To the Graduate Council:

I am submitting herewith a dissertation written by Dong Woo Ha entitled "Capacity Management in the Container Shipping Industry: The Application of Yield Management Techniques." I have examined the final copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy with a major in Business Administration.

Gary N. Dicer

Gary N. Dicer, Major Professor

We have read this dissertation
and recommend its acceptance:

Accepted for the Council

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Associate Vice Chancellor
and Dean of The Graduate School

Capacity Management in the Container Shipping Industry: The Application of Yield Management Techniques

A Dissertation
Presented for the
Doctor of Philosophy
Degree
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Dong Woo Ha

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DEDICATION

This dissertation is dedicated to

KOREA MARITIME INSTITUTE

in Seoul, Korea,

which has given me invaluable educational opportunities.

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ABSTRACT

This research attempted to investigate the applicability of yield management techniques to the international container shipping industry. Considering the wide demand fluctuation and the inflexibility in scheduling capacity inherent in the container shipping business, it was very plausible that the industry could benefit from the implementation of yield management. By assuming the given price structure, this research focused on market segmentation and capacity control techniques to determine whether to accept early booking requests from a segment, or reject early requests to sell the capacity to a later booking higher paying segment to maximize freight revenue.

Using actual booking data of the trans-Pacific westbound voyages, this research examined the booking patterns of major commodities. The difference in booking patterns made it possible to segment the market on the basis of booking patterns as well as freight rate levels of cargoes. The trans-Pacific westbound market was segmented into 4 cargo groups for yield management application. Instead of traditional statistical approaches, the multi-sample cluster analysis using information theoretic statistics was performed to test the difference in booking patterns and to segment the market.

On the basis of the 4-group segments, this research applied two capacity control techniques (the expected marginal revenue model and the threshold curve model) to the actual booking data. The results of a total of 102 simulation runs showed that the yield management models effectively increased the freight revenue by controlling the booking requests. However, the revenue impacts of the models varied greatly depending on the level of capacity scheduled and demand per capacity ratio of individual voyages. The results implied that the performance of yield management would be minimal at the

current level of scheduled capacity, which is almost sufficient to meet peak demand, and strongly suggested the importance of scheduling adequate capacity. This research concluded that the container shipping industry is a good candidate for yield management application, but for successful yield management implementation, pricing strategy should be incorporated in the yield management system to shift demand between voyages.

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CHAPTER 1

INTRODUCTION

One morning, a local manager of a hotel receives a call from a director at the head office. The director complains that occupancy rates are too low. The local manager is asked to increase the occupancy rate and he complies with the request. One month later, the director calls the local manager to report that the occupancy rates are good, but room rates are too low to make a profit. This time, the local manager is admonished to increase the room rates.

This is a dramatized scene in a video[1] that shows how yield management balances two important performance criteria, capacity utilization and average price. International container shipping firms, as well as other service industries, are also faced with very similar situations. Capacity utilization, which is measured by load factor, is a key element of performance in the container shipping business; but average price should be high enough to cover fully allocated costs to stay in business in the long run. Capacity management is the most important area in the service industry. For a service firm, capacity management is analogous to inventory management for a manufacturing firm.[2]

The first chapter of this dissertation discusses the importance of capacity management in the service industry. The basic concept of yield management is introduced as a capacity management tool. Then, service characteristics of container shipping are discussed from the viewpoint of yield management application. The final

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1 American Hotels and Motels Association, *Yield Management*, Educational Institute Video Productions, VHS, 1990.

2 Arthur D. Little and The Pennsylvania State University, *Logistics in Service Industries*, Council of Logistics Management, Ill., 1991, p. 37.

section presents the objectives of this dissertation and the research questions to be answered.

CAPACITY MANAGEMENT IN THE SERVICE INDUSTRY

Three temporal dimensions for capacity decisions

A firm's capacity places physical constraints on the quantity of products or services that it can provide to customers. Excess capacity equals high cost, and insufficient capacity means lost sales. Capacity management involves making decisions to match capacity to forecasted demand level.

There are three different temporal dimensions for capacity decisions, just as price equilibrium in microeconomics distinguishes three time periods (long run, short run, and momentary equilibrium) in which supply elements have time to make adjustments.[3] In the long run, a firm can fully adjust supply through acquisition or abandonment of facilities and major equipment. In the short run, supply can be somewhat adjusted by scheduling the facilities and equipment, even though they are fixed, for specific production or service provision. These long run and short run capacity decisions are made based on demand forecast. Finally, in the nearest time horizon of every moment, a firm's supply is fixed and cannot be adjusted at all. Therefore, in this case, focus of capacity decisions should be upon complying with immediate demand variations of individual product orders or service deliveries in the most effective way.

Capacity management plays an important role in both product manufacturing firms and service organizations. However, capacity consideration in the service industry

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3 Paul A. Samuelson and William D. Nordhaus, *Economics*, 12th ed., McGraw-Hill, New York, N.Y., 1985, pp. 384-385.

is different from that of manufacturing firms, because unique characteristics of services distinguish the demand and cost structure of service firms from product manufacturers.

Services cannot be inventoried

A simple characteristic that distinguishes services from products is whether the benefits can be defined and produced in advance of sale.[4] The benefits of products can be pre-defined and pre-produced. So the values of products can be maintained in inventory. Since the inventory works as a buffer to cushion fluctuations in demand, the product manufacturing firms can ignore immediate demand fluctuations such as day-to-day variations. Therefore, in the case of manufacturing firms, the major emphasis of capacity decisions is on achieving the economies of scale in the long run[5] and enjoying the economies derived from operating plants at a steady level of production in the short run.[6]

Service firms likewise make long run and short run capacity decisions based upon expected demand. For example, container shipping lines construct container ships and contract for port facilities in the long run. In the short run, they schedule the voyages and allocate the ships to each voyage route.

However, unlike manufactured products, services cannot be inventoried for sale at a later date. The service firms without inventory face difficulties when day-to-day demand for services does not match the scheduled capacity. When demand is low, the excess capacity is wasted. The potential revenue from empty space on a container ship is lost forever once that voyage departs. Conversely, if the demand is so high that it

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4 Frank W. Davis Jr. and James R. McMillan, *Have we defined services as an intangible good to find a use for existing marketing tools?*, College of Business Administration Working Paper Series No. 224, The University of Tennessee, Knoxville, Tenn., August 1986, p. 13.

5 Frank W. Davis Jr. and James R. McMillan, *ibid.*, 1986, p. 14.

6 Christopher H. Lovelock, "Classifying Services to Gain Strategic Marketing Insights", *Journal of Marketing*, vol. 47, no. 3, Summer 1983, pp. 16.

exceeds the capacity, another unit of capacity cannot easily be added, and potential business is likely to be lost to other carriers.

It is impossible to respond to immediate demand fluctuations by long run capacity decisions of adding or disposing capacity. It is also almost impossible to meet actual demand fluctuations through short run decisions of scheduling capacity unless the demand fluctuates regularly and thus it can be forecasted quite accurately. This requires the service firms to focus on the capacity decision to balance the scheduled capacity with the fluctuating demand on the immediate run basis.[7]

Services are heterogeneous and inseparable

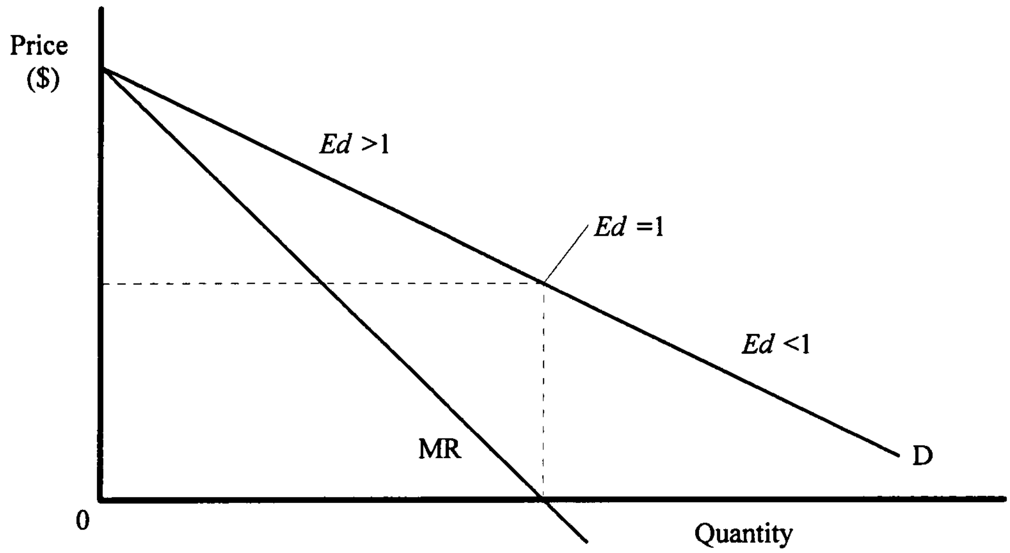
The benefits of manufactured products can be defined and produced prior to the sale. Since they are homogeneous, the standard packages of benefits are acceptable to a large market,[8] and thus can be exchanged instantaneously. Therefore, in the case of a manufactured product, a single price must be charged to all customers. Unless the firm is in perfect competition with a horizontal demand curve, it has to lower the price in order to sell additional units not only for new buyers but for all the previous buyers. As shown in Figure 1-1, the marginal revenue curve evidently lies below the demand curve due to the loss on previous units from the price drop.[9] The marginal revenue is positive when demand is still price elastic ($Ed > 1$). If demand is price inelastic ($Ed < 1$), however, the

7 Whereas the short run decisions are based on the firm's scheduling horizon, the immediate run is determined by the capacity life of the service. For instance, the immediate run for a container ship is determined by the booking period prior to departure of the voyage (Frank W. Davis Jr. and James R. McMillan, *op. cit.*, 1986, p. 16).

