected remaining capacity greater than K_j of j^{th} period. In other terms;

$$f_{ijk}^* \geq \sum_{l=0}^{K_i-1} p_i(l) f_l^r + \sum_{l=K_j+1}^{c_j} p_j(l) f_l^r \tag{5.22}$$

Thus, the above analysis provides an upper and lower bound for the optimal discounted price of an order which arrives in period i and delayed into period j.

$$f_k^r - \frac{f_k^r(j-i)}{h\varepsilon_{ijk}} \geq \; f_{ijk}^* \;\; \geq \sum_{l=0}^{K_i-1} p_i(l) f_l^r + \sum_{l=K_j+1}^{c_j} p_j(l) f_l^r \tag{5.23}$$

$$f_{ijk}^- \leq f_{ijk}^* \leq f_{ijk}^+ \tag{5.24}$$

5.4 The Algorithm Selection

The problem shown in the previous sections is a multi-period knapsack problem, which is NP-hard. Such problems are usually solved with greedy algorithms in literature. Hence, we first search a heuristic solution algorithm to solve our model. Afterwards we modify the model without loosing its accuracy and develop a dynamic programming algorithm to solve the converged multi-period knapsack problem optimally.

Greedy algorithms are one set of algorithms designed to solve large optimization problems. They function by calculating the locally optimal solution at every iteration in the hope that this local solution will be part of the optimal global solution. One of the largest downfalls of greedy algorithms is that they do not always produce optimal results.

We are given a set of n items from which we are to select some number of items to be carried in a knapsack. Each item has both a weight and a profit. The objective is to choose the set of items that fits in the knapsack and maximizes the profit.

Let u_i be the weight of the i^{th} item, v_i be the value accrued when the i^{th} item is carried in the knapsack, and U be the capacity of the knapsack. Let x_i be a variable the value of which is either zero or one. The variable x_i has the value one when the i^{th} item is carried in the knapsack.

Given $\{u_1, u_2....u_n\}$ and $\{v_1, v_2....v_n\}$, our *objective* is to maximize

$$\sum_{i=1}^{n} v_i * x_i$$

subject to the constraint

$$\sum_{i=1}^{n} u_i * x_i \leq U \tag{5.25}$$

Clearly, we can solve this problem using a greedy solution strategy in which the problem is solved by putting items into the knapsack one-by-one.

A problem exhibits optimal substructure if an optimal solution to the problem contains within its optimal solutions to sub-problems. In other terms, the principle of optimality holds if every optimal solution to a problem contains optimal solutions to all sub problems. 0-1 knapsack problem exhibits optimal substructure. If item j is removed from an optimal packing, the remaining packing is an optimal packing with weight at most $U-u_j$. Although the 0-1 knapsack problem exhibits the optimal substructure property, it is not optimally solvable by a greedy algorithm. However it could be solved with dynamic programming which is discussed in the following section.

5.4.1 Dynamic Programming Algorithm

According to the literature on knapsack problems multi-period knapsack problems could not be solved optimally. In multi-period knapsack problem, the objective is to assign an item into a knapsack among many knapsacks. In our maintenance service context, an order is placed in any time period to be processed being indifferent between time periods considering the whole planning period as one unit. For each order, the assignment is done recursively searching all possible capacity allocations.

In our work, we converge our problem from 0-1 knapsack problem to multi-period knapsack problem by ranking orders, employing price elasticity and calculating expected marginal order revenues. First we examine price elasticity to decide whether or not an order could be delayed. Next, if a delay decision has been made for an order, associated expected marginal revenue is calculated to find the optimal set of orders to be processed.

In other terms, for each time period we design a 0-1 knapsack model and then by creating links between time periods we meet the multi-period knapsack problem mechanism which allows alternative placement of orders for various time periods.

As mentioned before, a dynamic programming algorithm solves 0-1 knapsack problem optimally.

Dynamic programming is a strategy for designing algorithms. In other terms, it enables an algorithm by exhaustively enumerating the feasible solutions and selecting the one with the highest profit. However, since there are 2^n possible solutions, the running time required for the solution becomes prohibitive as n gets large. In order to solve a problem by dynamic programming, the problem itself must exhibit an optimal substructure, which is already confirmed.

Let i be the highest-numbered item in an optimal solution S for U pounds. Then $S^{`} = S - \{i\}$ is an optimal solution for $U - u_i$ pounds and the value to the solution S is V_i plus the value of the sub problem.

We can express this fact in the following formula: define $c[i,\ u]$ to be the solution for items 1, 2,..., i and maximum weight U. Then:

$$c[i,u]=\begin{cases}0 & i=0 \text{ or } u=0\\ c[i-1,u] & u_i\geq 0\\ \max\{v_i+c[i-1,u-u_i],\ c[i-1,u]\} & i>0 \text{ and } u\geq u_i\end{cases} \tag{5.26}$$

In other words, the value of the solution to i items either include i^{th} item, in which case it is v_i plus a sub problem's solution for $(i-1)$ items and the weight excluding u_i, or does not include i^{th} item, in which case it is a sub problem's solution for $(i-1)$ items and the same weight. That is, if we pick item i, we take v_i value, and we can choose from items $u-u_i$, and get $c[i-1,u-u_i]$ additional value. On the other hand, if we decide not to take item i, we can choose from items 1, 2,…, $i-1$ up to the weight limit u and get $c[i-1,\ u]$ value. The better of these two choices should be made.

Although the 0-1 knapsack problem, the above formula for c is similar to LCS (longest common subsequence problem-finding the longest subsequence common to all sequences in a set of sequences) formula; that is boundary values are 0, and other values are computed from the input and "earlier" values of c. So the 0-1 knapsack algorithm is like the LCS-length algorithm given in Cormen, Leiserson, Rivest and Stein (1990) for finding a longest common subsequence of two sequences. The algorithm takes as input the maximum weight U, the number of items n and the two sequences $v=<v_1,v_2...v_n>$ and $u=<u_1,u_2...u_n>$. It stores the $c[i,j]$ values in the table, that is, a two dimensional array, $c[0...n,\ 0...u]$ whose entries are computed in a row-major order. That is, the first row of c is filled in from left to right, then the second row, and so on. At the end of the computation, $c[n, u]$ contains the maximum value that can be picked into the knapsack.

The 0-1 and multiple knapsack problems are coded in C++. The algorithm followed is shown below:

Dynamic-Programming Knapsack Algorithm (v, u, n, U)

FOR $u = 0$ to U

DO $c[0,u] = 0$

FOR $i = 1$ to n

DO $c[i,0] = 0$

FOR $u = 1$ to U

DO IF $u_i \le u$

THEN IF $v_i + c[i-1, u-u_i] > c[i-1,u]$

THEN $c[i,u] = v_i + c[i-1,u-u_i]$

ELSE $c[i,u] = c[i-1,u]$

ELSE

$c[i,u] = c[i-1,u]$

The set of items to take can be deduced from the table, starting at $c[n,u]$ and tracing backwards where the optimal values came from. If

$c[i,u] = c[i-1,u]$ item i is not part of the solution, and we continue tracing with $c[i-1,u]$. Otherwise item i is part of the solution, and we continue tracing with $c[i-1,u-u_i]$. The array has the size of $(n+1)*(U+1)$.

5.5 The Results

A mathematical model may not address the real life issues exactly, so we test our model by a simulation analysis. In order to test the performance of the proposed capacity management model for maintenance, we develop a simulation model that enables users to test both 0/1- knapsack or multiple knapsack algorithms with varying input parameters. Simulation model enables the user to select the following parameters:

- price elasticity type: "read from a file"; "fixed and randomly determined"; or "changing over periods and randomly determined"
- threshold value for the probability of accepting a delay associated with price elasticity: any value between 0 and 1.
- integer price discount % per delay: any value between 0 and 100.
- maximum number of allowable delays: any integer value between 0 and 12.

The simulation model has been executed 48 times generating 48 cases. Some predetermined values are used to build these cases:

There are 12 time periods, each corresponding to a month. Capacity is fixed at 100 units for each time period. In order to encourage customers to delay their orders to future periods, price discounts are offered to the customers. If the current periods' demand, period i, is larger than the capacity and one of the future periods, period j, has the excess capacity, $if\left(D_i \geq C_i \text{ AND } D_j < C_j\right) \Rightarrow f^d{}_{ijk} = f^r{}_{ik}\left(1-(j-i)\gamma_{ijk}\right)$. In the simulation study, the price discount rate γ_{ijk} is selected by the user. If the order is delayed more than the maximum allowable delay periods, it is denied at the beginning of our planning horizon. For the maximum allowable delays, 1 month, 3 months and 6 months cases are examined in the simulation study. The price elasticity of each order is generated randomly resulting in a probability of delay between 0 and 1. The cases with fixed price elasticity and changing price elasticity per order over time periods are analyzed separately. Besides demand is assumed either seasonal, patterned or normally distributed with high and low level of variances. The capacity utilization rates and revenues are calculated for each demand type, for each price discount %, for each maximum number of allowable delays and for each statue of price elasticity of orders. The results of the proposed model and the traditional model are compared for each and every case. For each demand type, the best cases producing the highest capacity utilization and revenues are selected.

Since maintenance service demand is observed as seasonal in practice, first we randomly generate seasonal demand data (Table 5.1) to analyze our model. Then we randomly generate patterned and normally distributed demand data to examine results more thoroughly. This sensitivity analysis on demand enables us to remark the consequences of these demand types on the capacity utilization rates and revenues. The patterned and normally distributed demand data used in the simulation are also shown in Table 5.1.

Table 5.1: Demand Data

Period #	Demands			
	Seasonal	Patterned	N (100, 40)	N (100, 10)
1	72	60	159	102
2	72	110	136	104
3	84	140	85	106
4	89	60	174	82
5	101	110	154	82
6	111	140	137	96
7	132	60	94	96
8	144	110	117	120
9	138	140	115	85
10	116	60	109	93
11	96	110	110	83
12	83	140	121	100
13	71	60	116	108
14	73	110	68	95
15	86	140	155	101
16	84	60	116	103
17	92	110	86	101
18	108	140	123	105
19	135	60	99	95
20	143	110	78	99
21	139	140	130	101
22	117	60	145	94
23	96	110	72	73
24	75	140	56	96

In our analysis; the proposed model produces better results then the traditional model in terms of capacity utilization rates and revenues for all cases. These cases are determined by the price discounts (%), maximum allowable delays, statue of price elasticity, and demand types. As an example let us examine the results of the best case of the proposed method and the results of the traditional approach for seasonal demand. The results are provided in Fig. 5.2 and Fig. 5.3. It is seen that the proposed model generates better values for capacity utilization and revenues than the traditional approach; especially in the off peak season.

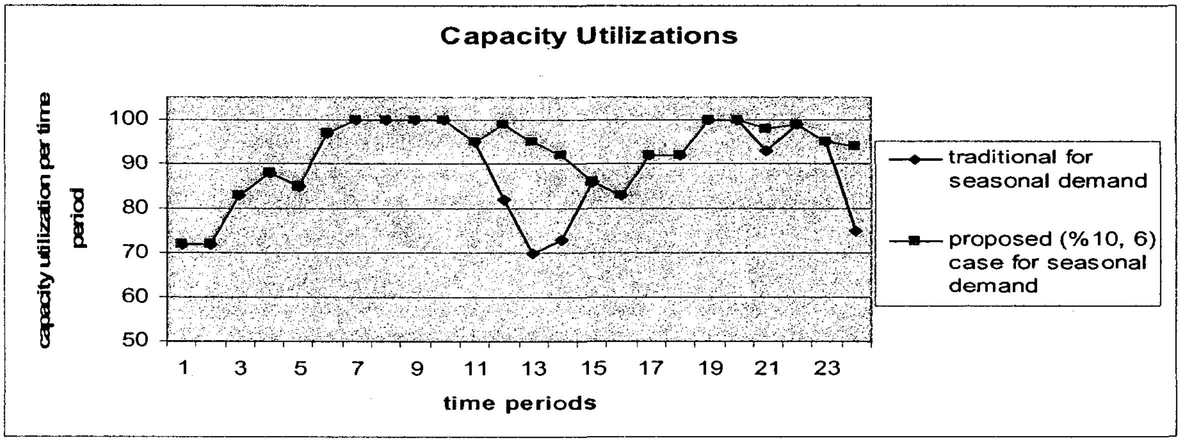

Figure 5.2: Capacity utilization improvement for seasonal demand

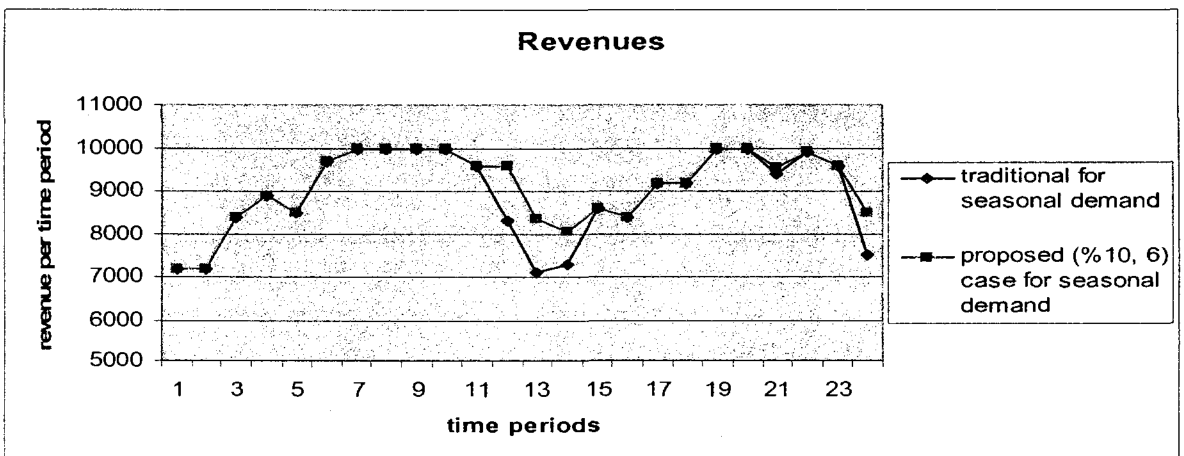

Figure 5.3: Revenue improvement for seasonal demand

Similarly the results of the best case of the proposed method and the results of the traditional approach for normal demand whose mean is 100 and standard deviation is 10 are summarized in Fig. 5.4 and Fig 5.5. Again, the proposed model generates better values for capacity utilization and revenues than the traditional approach. In this case, the improvements are not peculiar to certain time periods as the demand is normally distributed.