8 Frank W. Davis, Jr., Marley H. Davis, William J. Hewa, and W. David Smith, *Services Require a Reexamination of the Marketing Paradigm*, College of Business Administration Working Paper Series, No. 234, The University of Tennessee, Knoxville, Tenn., September 1987, pp. 16-17.

9 Paul A. Samuelson and William D. Nordhaus, *op. cit.*, 1985, p. 513.

marginal revenue curve falls below zero, which means a drop in price will decrease total revenue.

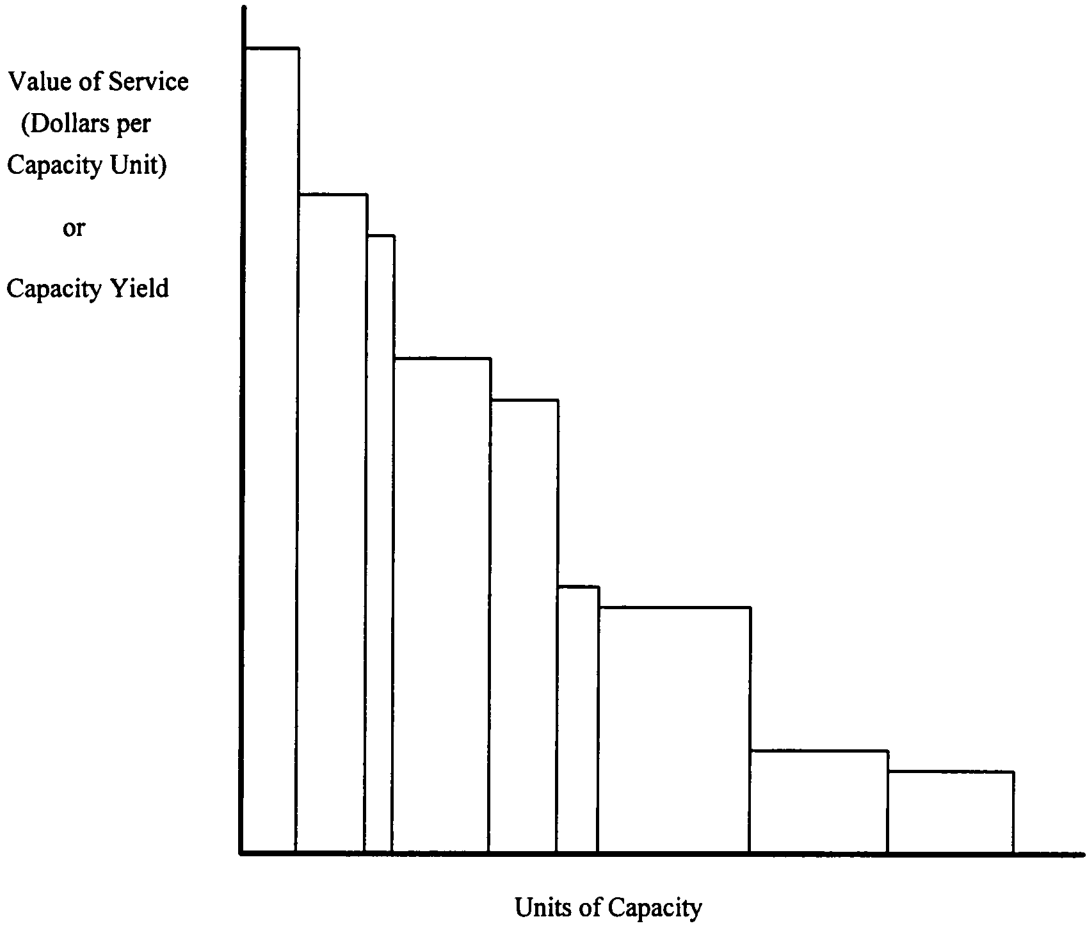


Product Demand and Marginal Revenue

Figure 1-1

Unlike the products, benefits of services are heterogeneous. The value of service varies from customer to customer. Each customer has a unique intensity of need and ability to pay. Benefits of services are inseparable from the beneficiary, and cannot be transferred or exchanged.

Within a service sector whose benefits are heterogeneous and inseparable, value of service pricing is a familiar feature of pricing policy. Value of service pricing, which is called price discrimination in the classic microeconomics theory, involves charging "what the users will bear." Each customer can be charged a different price according to the value of service (see Figure 1-2).



Source: Frank W. Davis Jr., *Customer Responsive Management: The Flexible Advantage*, Blackwell, Boston, Mass., 1994 (forthcoming).

Service Demand Schedule

Figure 1-2

Since the demand schedule reflects the value of service per unit of capacity[10] that customers are willing to pay, a supplier can charge down this schedule to confiscate the consumers' surplus as much as possible. In this case, a service provider does not have to lower the price for all the previous customers to serve additional customers. Therefore, the marginal revenue curve coincides with the demand schedule, and never becomes zero. Additional revenue can always be generated by serving additional customers.

Services have high fixed and low variable cost structure

In most manufacturing industries, variable costs tend to range from 60 to 90 percent of total costs, while fixed costs range between 10 and 40 percent.[11] This implies that the short run cost of a product varies greatly depending upon quantity produced, and thus, determining the quantity to produce becomes important for management.

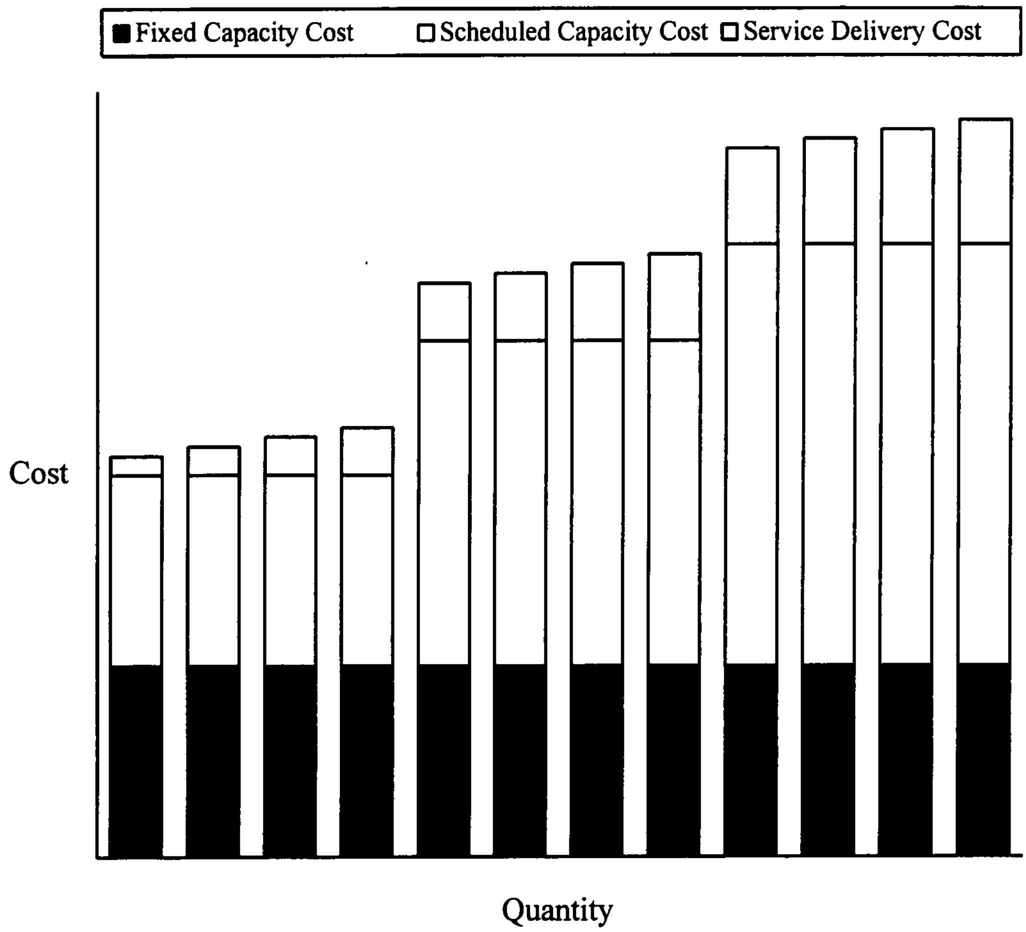
Service firms, however, usually have relatively high fixed costs. Fixed costs, including labor (salaries and benefits) and capital investment, account for more than 75 percent of total operating costs in most service firms.[12] In addition, once capacity is scheduled, there is very little difference in the out-of-pocket costs of delivering services, whether the scheduled capacity is fully utilized or not (see Figure 1-3).