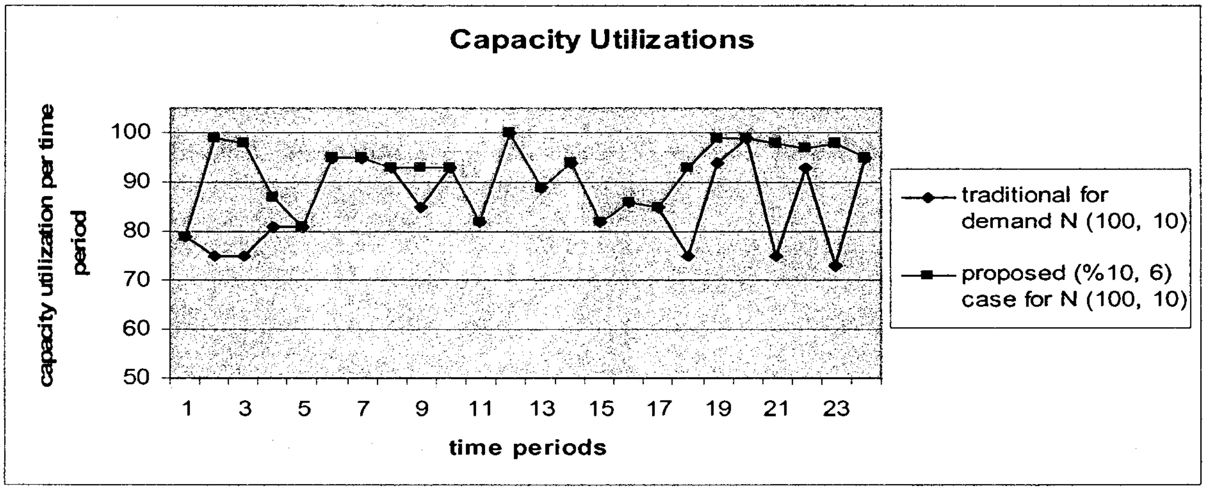

Figure 5.4: Capacity utilization improvement for the demand N (100, 10)

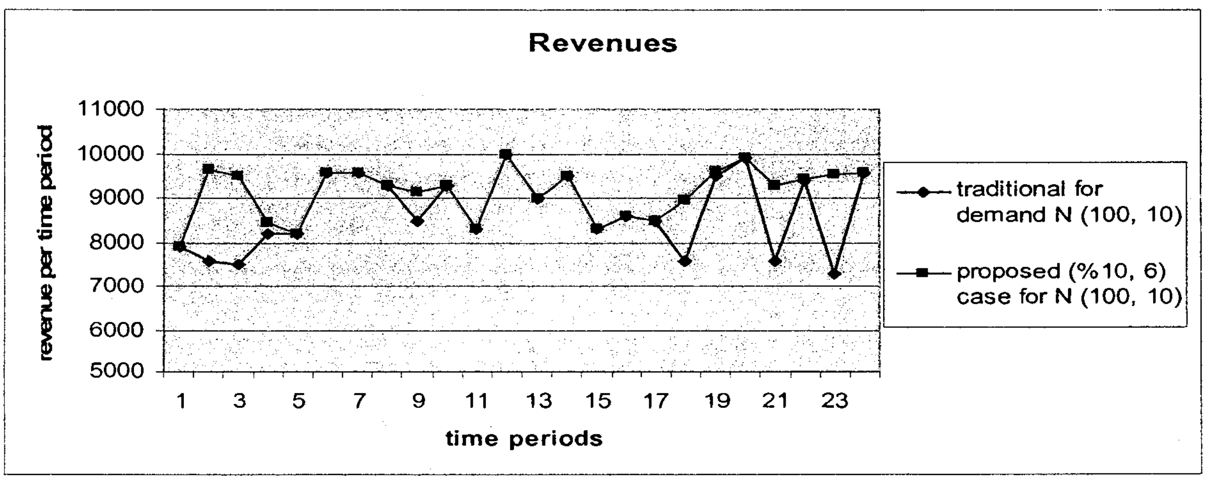

Figure 5.5: Revenue improvement for the demand N (100, 10)

The best case is selected as the case generating maximum capacity utilization and maximum revenue for each demand type. The capacity utilization and revenues of these best cases for each demand type is shown Fig. 5.6 and 5.7 respectively. As seen, our model produces robust improvements for all demand types.