Therefore, in the service firms, capacity utilization is the most critical factor to the management's goal. Revenue can be maximized by simply maximizing capacity utilization. The profit maximization goal can be achieved by increasing capacity

10 From the service provider's point of view, this indicates the yield from selling capacity to each customer.

11 John Dearden, "Cost account comes to service industries", *Harvard Business Review*, vol. 56, no. 5, September-October 1978, p. 134.

12 Arthur D. Little and The Pennsylvania State University, *op. cit.*, 1991, p. 16.



Note: Immediate run costs are totally different from short run costs. There are fixed capacity costs (costs that are variable in the long run but fixed in the short run), variable capacity costs (costs that are variable in the short run but fixed in the immediate run), and service delivery costs (costs that are variable in the immediate run). In the immediate run decision making process, only service delivery costs are taken into consideration.

Source: Frank W. Davis, Jr., and James R. McMillan, *Service Logistics: A New Window of Opportunity for Logistics Managers*, College of Business Administration Working Paper No. 218, April 1986, p.18.

Cost Structure of the Service Industry

Figure 1-3

utilization as long as additional customers can be charged more than very small incremental costs to deliver the service.

Immediate run: fixed capacity and fluctuating demand

The lack of inventories of services is not an issue when demand levels are relatively stable and predictable. However, individual demands for service capacity tend to fluctuate widely over time, because services primarily benefit current needs rather than future or speculative needs. At any given point in time, a fixed-capacity service firm may be faced with one of the following capacity situations relative to demand: insufficient capacity, sufficient capacity, and excess capacity.[13]

Therefore, it is not sufficient to just maximize capacity utilization. Fluctuating demand should be balanced against available capacity. An approach to this is to focus upon managing the level of demand by smoothing out the peaks and filling in the valleys to generate a more consistent flow of requests for service.[14] It takes active steps like pricing to reduce the demand during peak periods and to increase the demand when it is low. Another approach to match the capacity with the demand is to segment the market and to try to ensure the most profitable mix of business. During the peak period, priority is given to the most desirable segments, making other customers shift outside the peak period. In excess capacity situations, managerial focus should be upon maximizing capacity utilization.

The immediate run management of capacity is important especially for capital intensive service firms such as hospitals, hotels, airlines, and shipping lines. In the case

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13 Christopher H. Lovelock, "Strategies for Managing Capacity-Constrained Services", in C. H. Lovelock ed., *Managing Services: Marketing, Operations, and Human Resources*, 2nd ed., Prentice Hall, Englewood Cliff, N.J., 1992, p. 160.

14 Christopher H. Lovelock, *ibid.*, 1992, p. 156.

of services with high labor intensity like retailing, the capacity to deliver services can be adjusted in some degree by using part-time employee or by cross-training employees to perform a variety of tasks. In capital intensive services, however, the inflexibility of capacity is heightened.[15]

YIELD MANAGEMENT AS AN IMMEDIATE RUN DECISION TOOL

Yield management is a capacity decision technique for service firms that helps them achieve the goal of maximum revenue in the immediate run. The scheduled capacity for delivering services perishes with the passage of time. Due to the high fixed and low variable cost structure of services, providing additional capacity is very expensive, while serving another customer with available capacity is relatively inexpensive. Therefore, the idea is to use the scheduled capacity as efficiently and as profitably as possible.

When demand is below the scheduled capacity, yield management dictates decisions to maximize capacity utilization, even at the expense of average price. Maximum capacity utilization can be achieved simply by delivering additional service as long as it makes a contribution to fixed costs.

When demand exceeds the scheduled capacity, the objective shifts to the maximization of the price per unit capacity. The customers who want low prices should be denied to serve those who are willing to pay more. To maximize the average price, the firm needs to forecast expected demand and develop appropriate cutoff points.

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15 Roger W. Schmenner, "How Can Service Business Survive and Prosper?", *Sloan Management Review*, vol. 27, no. 3, Spring 1986, pp. 25.

Yield management combines two separate performance criteria to produce the basic yield formula that measures performance -- capacity utilization and average price. This formula is expressed as follows:[16]

$$\text{Yield} = \frac{\text{Revenue Realized}}{\text{Revenue Potential}}$$

$$= \frac{\text{Capacity Sold}}{\text{Capacity Scheduled}} \times \frac{\text{Average Price}}{\text{Average Price Potential}}$$

Revenue potential is a theoretical target revenue that could be earned if 100 percent of scheduled capacities are sold to the highest paying customers. Revenue realized is the actual sales revenue. The objective of yield management is to maximize this value. Yield can be maximized by increasing capacity utilization, increasing average price, or both.[17]

Therefore, yield management involves both pricing and capacity management. Pricing includes not only determination of the price level to generate the desirable level of demand corresponding to scheduled capacity, but also market segmentation. Capacity management concerns maximization of capacity utilization and capacity allocation to each segment of market.

Yield management includes a reservation system in which units of capacity are sold in advance of actual use. However, customers do not line up according to their value of service or yield. Service firms must forecast demand for service and make the

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16 Eric B. Orkin, "Boosting Your Bottom Line with Yield Management", *The Cornell H.R.A. Quarterly*, February 1988, p. 52.

17 This yield statistic implies that the incremental out-of-pocket cost is zero, which is very plausible in the service firms, especially those with low labor intensity. If the out-of-pocket cost is too large to be ignored, it must be considered, however.

immediate run decision: "Whether to accept an early reservation of a customer who wants a low price, or wait and see if higher paying customers will appear."[18] Reservation systems provide the firm with real time data about capacity availability and commitment for that capacity.

Yield management is not a new concept at all. Yield management is simply new recognition of "price discrimination" or "value of service pricing." Before the mid-1980's when many yield management systems began to appear in the major airlines, almost all airlines had a system of space and inventory control to allocate seat capacity. Sometimes this was left to individual sales people or sometimes to the reservation managers based on their experience and judgment.[19] However, due to significant advances in information technology the tools for yield management became much more powerful than before. Computers, software, and improvement in data analysis allow the capacity-constrained service firms to make immediate run decisions as to whether or not a certain customer should be served. A good yield management system permits almost instantaneous adjustments in pricing and inventory positions on a real time basis.

YIELD MANAGEMENT APPLICATION TO CONTAINER SHIPPING

Container shipping is a service industry, with low labor intensity, in which the importance of immediate run capacity management is recognized. Container shipping firms do not sell products, but sell the capacity that delivers benefits or value to individual shippers.

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18 Sheryl E. Kimes, "Yield Management: A Tool for Capacity-Constrained Service Firms", in C. H. Lovelock ed., *Managing Services: Marketing, Operations, and Human Resources*, 2nd ed., Prentice Hall, Englewood Cliff, N.J., 1992, p. 190.

19 *Lloyd's Aviation Economist*, "Yield managers now control tactical marketing", May 1985, p. 12.

Container shipping companies have the characteristics that are usually found in typical service firms. Once a vessel is scheduled, the shipping capacity is fixed. The unsold capacity cannot be put into inventory for later delivery. The revenue potential of unsold space is obviously wasted. When demand is unexpectedly high and exceeds the scheduled capacity, potential business is lost. The ship cannot be enlarged, although it may be possible to put the cargoes on a later voyage to some degree. Liner companies can sell capacity only when it is currently demanded. The imbalance between scheduled capacity and demand frequently occurs, since the demand for international container shipping fluctuates radically due to unpredictable occurrences such as political upheavals and strikes, as well as predictable cyclical seasonality.

The container shipping business is capital intensive. It has a high fixed and low variable cost structure. Since the service routes are usually constant in container ship operation, only port charges and cargo handling expenses are variable in the immediate run depending upon the quantity and characteristics of cargo.[20]

Container shipping services are not homogeneous. An individual shipper has a unique value of service and different ability to pay for the service. The benefits of services are inseparable from the shippers, and cannot be transferred or exchanged. Therefore, the single most important pricing concept of liner shipping is the principle of charging what traffic can bear, value of service pricing, or price discrimination.[21] Higher rates are charged to valuable commodities and lower rates to low value goods. Figure 1-4

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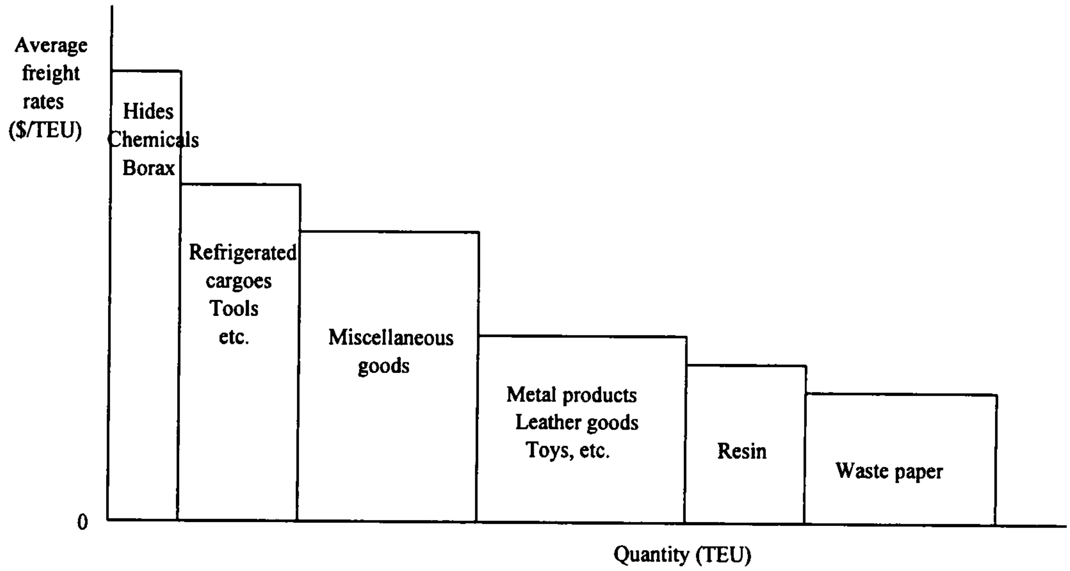
20 Tetsuji Shimojo, *Cost Analysis and Business Simulation for Shipping Decision Making: Japanese Traditions*, Lectures and Contributions No. 18/19, Institute of Shipping Economics, Bremen, Germany, 1978, p. 6.