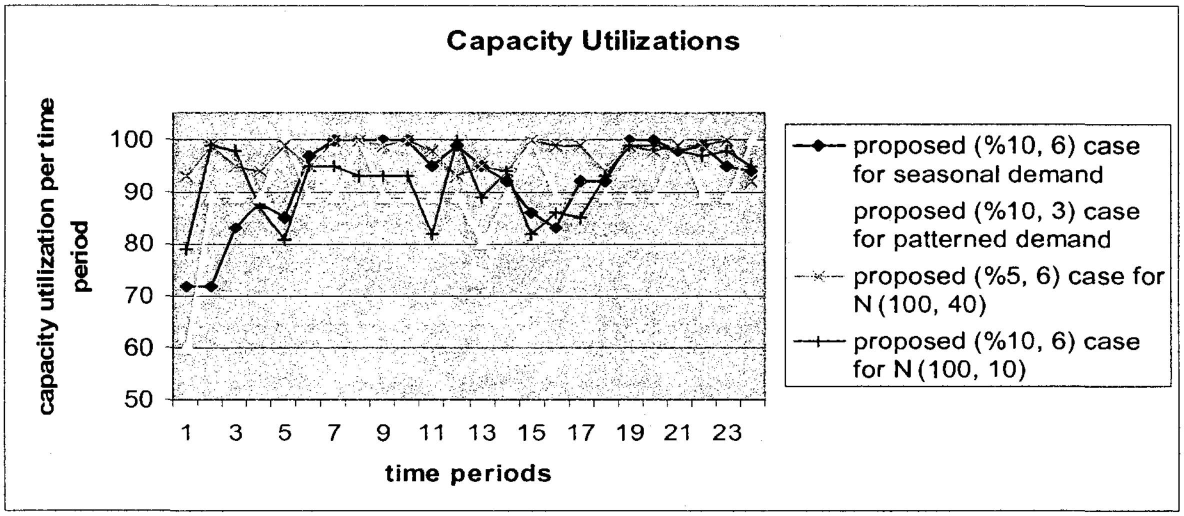

Figure 5.6: Capacity Utilization Rates

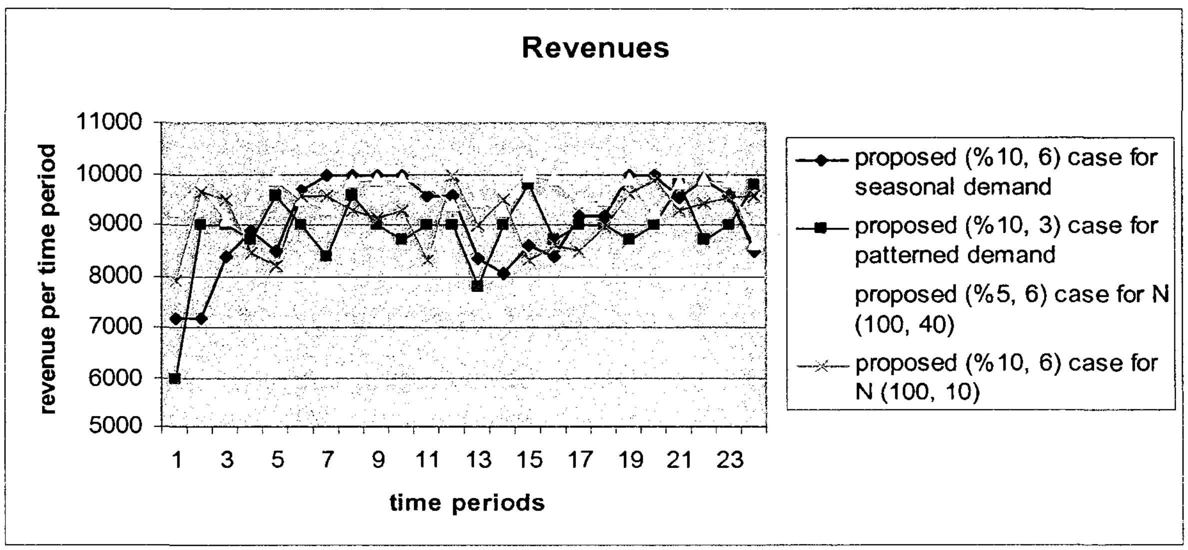

Figure 5.7: Revenues

Although the proposed model regards continues time in horizon, in the simulation study we examine 24 demand data corresponding to 24 months. Accordingly; the first part of the Fig. 5.6 and Fig. 5.7 shows relatively low level of capacity utilization and revenues because we do not consider delayed demand coming from the previous time periods; namely the time periods before time period 1. As expected, this circumstance is especially valid for seasonal demand which starts with off peak season and for patterned demand which starts from the minimum demand data in the beginning of the considered time periods and follows a pattern as shown in Table 5.1. On the other hand, this effect is not as much for normally distributed demand duly, even though we ignore the delayed demand coming from the previous time periods of time period 1 as usual. So it is advised to focus on the middle section of the capacity utilization and revenue figures to disregard this drawback of simulation study in order to see the true impact of the proposed model; especially in seasonal and patterned demand cases.

After observing the trend of capacity utilization and revenues over time periods, we calculate annual capacity utilizations (%) and annual revenue ($) values generated by the traditional and the proposed models for seasonal, patterned, and normally distributed (N (100, 40) and N (100, 10)) demand types. We selected some cases; shown by the pairs of % price discounts and the maximum allowable delays for the proposed model. The results are summarized in Table 5.2.

Table 5.2: Annual capacity utilization (%) and revenue ($) values

		Cases					
		Traditional	Proposed (%5,6)	Proposed (%10,6)	Proposed (%20,6)	Proposed (%10,1)	Proposed (10,3)
Seasonal Demand	Annual Capacity Utilization	88.83	91.25	92.38	91.50	89.13	90.46
	Annual Revenue	107000	109195	109225	107950	107205	108325
Patterned Demand	Annual Capacity Utilization	79.33	88.50	88.04	86.00	85.17	89.71
	Annual Revenue	96000	106050	104800	102000	102150	106650
Normal Demand N (100, 40)	Annual Capacity Utilization	89.67	97.21	94.79	93.08	91.75	96.79
	Annual Revenue	107950	115160	112555	109710	109675	113855
Normal Demand N (100, 10)	Annual Capacity Utilization	86.42	89.50	92.08	90.88	89.33	90.96
	Annual Revenue	104400	107458	109600	107710	107020	108655

Annual capacity utilization and revenue values need to be carefully analyzed. Since peak load pricing strategy gives us the flexibility to use the capacity effectively, it results in better capacity utilization rates than the traditional approach in all cases, shown in Table 5.2. Especially if long periods of delays are available, it helps to improve capacity utilization more. The best cases generating the maximum capacity utilization ratios and the maximum revenues for each demand type are shaded in Table 5.2.

As seen from Table 5.2, better capacity utilization does not guarantee better revenue as expected. For example; although the case of 20% discount and 6 months of allowable delay results in higher capacity utilization, it produces less revenue than the case of 5% discount and 6 months of allowable delay assuming seasonal demand. Besides it is observed that the increase in capacity utilization and the increase in revenue are not proportional as revenue improves more niggardly due to price discounts. When we analyze the case with 10% price discount and 6 months of delay assuming seasonal demand, it is seen that this case generates 3.9 % more capacity utilization and 2.1 % more revenues than the traditional approach. Capacity is only a constraint in our model, which we satisfy without losing the ultimate objective of maximizing revenue from our sights. Since we control some of the spilled demand of traditional approach by offering price discounts and delaying the orders which are sensitive to price changes towards following periods, we get higher revenues taking advantage of market segmentation by recognizing customers with varying needs and expectations. If we assume the demand is normally distributed, the results are similar to the results of seasonal or patterned demand. We generate normally distributed random demands for 24 months. We set the mean value of the demand is equal to the capacity and defined two levels of variance; high (1600) and low (100) to see the results of extreme conditions of fluctuations in demand. The improvements in capacity utilization and revenues achieved by the selected cases of the proposed model are summarized in Table 5.3.

Table 5.3: Summary of improvements in capacity utilization and revenues

Demand type	Selected Case (The best pair of % price discount and maximum allowable delays)	% improvement in capacity utilization (compared to the traditional approach to the selected case)	% improvement in revenue (compared to the traditional approach)
Seasonal	(10, 6)	3.9	2.1
Patterned	(10, 3)	13	11
N (100, 40)	(5, 6)	8.4	6.7
N (100, 10)	(10, 6)	6.6	5.0

First of all, we achieve higher capacity utilization rates and revenues with the proposed model for all types of demand considered in this study. Besides, it is clear that when we consider patterned demand instead of seasonal or normal demand, the improvements in capacity utilization and revenue values is the greatest. On the other hand normally distributed demand offers more opportunity in terms of increasing capacity utilization and revenues than the seasonal demand. When we have normally distributed demand data whose variance is high, improvement in capacity utilization rate and revenues is high. In other words, the higher the variance in demand, the better the improvements in capacity utilization and revenues. At the end; the various demand types considered in this study allows even more improvements than our originally considered seasonal demand showing that the proposed model enables us to achieve significant improvements for a broad selection of demand data.

Our program provides solution for any price elasticity status, threshold value, discount ratio, allowable number of delays, price and capacity values. Thus it gives flexibility to the analyzer who wants to explore various scenarios about these variables.

5.6 Summary and Conclusion

The Benefits of the Proposed Model in Short-Medium Term (Operational Planning)

Pricing Decisions: The program could be used to see the effect of various price discount schemes so that the user could choose the best % price discount, ceteris paribus.

Flexibility of Delays: The consequence of various levels of possible number of delays could be searched by entering the corresponding delay value.

Overhead costs: The user could figure a strategy to choose the minimum number of orders producing the same revenue to minimize overhead costs.

The Benefits of the Proposed Model in Long Term (Strategic Planning)

Market share strategy (Number of orders or clients preference): The user could figure a strategy to choose the maximum number of orders producing the same revenue to maximize market share.

Capacity change decisions in long term: If the capacity utilization rates are relatively too low or too high, the program could be employed to see the effect of possible capacity changes in the long run. It serves as a decision making tool for capacity changes.

We provided computational results that give insight into the revenue improvement potentials of peak load pricing for different expected values of demand scenarios. In general the pricing strategy gives superior revenues in comparison to the traditional approach. Our results reveal that the revenue improvement is much higher when demand is highly fluctuated.

Chapter 6

6. Summary, Conclusion and Future Research

We tackled two RM problems in airline industry. While we adapted financial options in the booking process, we brought a new dimension to the aircraft maintenance problem by borrowing some RM literature.

6.1 Summary and Conclusions

In the last few decades, the decision making process has gained more importance in airline booking systems due to the high competition in airline business. Airlines are eager to apply various RM models to achieve sustainable development against the shrinking profit margins. Seat inventory control and pricing are the major subjects in the field to obtain higher revenues. In this thesis, we discussed a new method of inventory control (seat control in the airline business) considering both higher capacity utilization and more precise pricing of seats with respect to the changing market conditions. The proposed model anticipates using financial options; calls and puts in the booking process. It could be regarded as an instrument to adjust the environment in the decision making process.

On the other hand, although RM applications do not take into account cost, we recognize that the main cost contributors for airlines are fuel and aircraft maintenance. Fuel prices are very complex to predict and under influence of many factors. The aircraft maintenance service suppliers also has inventory control problem and they could not satisfy the customers due to frequent backorders. So, as a second major contribution in this thesis, we proposed a RM model for the aircraft maintenance centers to manage the capacity through controlling the demand and supply using pricing strategies. We offer price incentives to shift the excess demand from the peak seasons to the off-peak seasons which is a common practice for peak load pricing of utilities. We segment the market by evaluating price elasticity of customers. The price incentives are provided for price sensitive customers' orders so the capacity is used for price insensitive customers' orders. Thereby, we shift some demand to better utilize the steady capacity against the seasonal demand. Our model acquires higher capacity utilization and revenues while increasing customer satisfaction.

6.1.1 Contributions in Airline RM Model with Options Approach

A new approach for selling airline tickets which allows pricing of seat value from customers view is proposed. We develop a mathematical model and conduct a simulation study to explore the effectiveness and the potentials of the financial options in airline reservation systems. Simulation analysis is conducted to show revenue and load factor improvements via options. We developed an "option" based seat management strategy, which would potentially serve as a more revenue generating alternative to the existing "overbooking" based RM. Efficient capacity utilization brings operational efficiency with higher load-factors and presents a profit opportunity. To this date, there is no theoretical study or a practice investigating the utilization and potentials of financial options in the booking process of airlines.

6.1.2 Contributions in Aircraft Maintenance Order Control through RM

A peak load pricing model is designed to maximize revenue of an aircraft maintenance company by shifting demand through pricing. We model our problem only allowing discounts to attract customers at off-peak periods and leaving regular prices as they are at peak periods. The algorithm requires the solution of m single knapsack problems, which can be solved by dynamic programming. We further mathematically investigated the upper and lower bounds for the offered price discounts. To our knowledge, this peak load pricing problem has not been studied in the literature with a comprehensive approach for maintenance services but the dynamic programming knapsack algorithm is used in various contexts in the literature.

6.2 Future Research

6.2.1 Future Research on Options Approach

Even though, "*options*" approach lays an opportunity for the airline industry, at the implementation phase, the pricing of options and premiums, and the number of options traded are the challenging issues that airline companies should carefully evaluate. Here, the important question is how many puts and calls to sell or buy at what exercise price. We will be extending our research to address to these questions. If the airline buys excess amount of put options when the demand for high-fare customers is higher than expected, then airline does not exercise those puts at all although having paid for them. Hence, buying puts that are not exercised is a cost for the airline. Likewise, if the airline sells excess amount of tickets while buying call options, there is a possibility of low demand, in which case airline does not exercise those calls to recall the tickets. Although, the simulation results clearly demonstrate the strength of using financial options in the airline booking process, the determination of optimal trading conditions, the number of call and puts to be traded by the airline, with the given forecasted demand, market conditions and the cost of the option's premium constitute natural extensions of our research.

6.2.2 Future Research on Aircraft Maintenance

In the order acceptance decision model, we applied multiple 0/1 knapsack problem that is, an order is proceeded as a whole and demand is satisfied or delayed entirely. A model development idea could be the implementation of fractional knapsack strategy where a part of demand is satisfied in a period and the rest is satisfied in another period and so on. This strategy may provide tools to have even higher load factors and revenues.

Discount ratios are fixed per delays for all orders but they do not have to be fixed. They might be read from a file for each order. We provide the upper and lower bounds for the discounted price which is updated after each arrival. Numerical results given in this study are based on fixed discount ratios. If they were calculated regarding dynamic price discounts for which the upper and lower bounds are already retrieved, we would get even higher improvements in terms of revenue. Customer priority apart from price elasticity could be assigned when defining the weights of each order as well.

On the other hand, fixed capacity constraint can be relaxed according to the results of our model. If there are strategic planning decisions to be made for all kind of resources such as working force, equipments etc. that constitutes the capacity, our model's results provide feedbacks to support the capacity change decisions.

The same strategies could be used for ships, locomotives, and other heavy equipment maintenance businesses. In fact, the proposed model could be used for all kind of manufacturing or service industries that work with the principles of make/serve to order. Although some of these industries may have higher flexibilities than the aircraft maintenance centers in terms of the capacity changes, for all the make/serve to order businesses, an unused capacity is revenue lost forever similar to a flight departing with empty seats. Thus, the findings of this study could be used in other application areas to apply peak load pricing strategy in particular and RM principles in general in order to achieve higher revenues by using the resources more efficiently.