21 J. O. Jansson and D. Shneerson, *Liner Shipping Economics*, Chapman and Hall Ltd., London, UK, 1987, p. 70.

shows that the demand schedule of liner shipping is very similar to those of many service industries.



Notes: Based on the actual booking data of trans-Pacific westbound trade provided by a container shipping company.

Demand Schedule of Container Shipping

Figure 1-4

With these service characteristics, container shipping firms are exposed to immediate run decisions in day-to-day business to match fluctuating demand with scheduled capacity. Sales managers are asked to maximize the capacity utilization while filling the capacity with high freight cargoes. Simply maximizing the capacity utilization or maximizing the average freight rate does not guarantee the maximum revenue or maximum profit. A good yield management system may guide the immediate run decisions to maximize yield on the basis of current demand situation that can be grasped through real time booking data.

OBJECTIVES OF THE RESEARCH

Yield management technique has recently been widely accepted in capacity-constrained service firms such as those in the airline and the hotel industries. It presents a great opportunity for service firms to enhance revenue by balancing fluctuating demand against scheduled capacity. Experiences in the airline industry have shown that yield management can contribute 2.5 percent to revenue, of which over 85 percent goes straight to the bottom line.[22] A study that applied a yield management model to an airline reported that the net potential revenue increase was about two million dollars per year.[23]

On the basis of past experience of yield management strategies in the airline and the hotel industries, several necessary conditions for yield management application have been identified. Yield management techniques are appropriate (1) when a firm is operating with a relatively fixed capacity, (2) when demand can be segmented into clearly identified partitions, (3) when inventory is perishable, (4) when the product or service is sold well in advance, (5) when demand fluctuates substantially, and (6) when marginal sales costs and production costs are low, but capacity change costs are high.[24]

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22 David C. Bristle, "Yield Management: The Marketing Tool of the Nineties", presented to Yield Management Multi Industry Conference, Charlotte, NC, March 22-23, 1990.

23 Alstrup, Jens, Sven-Eric Andersson, Soren Boas, Oli B. G. Madsen, and Rene Victor V. Vidal, "Booking Control Increases Profit at Scandinavian Airlines", *Interfaces*, vol. 19, no. 4, 1989, pp. 10-19.

24 Sheryl E. Kimes, *op. cit.*, 1992, p. 189.

At a glance, the international container shipping industry is a good candidate to which yield management can be applied. The industry has been suffering an insufficient return on investment, even not in a low single digit, while most industries expect a 15 percent return on capital.[25] For example, the ocean carriers on the North Atlantic lost $400 million in 1992, and $150 million in 1993. Although they have launched the Trans-Atlantic Agreement (TAA)[26] to boost rates by cutting carrying capacities, they are still estimated to lose $75 million in 1994.[27] The fundamental problem is in excess supply. However, if yield management can be applied to container shipping, it may really improve the profitability of the industry as in the airline industry.

Research on solution techniques is fairly advanced in the airline and the hotel industries, but little has been done in the maritime field. The objectives of this research are to investigate the applicability of yield management techniques to the container shipping industry and to provide the basis for further research and development of yield management systems for container shipping firms.

As mentioned earlier, there are two basic approaches to match immediate fluctuations of actual demand with the scheduled capacity: (1) to raise or lower the price level to temper the demand fluctuation, and (2) to segment the market and sell the scheduled capacity to the most desirable mix of segments. In the container shipping industry, however, an individual firm cannot easily change prices to affect demand

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25 James I. Newsome, III, "International Container Shipping: The Real Issues", presented to 10th Annual University of Tennessee Logistics and Transportation Alumni Symposium, Knoxville, Tenn., November 20, 1992, p. 3.

26 TAA, signed in 1992, is an agreement of 15 trans-Atlantic carriers that controls more than 70% of the traffic between the United States and Europe. Unlike traditional shipping conferences, TAA not only sets the rates but also controls the capacity. In the Pacific route, the Trans-Pacific Stabilization Agreement was formed in 1989, in which 12 member carriers now withhold 8% of the capacity on their container ships sailing from Asia to North America.

27 *American Shipper*, "TAA to Take Half a Loaf", January 1994, p. 6.

patterns, because the price structures are set by conferences and the independent lines set the price based upon the conference rates. In some cases, government regulation does not allow individual carriers to change rate in the immediate run. The U.S. Shipping Act of 1984 provides that each common carrier and conference serving the U.S. related trades shall file tariffs[28] with the Federal Maritime Commission (FMC),[29] and no new or increased rate may become effective earlier than 30 days after filing with the Commission.[30]

Therefore, yield management in the container shipping industry should follow the second approach that deals with two basic tasks: (1) develop a discriminatory price structure by dividing customers into several distinct groups according to the value of service, and (2) decide which group or groups of customers should be served on the immediate run basis.

This research answers the following research questions to confirm the discriminatory price structure.

- What are the characteristics of the market segmentation of the container shipping industry?
- What are the major factors that discriminate among different cargo groups?
- Are the booking patterns different between high value cargoes and low value cargoes?

Since the value of service pricing is a very familiar feature of container shipping, the first two questions can be answered through literature review. The third question is answered

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28 Bulk cargoes, forest products, recycled metal scrap, waste paper, and paper waste are exempted from tariff filing (The Shipping Act of 1984, Sec. 8 (a)(1)).

29 The Shipping Act of 1984, Sec. 8 (a)(1).

30 The Shipping Act of 1984, Sec. 8 (d).

by examining actual booking data to test if the discriminatory price structure of container shipping is appropriate in terms of yield management application.

Then, the various techniques of yield management developed in the airline and the hotel industries will be reviewed, and applied to actual data from a container shipping firm. During the course of application, several research questions are answered.

- Does the shipping demand really fluctuate substantially so that the yield management techniques can be applied?
- Will yield management be effective even if freight rates cannot be changed immediately due to the tariff filing system, and the only way to control the demand is to decide whether to accept a certain cargo or not?
- At what level of demand ratio is yield management most effective or least effective?

Finally, the research is concluded with a discussion about the questions on the future implementation of yield management:

- What are the managerial implications for implementing the yield management system?
- What are the directions for further research?

CHAPTER 2

REVIEW OF THE YIELD MANAGEMENT MODELS

Yield management involves both pricing and capacity control, as the yield formula implies:

$$\text{Yield} = \frac{\text{Capacity Sold}}{\text{Capacity Scheduled}} \times \frac{\text{Average Price}}{\text{Average Price Potential}}$$

Pricing involves in two tasks: first, determining price level to smooth out the demand fluctuation, and second, segmenting the market according to the value of service to individual customers. Capacity control deals with the capacity allocation to each market segment to maximize the revenue.

The various solution techniques of yield management were studied quite extensively in the airline industry, and some of them have been applied to the hotel industry. While some of the techniques may be used to manage demand to smooth out the peak, most approaches concentrate on controlling the capacity by assuming that the price structure is given in the immediate run decision.[1] A firm can seldom change the price level without taking the reactions of the competitors into account. On the other hand, capacity management is entirely under the control of each of individual firm.

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1 Peter P. Belobaba, "Application of a Probabilistic Decision Model to Airline Seat Inventory Control", *Operations Research*, vol. 37, no. 2, March-April 1989, p. 183.

In the container shipping industry, while the pricing issues of the liner conferences have been dealt with extensively in many studies,[2] almost no research has addressed the capacity control issues. However, some studies recognized the operational characteristics unique to the liner shipping industry, which may necessitate effective capacity utilization in the industry.[3]

This chapter reviews the previous studies on the two issues regarding yield management: (1) market segmentation, and (2) capacity control. First, it examines the major factors upon which the segmentation of the airline passenger market is based. Then, the literature on the segmentation pricing of the liner conferences is reviewed to identify any difference from that of airlines. Secondly, various capacity control techniques adopted in the airlines are reviewed. This includes the studies on yield management application to other industries such as hotel and health care. The final section addresses implications from literature review to identify major problems and issues that need investigation in this research.

MARKET SEGMENTATION

Market segmentation is the division of customers into distinct subsets or segments according to the characteristics that distinguish them. A market can be segmented by one or more characteristics such as price sensitivity, ability to pay, cost to serve, time of

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2 One of the comprehensive studies is B. M. Deakin and T. Seward, *Shipping Conferences: A study of their origin, development and economic practices*, Cambridge University Press, UK, 1973.