References

[1] Adams, M., 03/29/2005, 'Delta to outsource more jet maintenance', USA TODAY.

[2] Ahire, S., Greenwood, G., Gupta, A. and Terwilliger, M., 2000, 'Workforce-Constrained Preventive Maintenance Scheduling Using Evolution Strategies', Decision Sciences, 31, 4, pp. 833-859.

[3] Akgunduz A., Turkmen B. and Bulgak A.A., 2007, 'Using Financial Options in the Airline Booking Process', Journal of Revenue & Pricing Management, 6, 2, pp. 135-150.

[4] Amram, M. and Kulatilaka, N., 1999, 'Real Options: Managing Strategic Investment in an Uncertain World', Harvard Business School Press.

[5] Anderson, C.K. and Blair, M., 2004, 'Performance monitor: the opportunity costs of revenue management', Journal of Revenue & Pricing Management, Vol. 2, pp. 353–367.

[6] Anderson, C.K., Davison, M. and Rasmussen, H., 2004, 'Revenue management: A real options approach', Naval Research Logistics, 51, 5, pp. 686–703.

[7] Air Transport Association (ATA), the Airline Handbook.

[8] Air Transport Association (ATA), 2002, The Annual Report, www.airlines.org

[9] Baker, T.K. and Murthy, N.N., 2005, 'Viability of auction-based revenue management in sequential markets', Decision Sciences, Vol. 36, pp. 259–288.

[10] Beabout, B.A., 'Statistical Process Control: An Application in Aircraft Maintenance Management, PhD Thesis, Air Force Institute of Technology, 2003.

[11] Belobaba, P., 1987a, 'Air Travel Demand and Airline Seat Inventory Management', Ph.D. Thesis, Massachusetts Institute of Technology, U.S.A.

[12] Belobaba, P., 1987b, 'Airline Yield Management: An Overview of Seat Inventory Control', Transportation Science, 21, pp. 63-73.

[13] Belobaba, P., 1989, 'Application of a Probabilistic Decision Model to Airline Seat Inventory Control', Operations Research, 37, pp. 183-197.

[14] Belobaba, P. and Wilson, J. L., 1997, 'Impacts of Yield Management in Competitive Airline Markets', Journal of Air Transport Management, 3, pp. 3-9.

[15] Belobaba, P. and Parkas, A., 1999, 'Yield Management Impacts on Airline Spill Estimation', Transportation Science, 33, pp. 217-232.

[16] Bertsimas, D. and de Boer, S., 2000, 'Simulation-based optimization for airline network yield management', Working Paper, Massachusetts Institute of Technology, U.S.A.

[17] Bertsimas, D. and de Boer, S., 2005, 'Simulation-based booking limits for airline revenue management', Operations Research, Vol. 53, pp. 90–106.

[18] Bertsimas, D. and Popescu, I., 2000, 'Revenue Management in a Dynamic Network Environment', Working Paper, Massachusetts Institute of Technology, U.S.A.

[19] Bitran, G. and Mondschein, S., 1995, 'An application of yield management to the hotel industry considering multiple day stays', Operations Research, 43, pp. 427-444.

[20] Bitran, G. and Mondschein, S., 1997, 'Periodic pricing of seasonal products in retaining', Management Science, 43, pp. 64-79.

[21] Borenstein, S. and Rose, N. L., 1994, 'Competition and Price Dispersion in the U.S. Airline Industry', Journal of Political Economy, 102, 4, pp. 653-683.

[22] Braid, R. M., 1996, 'Peak Load Pricing of a Transportation Route with an Unpriced Substitute', Journal of Urban Economics, 40, 2, pp. 179-197.

[23] Brumell, S. L. and McGill J. I., 1993, 'Airline Seat Allocation with Multiple Nested Fare Classes', Operations Research, 41, pp. 127-137.

[24] Canadian Corporate News, November, 2000, 'Air Canada Announces New Technical Services Organization' http://findarticles.com/p/articles/mi_hb5559/is_200011/ai_n22597718

[25] Chatwin, R. E., 1996, 'Multi-Period Airline Overbooking with Multiple Fare Classes', Naval Research Logistics, 43, pp. 603-612.

[26] Chatwin, R. E., 1998, 'Multi-Period Airline Overbooking with A Single Fare Class', Operations Research, 46, pp. 805-819.

[27] Chatwin, R. E., 1999, 'Continuous-Time Airline Overbooking with Time-Dependent Fares and Refunds', Transportation Science, 33, pp. 182-191.

[28] Chatwin, R. E., 2000, 'Optimal Dynamic Pricing of Perishable Products with Stochastic Demand and a Finite Set of Prices', European Journal of Operations Research, 125, pp. 149-174.

[29] Chiang, W.C., Chen, J.C.H. and Xu, X., 2007, 'An overview of Research on Revenue Management: Current Issues and Future Research', International Journal of Revenue Management, 1, 1, pp. 97-128.

[30] Choi, S. and Mattila, A.S., 2005, 'Impact of information on customer fairness perceptions of hotel revenue management', Cornell Hotel and Restaurant Administration Quarterly, Vol. 46, pp. 444–451.

[31] Ciancimino, A., Inzerillo, G., Lucidi, S. and Palagi, L., 1999, 'A Mathematical Programming Approach for the Solution of the Railway Yield Management Problem', Transportation Science, Vol. 33, No. 2, pp. 168-181.

[32] Cooper, W.L. and Menich, R.P., 1998, 'Airline Ticket Auctions: Revenue Management and the Pivotal Mechanism', Technical report, University of Minnesota, MI, U.S.A.

[33] Cormen, T. H., Leiserson, C. E., Rivest, R. L., 1990, 'Introduction to Algorithms', first edition, MIT Press and McGraw-Hill. ISBN 0-262-03141-8.

[34] Cope, J., 2002, 'Tuning into Travel Savings', Computerworld, April 1, 36.

[35] Coughlan, J., 1999, 'Airline Overbooking in the Multi-Class Case', Journal of the Operational Research Society, 50, pp. 1098-1103.

[36] Crew, M. A., Fernando, C. S. and Kleindorfer, P. R., 1995, 'the Theory of Peak Load Pricing: A Survey', Journal of Regulatory Economics, 8, pp. 215-248.

[37] Cross, R.C., 1997, 'Revenue Management - Hard-core Tactics for Market Domination', Broadway Books.

[38] Curry, R. E., 1990, 'Optimal airline Seat Allocation with Fare Classes Nested by Origins and Destinations', Transportation Science, 24, pp. 193-204.

[39] Dijkstra, M. C., Kroon, L. G., Salomon, M., Van Nunen, J., and Van Wassenhove, L. N., 1994, 'Planning the size and organization of KLM's aircraft maintenance personnel', Interfaces, 24, 6, pp. 47-58.

[40] Dixit, A.K. and Pindyck, R.S., 1994, 'Investment under Uncertainty', Princeton University Press.