3 J. E. Davies, "On the nature and sources of controversy in the economic analysis of the liner shipping industry", *Maritime Policy and Management*, vol. 14, no. 3, 1987, pp. 249-261; J. O. Jansson, "Intra-tariff cross subsidisation in liner shipping", *Journal of Transport Economics and Policy*, vol. 4, no. 3, September 1974, pp. 294-311; J. E. Davies, "An analysis of cost and supply conditions in the liner shipping industry", *Journal of Industrial Economics*, vol. 31, June 1983, pp. 417-435.

purchase, purchase quantity, purchase location, competition, and so on.[4] Market segmentation makes it possible to develop pricing strategies that are appropriate for the customers in each market segment. For example, customers who are less price sensitive, more costly to serve, or less well served by competitors can be charged more than those who are price sensitive, cheaper to serve, or well served by competitors.[5]

Airlines

Airline passengers can generally be divided into two distinct segments: (1) "leisure" travelers who are price sensitive and time insensitive, and (2) "business" travelers who are time sensitive and price insensitive. If an airline only used one fare to serve both groups of customers, it would probably choose a fare in the middle. However, the fare would not be low enough to attract discount seekers to fill in the low demand flights or high enough to smooth out the demand from peak flights.[6] Therefore, airlines charge lower fares to leisure travelers than to business travelers. This two-tiered fare structure enables an airline to serve a larger share of the potential market than other carriers that charge only one fare to all customers.[7]

Leisure and business travelers are also distinguished by their booking patterns as in Figure 2-1. Leisure travelers normally book early to get low fares since they plan

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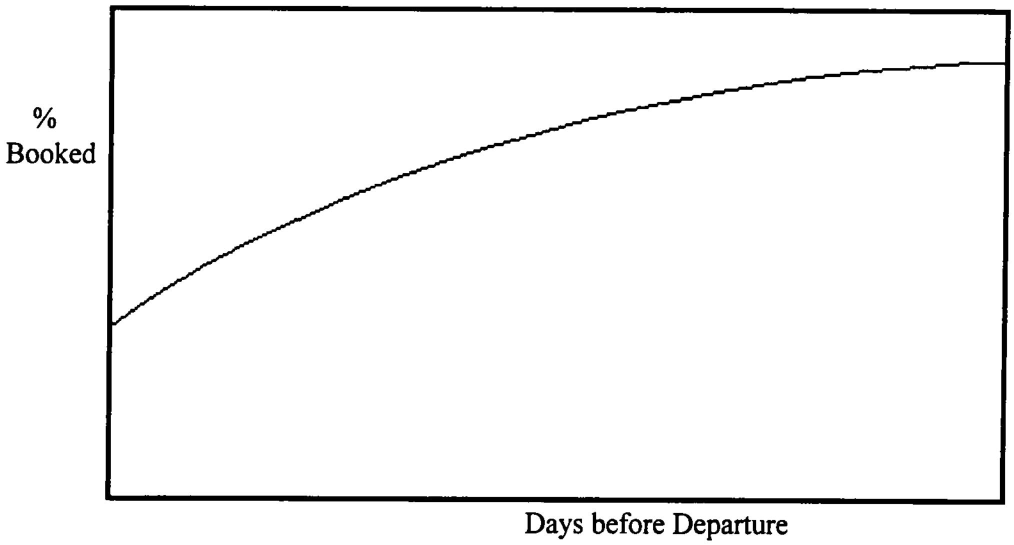
4 Thomas T. Nagle, *The Strategy and Tactics of Pricing: A guide to profitable decision making*, Prentice Hall, N.J., 1987, p. 156.

5 Thomas T. Nagle, *ibid.*, 1987, p. 156.

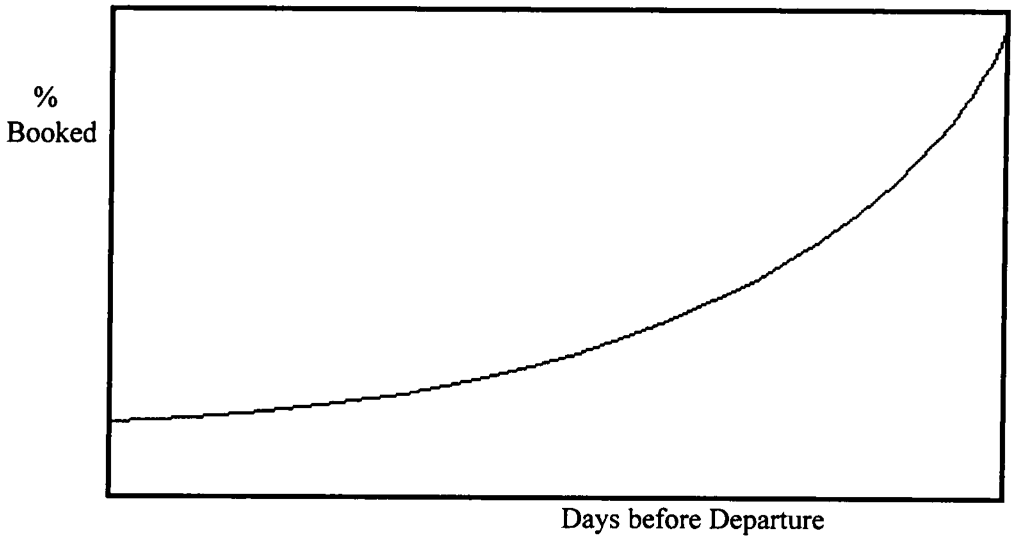
6 Robert G. Cross, "The Employment of Yield Management Methodologies to Overcome Cost Disadvantages", presented to The Ohio State University First International Symposium and Workshop on Airline Economics, April 7, 1988, pp. 12-13.

7 Robert G. Cross, *Ibid.*

Leisure Travelers



Business Travelers



Source: Robert G. Cross, "Strategic Selling: Yield Management Techniques to Enhance Revenue", presented to Shearson Lehman Brothers, Inc. 1986 Airline Industry Seminar, Key Largo, Fla., February 14, 1986, p. 4.

Booking Patterns of Airline Passengers

Figure 2-1

holidays in advance, and airlines often place advance purchase restriction on the discount fares. Business travelers, on the other hand, book late, because they are time sensitive and have ability to pay high fares.[8]

These different booking patterns between market segments imply the importance of capacity management. If the capacity is not accurately controlled, the flight will fill early with low fare leisure travelers. This can be prevented by reserving some seats for late booking high fare business travelers. However, if too many seats are saved and the late booking fails to materialize, the flight will take off with empty seats, resulting in the revenue lost forever.

Many studies on airline capacity management dealt with these two types of passengers. Thompson (1961) examined the booking and cancellation patterns for two types of passengers, first class and tourist class.[9] Alstrup et. al. (1986, 1989) developed airline booking models with two market segments.[10] [11] Peacock (1989) illustrated yield management with a simple airline case of two market segments.[12] Pfeifer (1989)

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8 Robert G. Cross, "Strategic Selling: Yield Management Techniques to Enhance Revenue", presented to Shearson Lehman Brothers, Inc. 1986 Airline Industry Seminar, Key Largo, Fla., February 14, 1986, p. 4.

9 H. R. Thompson, "Statistical Problems in Airline Reservation Control", *Operational Research Quarterly*, vol. 12, no. 3, 1961, pp. 167-185.

10 Jens Alstrup, Soren Boas, Oli B. G. Madsen, and Rene Victor Valqui Vidal, "Booking policy for flights with two types of passengers", *European Journal of Operational Research*, vol. 27, August 1986, pp. 274-288.

11 Jens Alstrup, Sven-Eric Andersson, Soren Boas, Oli B. G. Madsen, and Rene Victor Valqui Vidal, "Booking Control Increases Profit at Scandinavian Airlines", *Interfaces*, vol. 19, no. 4, July-August 1989, pp. 10-19.

12 Peter Peacock, "Yield Management and Marginal Analysis", presented to Yield Management Multi Industry Conference, Charlotte, N.C., February 16-17, 1989, pp. 1-17.

examined the two-tier pricing strategy as a simple form of the airline discount fare allocation problem.[13]

However, some studies dealt with more than two market segments. Given that many U.S. domestic airlines make use of at least four fare classes to manage their seat inventory, Belobaba (1987) presented the yield management model for the four-class problem.[14] Smith et. al. (1992) examined the discount seat allocation problem for three fare classes of full fare, moderate discount, and deep discount.[15]

Hotels

Market segmentation in the hotel industry is very similar to that of the airlines. Relihan (1989) described a yield management system for the hotel industry with two groups of customers, business and leisure.[16] Recently, Gilbert (1993) described a hotel's yield management system that features four tiers of pricing structure: transient rates for individual rooms, group pricing, high-volume transient and group accounts, and individual contract account or linked group account (covering multiple groups on a single-contract basis).[17]

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13 Phillip E. Pfeifer, "The Airline Discount Fare Allocation Problem", *Decision Sciences*, vol. 20, no. 1, Winter 1989, pp. 149-157.

14 Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987.

15 Barry C. Smith, John F. Leimkuhler, and Ross M. Darrow, "Yield Management at American Airlines", *Interfaces*, vol. 22, no. 1, January-February 1992, pp. 8-31.

16 Walter J. Relihan III, "The Yield-Management Approach to Hotel-Room Pricing", *The Cornell H.R.A. Quarterly*, vol. 30, May 1989, pp. 40-45.

17 Bob Gilbert, "Richfield's Management: Focusing on the Top Line", *The Cornell H.R.A. Quarterly*, vol. 34, April 1993, pp. 46-51.