[41] Duffuaa, S. O. and Andijani, A. A., 1999, 'An integrated simulation model for effective planning of maintenance operations for Saudi Arabian Airlines (SAUDIA)', Production Planning & Control, 10, 6, pp. 579-584.

[42] Duffuaa, S. O., Ben-Daya, M., Al-Sultan, K.S., Andijani, A. A., 2001, 'A generic conceptual simulation model for maintenance systems', Journal of Quality in Maintenance Engineering, 7, 3, pp. 207-219.

[43] Edgar, D.A., 2000, 'Economic theory of pricing for the hospitality and tourism industry', Yield Management: Strategies for the Service Industries, pp. 15–31, London, UK.

[44] Eguchi, T. and Belobaba, P.P., 2004, 'Modelling and simulation of impact of revenue management on Japan's domestic market', Journal of Revenue & Pricing Management, Vol. 3, pp. 119–142.

[45] El-Haber, S. and El-Taha, M., 2004, 'Dynamic two-leg airline seat inventory control with overbooking, cancellations and no-shows', Journal of Revenue & Pricing Management, Vol. 3, pp. 143–170.

[46] Elmaghraby, W. and Keskinocak, P., 2003, 'Dynamic pricing in the presence of inventory considerations: research overview, current practices, and future directions', Management Science, Vol. 49, pp. 1287-1309.

[47] Federal Reserve Bank of Atlanta, 2003, 'Taking off: Discount airlines transform flying', EconSouth, Third Quarter, 13.

[48] Feng, Y. and Gallego, G., 2000, 'Perishable Asset Revenue Management with Markovian Time Dependent Demand Intensities', Management Science, 46, pp. 941-956.

[49] Feng, Y. and Xiao, B., 2000, 'Optimal Policies of Yield Management with Multiple Predetermined Prices', Operations Research, 48, pp. 332-343.

[50] Feng, Y. and Xiao, B., 2001, 'A Dynamic Airline Seat Inventory Control Model and Its Optimal Policy', Operations Research, 49, pp. 938-949.

[51] Franke, M., 2004, 'Competition between Network Carriers and Low-Cost-Carriers- Retreat Battle or Breakthrough to a New Level of Efficiency?', Journal of Air Transport Management, 10, pp. 15-21.

[52] Gaffey, P., 1995, 'Spreading the word', the 7th International Revenue Management Conference, IATA, Toronto, Ca.

[53] Gallego, G., 1996, 'A Demand Model for Yield Management', Technical Report, Columbia University, U.S.A.

[54] Gallego, G. and Phillips, R., 2004, 'Revenue management of flexible products', Manufacturing & Service Operations Management, 6, pp. 321-337.

[55] Gallego, G. and van Ryzin G., 1997, 'A Multi-Product Dynamic Pricing Problem and its Applications to Network Yield Management', Operations Research, 45, pp. 24-41.

[56] Gatland, R., Yang, E. and Buxton, K., 1997, 'Solving Engine Maintenance Capacity Problems with Simulation', Proceedings of the 1997 Winter Simulation Conference, pp. 892-899.

[57] Gorin, T. and Belobaba, P., 2004, 'Revenue Management Performance in a low fare Airline Environment: Insights from the Passenger Origin-destination Simulator', Journal of Revenue and Pricing Management, 3, 3, pg. 216.

[58] Gosavi, A., Bandla, N. and Das, T.K., 2002, 'A reinforcement learning approach to a single leg airline revenue management problem with multiple fare classes and overbooking', IIE Transactions, 34, pp. 729-742.

[59] Groenewege, A.D., 2003, 'The compendium of international civil aviation', The International Centre for Aviation Management Education and Research.

[60] Headley, D. E. and Bowen, B. D., 1997, 'International Airline Quality' Journal of Air Transportation World Wide, 2, pp. 55-63.

[61] Hull, J.C., 2003, 'Options, Futures and Other Derivatives', Prentice Hall.

[62] Iatrou, K. and Alamdari, F., 2005, 'The empirical study of the impact of alliances on airline operations', The Journal of Air Transport Management, Vol. 11, Issue 3, pp. 127-134.

[63] Kasilingam, R.G., 1997, 'An economic model for air cargo overbooking under stochastic capacity', Computers & Industrial Engineering, Vol. 32, pp. 221–226.

[64] Kimes, S.E., 1989, 'Yield Management: A tool for capacity constrained Service Firms', Journal of Operations Management, 8, pp. 348-363.

[65] Kimes, S.E. and Wirtz, J., 2003, 'Has revenue management become acceptable?', Journal of Service Research, Vol. 6, pp. 125–135.

[66] Klemperer, P., 1999, 'Auction theory: A guide to the literature', Journal of Economic Surveys, 13, pp. 227-286.

[67] Kleywegt, A. J. and Papastavrou, J. D., 1998, 'The Dynamic and Stochastic Knapsack Problem', Operations Research, 46, pp. 17-35.

[68] Kleywegt, A. J. and Papastavrou, J. D., 2001, 'The dynamic and Stochastic Knapsack Problem with Random Sized Items', Operations Research, 49, pp. 26-41.

[69] Koschat, M. A., Srinagesh P. and Uhler, L. J., 1995 "Efficient price and capacity choices under uncertain demand: an empirical Analysis" Journal of Regulatory Economics, 7:5-26.

[70] Lautenbacher C. J. and Stidham, S. J., 1999, 'The Underlying Markov Decision Process in the Single Leg Airline Yield Management Problem', Transportation Science, 33, pp. 136-146.

[71] Lee, A. O., 1990, 'Airline Reservations Forecasting: Probabilistic and Statistical Models of the Booking Process', PhD Thesis, Massachusetts Institute of Technology, U.S.A.

[72] Lee, T. C. and Hersh, M., 1993, 'A Model for Dynamic Airline Seat Inventory Control with Multiple Seat Bookings', Transportation Science, 27, pp. 252-265.

[73] Li, D., 1998, 'Revenue Management at Air China: A Feasibility Report', International Aviation MBA Program, Concordia University.

[74] Liang, Y., 1999, 'Solution to the Continuous Time Dynamic Yield Management Model', Transportation Science, 33, pp. 117-123.

[75] Littlewood, K., 1972, 'Forecasting and Control of Passenger Bookings', AGIFORS Symposium, Proc. 12, Israel.

[76] Lopez, P. and Centeno, G., 2006, 'Integrated system to maximize efficiency in transit maintenance departments', International Journal of Productivity and Performance Management, 55, 8, pp. 638-654.

[77] Mackinac Center for Public Policy, 1997, 'Price Elasticity of Demand', www.mackinac.org.

[78] Marn, M. and Rosiello, R., 1992, 'Managing price, gaining profit', Harvard Business Review, Sep-Oct, pp. 84-93.

[79] McGill, J. I., 1988, 'Airline Multiple Fare Class Seat Allocation', ORSA/TIMS Joint National Conference, U.S.A.

[80] McGill, J. and Van Ryzin, G. J., 1999, 'Revenue Management: Research Overview and prospects', Transportation Science, 33, pp. 233-256.

[81] Merton H. M., 1990, 'Leverage. The Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel', University of Chicago, U.S.A.

[82] Nair, S.K. and Bapna, P., 2001, 'An application of yield management for Internet service providers', Naval Research Logistics, 48, pp. 348-362.

[83] Ng, I.C.L., 2008, 'The Pricing and Revenue Management of Services, A strategic approach', Routledge.

[84] Pak, K., Dekker, R. and Kindervater, G., 2003, 'Airline Revenue Management with Shifting Capacity', Working Paper, Rotterdam School of Economics, Netherlands.

[85] Pak, K. and Piersma, N., 2002, 'Airline revenue management: an overview of OR techniques 1982–2001', Econometric Institute, Report EI 2002-2003.

[86] Paschalidis, I.C. and Tsitsiklis, J. N., 2000, 'Congestion-Dependent Pricing of Network Services', IEEE/ACM Transactions on Networking, Vol. 8, No. 2. pp. 171-184.

[87] Phillips, R.L., 2005, 'Pricing and Revenue Optimization', Stanford University Press.

[88] Robinson, L. W., 1995, 'Optimal and Approximate Control Policies for Airline Booking with Sequential Nonmonotonic Fare Classes', Operations Research, 43, pp. 252-263.

[89] Ross, Stephen A., Westerfield, Randolph W., Jaffe, Jeffrey F. and Roberts, Gordon S., 2003, 'Corporate Finance', McGraw-Hill Ryerson Limited, Pg. 633, 652.

[90] Rothstein, M., 1971, 'An Airline Overbooking Model', Transportation Science, 5, pp. 180-192.

[91] Rothstein, M., 1985, 'OR and the Airline Overbooking Problem', Operations Research, 33, pp. 237-248.

[92] Rubin, R.M. and Joy, J.N., 2005, 'Where are the airlines headed? Implications of airline industry structure and change for customers', The Journal of Consumer Affairs, Vol. 39, No.1, pp. 215-228.

[93] Seidenman, P. and Spanovich, D. J., 2005, 'Leveraging Line Maintenance', Overhaul & Maintenance, Dec.

[94] Slager, B. and Kapteijns, L., 2004, 'Implementation of cargo revenue management at KLM', Journal of Revenue & Pricing Management, Vol. 3, pp. 80–90.

[95] Smith, B. C., Leimkuhler, J. F. and Darrow, R. M., 1992, 'Yield Management at American Airlines', Interfaces, 22(1), pp. 8-31.

[96] Subramanian, J., Stidham, S. J. and Lautenbacher C. J., 1999, 'Yield Management with Overbooking, Cancellations and No-Shows', Transportation Science, 33, pp. 147-167.

[97] Talluri, K. T. and Van Ryzin, G. J., 1999, 'An Analysis of Bid-Price Controls for Network Revenue Management', Management Science, 44, pp. 1577-1593.

[98] Talluri, K. T. and Van Ryzin, G. J., 1999, 'A Randomized Linear Programming Method for Computing Network Bid Prices', Transportation Science, 33, pp. 207-216.

[99] Travel Industry Association of America, 2002, Press Release, www.tia.org.

[100] Valeika,R., 2007, 'MRO Migration Has Begun', Aviation Week.

[101] Valkov, T. and Secomandi, N., 2000, 'Capacity auctions-new challenges and opportunities for the natural gas pipeline industry', PROS Revenue Management.

[102] Van Ryzin, G. J. and McGill, J. I., 2000, 'Revenue Management Without Forecasting or Optimization: An Adaptive Algorithm for Determining Airline Seat Protection Levels', Management Science, 46, pp. 760-775.

[103] Van Ryzin, G.J. and Vulcano, G., 2002, 'Optimal auctioning and ordering in an infinite horizon inventory-pricing system', Working paper, Graduate School of Business, Columbia University, U.S.A.

[104] Van Ryzin, G. J. and Vulcano, G., 2004, 'Computing Virtual Nesting Controls for Network Revenue Management under Customer Choice Behavior', Working Paper, Columbia University, U.S.A.

[105] Van Slyke, R. and Young, Y., 2000, 'Finite Horizon Stochastic Knapsacks with Applications to Yield Management', Operations Research, 48, pp. 155-172.

[106] Vulcano, G., Van Ryzin, G.J. and Maglaras, C., 2002, 'Optimal dynamic auctions for revenue management,' Management Science, Vol. 48, pp. 1388–1408.

[107] Wang, X. and Regan, A. C., 2002, 'Stochastic and Dynamic Airline Yield Management when Aircraft Assignments are Subject to Change', Working Paper, University of California, U.S.A.

[108] Weatherford, L.R. and Bodily, S.E., 1992, 'A Taxonomy and Research Overview of Perishable-Asset Revenue Management: Yield Management, Overbooking and Pricing', Operations Research, 40, pp. 831-844.

[109] Weatherford, R., Bodily, S. E. and Pfeifer, P. E., 1993, 'Modeling the Customer Arrival Process and Comparing Decision Rules in Perishable Asset Revenue Management Situations', Transportation Science, 27, pp. 239-251.

[110] Williamson, E., L., 1992, 'Airline Network Seat Inventory Control: Methodologies and Revenue Impacts', Ph.D. Dissertation, Massachusetts Institute of Technology, U.S.A.

[111] Wilmott, P., 2000, 'Quantitative Finance', John Wiley & Sons.

[112] Wollmer, R. D., 1986, 'A Hub-Spoke Seat Management Model', Company Report, Douglas Aircraft Company, U.S.A.

[113] Wollmer, R. D., 1992, 'An Airline Seat Management Model for a Single Leg Route when Lower Fare Classes Book First', Operations Research, 40, pp. 26-37.

[114] Yeoman, I. and Ingold, A., 2000, 'Yield Management' Continuum, London.

[115] Yeoman, I., Ingold, A. and Kimes, S.E., 1999, 'Yield Management: Editorial Introduction", Journal of Operational Research Society, 50, pp. 1083-1084.

[116] You, P. S., 1999, 'Dynamic Pricing in Airline Seat Management for Flights with Multiple Flight Legs', Transportation Science, 33, pp. 192-206.

[117] Zhang, D. and Copper, W.L., 2005, 'Revenue management in parallel flights with customer choice behaviour', Operations Research, Vol. 53, pp. 415–434.

[118] Zhao, W. and Zheng, Y. S., 1998, 'General Dynamic Models for Airline Seat Allocation', Working Paper, University of Pennsylvania, U.S.A.

[119] Zhao, W. and Zheng, Y. S., 2000, 'Optimal Dynamic Pricing for Perishable Assets with Non-homogeneous Demand', Management Science, 46, pp. 375-388.

[120] Zhao, W., 1999, 'Dynamic and Static Yield Management Models', Ph.D. Dissertation, University of Pennsylvania, U.S.A.