Container shipping

Segmented pricing, price discrimination, value of service pricing, or charging what the traffic can bear is the single most important pricing concept of the liner shipping. Container shipping market can be segmented by the commodity to be shipped. Higher rates are charged to valuable commodities and lower rates to low-value goods (discrimination between commodities), although the same commodity rate is charged to all customers for a given commodity (non-discrimination between customers). While freight of all kinds (FAK) has been attempted in some routes to have an identical rate regardless of cargo values, shipping conferences seek to apply the value-based tariffs whenever possible.

The logic underlying this pricing policy is that high-value commodities are able to afford relatively high freight rates, which can be used to cross-subsidize low-value commodities. Otherwise, low-value commodities cannot use liner shipping service. If low-value goods were not carried, high-value commodities would paradoxically have to be rated even higher, because fixed shipping costs would have to be spread over a smaller cargo base.[18]

Price discrimination between commodities in the liner shipping industry is also based upon their stowage factors.[19] There is a strong relationship between stowage factor and liner freight rate. High stowage factor cargoes are charged higher rates than low stowage factor cargoes. The stowage factor is considered as representing elements of the operational costs of a vessel, in that the amount of cargoes that a ship can carry is constrained either by space or by the deadweight available.

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18 Gerard Verhaar, "Controversy: What the traffic can bear", *Containerisation International*, May 1993, pp. 50-51.

19 The stowage factor of commodities is given as the ratio of cubic feet to long ton(= 1,016 kg).

A number of empirical studies have been made to investigate the factors that underlie the structure of the liner freight rates. The Economic Commission for Latin America (ECLA, 1970) used a multiple regression analysis and found that the value of commodity and the stowage factor were statistically significant.[20] Heaver (1972) explained the freight rates of eastbound and westbound Trans-Pacific trades in terms of the stowage factor and the unit value of cargo. The regression results showed that the coefficients of the two explanatory variables were significant. He further demonstrated that stowage factor was the most significant explanatory variable; that is a cost factor, not a demand factor plays the major role in liner shipping pricing.[21] However, Jansson and Shneerson (1987) reinterpreted the low commodity value elasticity and high stowage factor elasticity. They asserted that even a relatively low value of the commodity value elasticity can be an indication of a high degree of price discrimination, because the commodity values span very widely indeed, and confirmed the principle of charging what the traffic can bear in the liner shipping pricing.[22]

The two main principles for charging what the traffic can bear are: (1) charge no rate so high as to stop the traffic moving,[23] and (2) charge no rate so low as not to cover the additional cost to which the traffic gives rise.[24] In other words, liner freight rates can

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20 ECLA, *Maritime Freight Rates in the Foreign Trade of Latin America*, November 1970.

21 T. D. Heaver, "Trans Pacific trade, liner shipping and conference rates", *Logistics and Transportation Review*, vol. 8, no. 2, 1972, pp. 3-28.

22 J. O. Jansson and D. Shneerson, *Liner Shipping Economics*, Chapman and Hall Ltd., London, UK, 1987, pp. 79-83.

23 Locklin explain this as "Not charging what the traffic will not bear" (D. Philip Locklin, *Economics of Transportation*, 5th ed., Richard D. Irwin Inc., Homewood, Ill., 1960, p. 146).

24 J. J. Evans, "Liner freight rates, discrimination and cross-subsidization", *Maritime Policy and Management*, vol. 4, no. 4, 1977, p. 229.

be considered as the sum of the incremental cargo handling cost plus a contribution margin that is determined according to the principle of charging what the traffic can bear.

In practice, the limits of liner freight are determined by competition. Liner companies are confronted with competition from air freight transportation for high-value cargoes, and from tramp shipping for low-value cargoes. In addition, the discriminatory nature of the pricing structure itself induces competition between conference members and outsiders. Since some rates are higher than the costs of carriage, they can be cut by outsiders to gain entry; and the conference cannot deter the outsiders from entering the segment of high-value cargoes by lowering rates for low-value cargoes.[25]

While many studies figured out that the commodity value and stowage factor are major factors that discriminate among cargo groups, no research has tried to identify the booking patterns of each segment. Examining booking patterns has an important meaning to the applicability of yield management techniques. In the airline cases, the markets are segmented not only by price sensitivity but by time sensitivity of the customers. Since high paying business travelers tend to book late, an airline has an opportunity to increase revenue by reserving some seats for those time sensitive customers. If high paying customers booked earlier than low fare customers, reserving seats would probably increase the risk of lost revenue due to empty seats. Likewise, if high freight cargoes tend to be booked later than low freight cargoes, container shipping lines have a chance to increase revenue by reserving some slots for those high freight cargoes.

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25 E. T. Laing, "The rationality of conference pricing and output policies", *Maritime Studies and Management*, vol. 3, no. 3, 1976, p. 142.

CAPACITY MANAGEMENT

Basically capacity management deals with the capacity allocation to each group of customers to maximize revenue. However, frequent cancellation and 'no shows' of reservations forces airlines to seek a deliberate overbooking policy.

Overbooking problem

Most early studies dealt with the airline's overbooking problem.[26] Before the deregulation of the industry, the airlines' major concern was to compensate the lost revenues of empty seats due to cancellation and 'no-shows' of reservations through overbooking. This raised the problem that some customers with reservations may be denied, causing damage in good will and additional costs of alternate transportation, airport dinner, and/or hotel charges, etc.

Beckmann (1958) developed a mathematical model that balances the lost revenue of empty seats with the costs of passengers denied boarding.[27] His model determines the optimal limit of reservations that minimizes the expected value of lost revenue due to empty seats plus the penalty costs of denied boarding with known probability distribution of demand and cancellation. Gamma (Γ) distribution was found to fit the demand as well as cancellation and no-shows.[28] This model is static, since the booking limit is determined only once at the start of the reservation process.

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26 Rothstein gives a comprehensive review of research on airline's overbooking problem (Marvin Rothstein, "OR and the Airline Overbooking Problem", *Operations Research*, vol. 33, no. 2, March-April 1985, pp. 237-248).

27 M. J. Beckmann, "Decision and Team Problem in Airline Reservations", *Econometrica*, vol. 26, 1958, pp. 134-145.

28 M. J. Beckmann and F. Bobkoski, "Airline Demand: An Analysis of Some Frequency Distribution", *Naval Research Logistics Quarterly*, vol. 5, no. 1, March 1958, pp. 43-51.

Kosten (1960) enhanced Beckmann's model by providing for the interspersion of reservations and subsequent cancellations, which Beckmann ignored as if all cancellations occurred at the time of departure. Therefore, the booking limit determined by Kosten's model depends upon the number of days prior to flight.[29]

Both Beckmann's and Kosten's models require not only an estimate of the costs of denied boarding, but also the probability distribution of passenger demand as well as that of cancellations of reservations. Especially, estimating the demand is very difficult due to its seasonality and unstableness in general.

To avoid this data limitation, Thompson (1961) developed the model that requires data only on the cancellation rate of any fixed number of reservations.[30] In this model, the costs and the probability distribution of demand are ignored, and only the probability distribution of cancellation is described. For example, when a certain number, n, of seats are reserved at the time period, t, prior to departure, the model provides the probability that any passenger with a reservation will be denied boarding even if no more booking is accepted. Therefore, for each time period t, one can determine the booking limit n which constrains the probability of denied boarding to some tolerable standard set by management. Thompson examined the booking records and found that distributions of cancellation were shown to be binomial. Although Thompson's model divided the capacity into two separate rate classes (first and tourist), its concern was not on allocating capacity, but only on determining the overbooking limit for each class.

Rothstein (1971) used dynamic programming to obtain solutions to the overbooking problem. His model maximizes expected gain (passenger revenue minus

29 Marvin Rothstein, *op. cit.*, 1985, pp. 239-240.

30 H. R. Thompson, "Statistical Problems in Airline Reservation Control", *Operational Research Quarterly*, vol. 12, no. 3, 1961, pp. 167-185.

costs of passengers denied boarding) given that *n* passengers are already booked at a certain time period *t* prior to departure, subject to the probability of passengers with reservations denied boarding is less than a prescribed standard value.[31] To determine the optimal booking limit that maximizes the expected gain, Rothstein's model included the demand distribution that Thompson ignored. Both demand and cancellation were assumed to follow a binomial distribution. Rothstein's model is more comprehensive than the previous models in that it considers 'standby' passengers (people without reservations seeking to board) and 'no record' passengers (people with tickets bearing a validated reservation but with no record in the reservation system, perhaps due to error) as well as cancellations and no shows. Regarding the rate classes, however, this model still treats each as an independent and essentially separate flight with its own capacity.

Rothstein (1974) later applied this model to the hotel overbooking problem.[32] The airline model was modified to account for two major aspects of the hotel problem: single versus double occupancy[33] and multiple-day stays.[34]

Capacity allocation problem

In later works, consideration has been given to seat allocation to different groups of customers. Capacity control techniques vary in sophistication, but generally fall into

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31 Marvin Rothstein, "An Airline Overbooking Model", Transportation Science, vol. 5, 1971, pp. 180-192.

32 Marvin Rothstein, "Hotel Overbooking as a Markovian Sequential Decision Process", *Decision Science*, vol. 5, 1974, pp. 389-404.

33 Hotel room rates depend upon the number of occupants while an airline seat can be used by only one person.

34 Hotel reservations are made for one or more consecutive nights. An airline flight is analogous to a hotel in which the guests stay for only one night. Rothstein assumed that a request for a multiple day reservation is equivalent to several independent requests for single day reservations, with a similar assumption for cancellation and no-shows.

three different categories: (1) mathematical optimization approaches, (2) marginal analysis approaches, and (3) threshold curve approaches.

(1) Mathematical optimization approaches

A basic capacity control model can be developed using simple linear programming. It maximizes the total revenue subject to constraints on (1) the sum of the number of units sold to each group of customers must be less than the total capacity, and (2) the number of units sold to each group of customers must be less than the expected demand for that group. Mathematically it can be expressed as:[35]

Maximize $\sum_{i=1}^{n} r_i X_i$

subject to $\sum_{i=1}^{n} X_i \leq C$

$X_i \leq d_i$ for all i

$X_i, d_i \geq 0$

where i = groups $(1, 2, \ldots\ldots\ldots, n)$

r_i = revenue from selling capacity to group i

X_i = the units of capacity sold to group i

d_i = expected demand for group i

C = total capacity

Although this basic model seeks the optimal solution, it assumes the deterministic demand that is unrealistic. In addition, it cannot incorporate the repetitive, sequential, and dynamic nature of the reservation process in capacity control. Booking limits should

35 Sheryl E. Kimes, "Yield Management: A Tool for Capacity-Constrained Service Firms", *Journal of Operations Management*, vol. 8, no. 4, October 1989, pp. 348-363.

be revised as actual bookings and cancellations occur, using additional information. Therefore, dynamic programming has been a popular approach found in many studies.

Hersh and Ladany (1978) dealt with the problem of allocating seats on the various legs of a flight with an intermediate stop.[36] He presented a two-variable dynamic programming model for finding the maximum allocations of seats to passengers for the full and the short flight spans such that the expected contribution to profit for the flight is maximized. The model utilizes the time distribution of reservations and cancellations for both spans. The overbooking problem was also taken into consideration. Probability distributions were reassessed based upon additional information obtained during the decision process.

A model to allocate airline seats to two types of passengers was developed by Alstrup et. al. (1986).[37] Their model is very similar to the model developed by Hersh and Ladany (1978). These models took into consideration upgrading and downgrading of the passengers as well as the overbooking problem.

Although these dynamic programming models provide the optimal solutions, most of these dynamic programming models have never been implemented to the real-life problems, because they require a huge amount of data and extensive computer time.[38] Computational intensity makes this approach impractical, unless the solution procedure is

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36 Marvin Hersh and Shaul P. Ladany, "Optimal Seat Allocation for Flights with One Intermediate Stop", *Computers and Operations Research*, vol. 5, 1978, pp. 31-37.

37 Jens Alstrup, Soren Boas, Oli B. G. Madsen and Rene Victor Valqui Vidal, "Booking policy for flights with two types of passengers", *European Journal of Operational Research*, vol. 27, 1986, pp. 274-288.

38 Jens Alstrup, Soren Boas, Oli B. G. Madsen and Rene Victor Valqui Vidal, *ibid.*, 1986, pp. 275-276.

adjusted by grouping the seats and reducing the range of the variables as in the application of Alstrup et. al.'s model.[39]

Furthermore this approach assumes distinct rate classes, which means it allocates separate units of capacity for each rate class and does not allow for allocating unsold lower class capacity to higher paying customers.

(2) Marginal analysis approaches

Marginal analysis is another approach to allocate the capacity to different groups of customers to maximize the total revenue. The basic idea of this approach is that the optimal seat allocation is achieved when the marginal revenue for the last unit sold in one group is the same as for another group.[40] The seats allocated to each group must share a total capacity. At optimal allocation, total revenue cannot be increased by taking one unit from one group and allocate it instead to another group. Therefore, marginal revenue of the last unit allocated to each group will be equal across the groups. That is:

$$\frac{\partial R}{\partial S_i} = \frac{\partial R}{\partial S_j} = \lambda, \qquad \text{for all groups } i \neq j$$

where R = total revenue

S_i = units of capacity allocated to group i

λ = marginal revenue for the last unit allocated to each group

39 Jens Alstrup, Soren Boas, Oli B. G. Madsen and Rene Victor Valqui Vidal, *ibid.*

40 Sheryl E. Kimes, *op. cit.*, 1989, p. 356.

Belobaba (1987) developed the expected marginal seat revenue (EMSR) model for airline seat inventory control.[41] The expected marginal revenue of the S_ith seat in fare class i, $\mathrm{EMSR}_i(S_i)$, is the average fare level in that class multiplied by the probability of selling S_i or more seats. Therefore, the optimal allocation can be achieved where:

$$\mathrm{EMSR}_i(S_i) = \mathrm{EMSR}_j(S_j) = \lambda, \qquad \text{for all } i \neq j$$

The expected marginal revenue at optimality (λ) is simply the average fare level in each rate class multiplied by the probability of receiving more reservation requests than the seats allocated (S_i^*). That is:

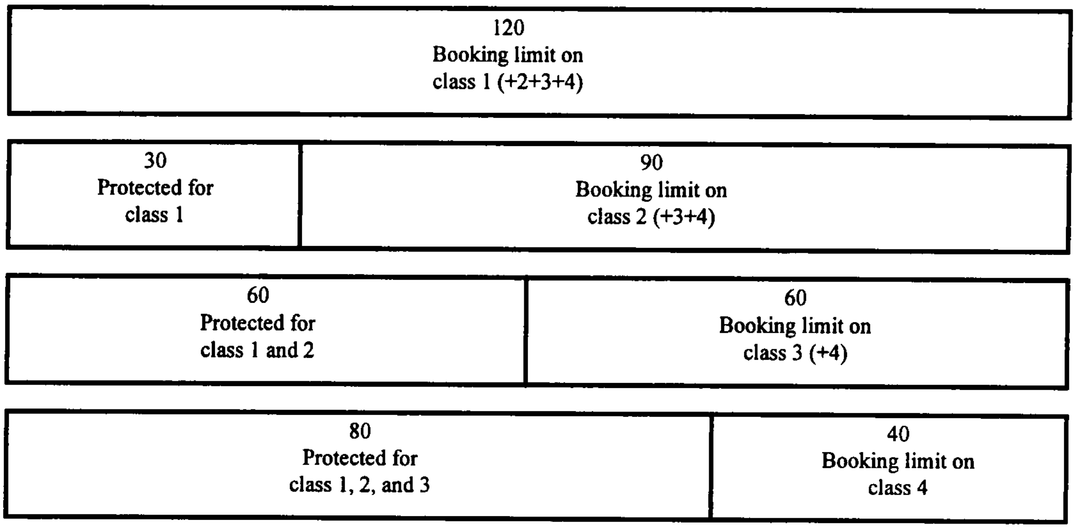
$$\lambda = f_i \cdot P\left[r_i > S_i^*\right] \qquad \text{for all } i$$

where f_i = the average fare in rate class i
r_i = total number of requests for reservation in rate class i
S_i^* = the optimal allocation to rate class i

The advantage of EMSR model is its ability to deal with the nested rate classes to determine how many seats not to sell in the lower fare class and to retain for possible sales in higher fare class. In this case, booking limits are binding for only lower rate classes, and a high rate request will not be refused as long as a seat is available in the lower rate class. In other words, in the nested model, the booking limit on the higher fare class takes over the seats set aside for lower fare classes. For example, as shown in Figure 2-2, the booking requests of the highest fare class, say Class 1, should be accepted

41 Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Ph.D. Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987.

up to the total capacity of 120 seats, while booking of Class 4, the lowest fare class, is limited to its own limit of 40 seats. The booking limit on Class 2 is set to 90 seats to ensure that at least 30 seats are reserved for Class 1. Likewise, the booking limit on Class 3 is 60 seats to protect at least 60 seats for Class 1 and 2, of which at least 30 seats are for Class 1.



Source: Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Ph.D. Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987, p. 85.

Booking Limits in the Nested Model

Figure 2-2

The EMSR model can also be applied to dynamic problems by updating information over time. The static model is applied repetitively over time with revised input data about reservations and cancellations. More details on the nested and dynamic models are explained with an example in Chapter 5.

(3) Threshold curve approaches

Cross (1986) presented the threshold curve approach to control the airline capacity utilization.[42] This is a statistical approach to control the booking levels within the optimal ranges.

The threshold curve approach constructs the optimized booking paths (threshold curves), based on the data on past booking behavior over time. Using the mean and standard deviation of booking for each day, simple threshold curves can be drawn at one, two, or three standard deviations from the mean. Then actual booking patterns are plotted against the optimal paths. If the actual booking level goes beyond the upper threshold curve, lower fare classes may be closed. If the actual booking level falls below the lower threshold curve, lower fare classes may be opened (see Figure 2-3).

Although this approach does not find optimal capacity allocations for different fare classes, it tends to provide good results by controlling the booking level within optimal ranges.[43] In addition, the segmented demand data are not necessarily required because the threshold curves may be fitted using aggregate demand data. Many commercial applications in the airline industry use this approach due to its simplicity and less requirement of data. Relihan (1989) applied the threshold curve approach to the hotel reservation problem.[44]

Since the threshold curves can be built using aggregate demand data, market segmentation is not a necessary condition to apply this method. In this case, the threshold

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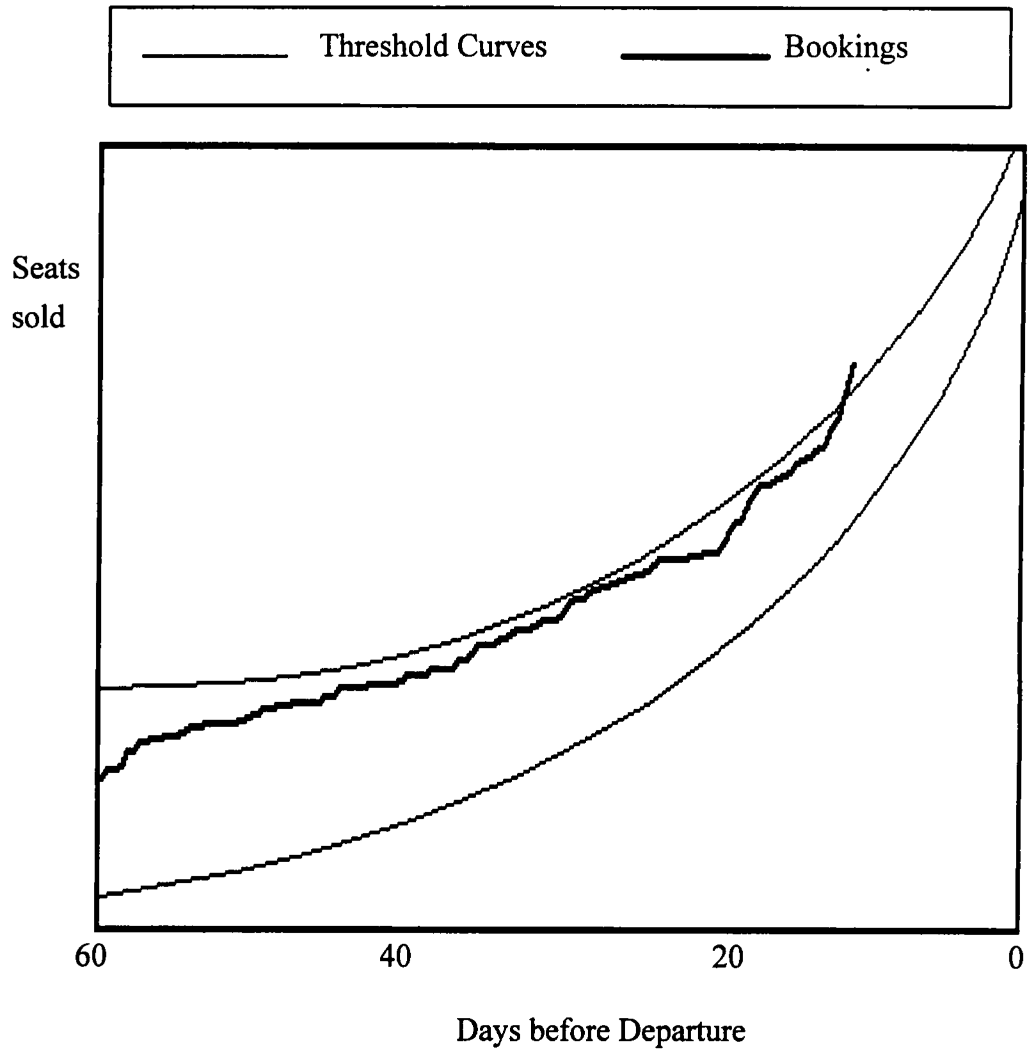
42 Robert G. Cross, "Strategic Selling: Yield Management Techniques to Enhance Revenue", presented to Shearson-Lehman Brothers, Inc. 1986 Airline Industry Seminar, Key Largo, Fla., February 14, 1986.

43 Sheryl E. Kimes, *op. cit.*, 1989, p. 359.

44 Walter J. Relihan III, "Yield Management Approach to Hotel-Room Pricing", *Cornell Hotel and Restaurant Administration Quarterly*, vol. 30, May 1989, pp. 40-45.



Source: Robert G. Cross, "Strategic Selling: Yield Management Techniques to Enhance Revenue", presented to Shearson Lehman Brothers, Inc. 1986 Airline Industry Seminar, Key Largo, Fla., February 14, 1986, p. 4.

Threshold Curves

Figure 2-3

curves can be used as criteria of changing price level to shift demand between periods to increase capacity utilization. Chapman and Carmel (1992) applied the threshold curve approach to one segment of health care services and found the yield management concepts were indeed applicable.[45]

IMPLICATIONS OF THE LITERATURE REVIEW

While the segmentation pricing issues of the liner conferences have been dealt with extensively in many studies, no research has been made to investigate the booking patterns of each segment. The expected effects of yield management application to the container shipping industry may depend on booking patterns of individual cargo groups.

Capacity management techniques vary greatly in sophistication. The dynamic and probabilistic nature of the reservation processes makes simple linear programming models unrealistic for real-life problems. Frequent cancellation and no-shows bring additional dimensions to incorporate into the model. The nested model is more realistic, but increases the number of variables that should be determined.[46]

It is almost impossible to apply the nested model to container shipping with a number of rate classes. Therefore, an important factor affecting the applicability of capacity control techniques to the container shipping industry is clustering the rate classes into a smaller manageable number.

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45 Stephen N. Chapman and Jonathan I. Carmel, "Demand/capacity management in health care: An application of yield management", *Health Care Management Review*, vol. 17, no. 4, Fall 1992, pp. 45-54.

46 The number of decision variables in the nested model is k(k-1)/2, where k = the number of rate classes (Peter Paul Belobaba, *op. cit.*, 1987, p. 118).

Although cancellation and no-shows are not so frequent as for airlines or hotel industries, the container shipping industry also faces the overbooking problem. This makes capacity control complicated, especially when the industry is in an excess demand situation.

Service contract[47] is another factor that should be considered in yield management application to a container shipping firm. Most shipping firms use the service contract as a means of obtaining the base cargoes as well as increasing market share. Since the service contract cargoes must be accepted up to a certain limit specified in the contract, they are beyond of the firm's control in immediate decision making. A certain amount of the capacity should be protected or reserved for the service contract cargoes, regardless of their freight rates or marginal revenues.

With the objective to investigate the applicability of yield management techniques to container shipping, the subsequent chapters are devoted to address:

- examination of booking patterns of container shipping cargoes,
- clustering the rate classes,
- confirming the advantages of yield management application in container shipping by simulating capacity control models using actual booking data as booking requests.

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47 Service contract is a contract between a shipper and an ocean carrier or a conference, in which the shipper makes a commitment to provide a certain minimum quantity of cargoes over a fixed time period, and the ocean carrier or conference commits to a certain rate schedule as well as a defined service level such as assured space, transit time, or other service features (N. Shaskikumar, "Service contracts: a case study of unfulfilled promises", *Maritime Policy and Management*, vol. 16, no. 1, 1989, p. 13).

CHAPTER 3
METHODOLOGY

The main objectives of this dissertation are to investigate the applicability of yield management techniques to the international container shipping business and to provide the basis for further research and development of yield management systems for container shipping firms. The research consists of three phases. The first phase examines the booking patterns of commodity groups to test if they are significantly different. In the second phase, a number of rate classes in a container tariff are clustered to a manageable number of commodity groups on the basis of booking patterns as well as freight rates. Segmenting the market not only based on revenue but also using booking patterns is considered important for yield management application. The first two phases use the statistical analysis. The third phase of the research is devoted to application of yield management techniques to the actual booking data. Two yield management approaches, the marginal revenue approach and the threshold curve method, are applied. To evaluate performance of the models, their revenue impacts are evaluated.

This chapter is intended to present the methodology and procedures employed in this research. The statistical methods used in the first and second phase are introduced and some details of these methods are presented. It also presents the procedures of implementing the yield management techniques to the actual data and evaluating the revenue impacts. Finally, the summary of the methodology of this research concludes the chapter.

DATA COLLECTION

The data used in this research are the actual booking data of the North America-Asia route. Data were provided by a container shipping company that was chosen due to availability. It is a major international container line whose service covers worldwide arterial routes including the trans-Pacific route in both directions. The North America-Asia route has a very complex tariff schedule of a number of freight rate classes. This route is served by both conference and independent carriers.

The detailed booking data were used. Data included the booking date, types of cargo, quantity (TEU), origin and destination, and actual freight rate ($/TEU) as in Table 3-1.

Table 3-1

Data Structure

Voyage #:	**Vessel:**		**Departure Date:**	
From:	**To:**		**Total Capacity:**	
Booking Date	Days before Departure	Quantity (TEU)	Cargo Type	Freight Rate ($/TEU)

PHASE 1: Examination of Booking Patterns

As discussed in Chapter 1, the first task of yield management is to develop a discriminatory price structure by dividing customers into several distinct groups. Therefore, this research attempted to examine the possibility of segmentation of the container shipping market by answering the questions:

- What are the characteristics of the market segmentation of the container shipping industry?
- What are the major factors that discriminate among different cargo groups?
- Are the booking patterns different between high value cargoes and low value cargoes?

As reviewed in Chapter 2, many empirical studies have been conducted to answer the first two questions. They figured out that commodity value and stowage factor were major factors that discriminated among cargo groups, and validated the principle of "value of service pricing" or "charging what the traffic can bear" in the liner shipping.

Together with the value of service pricing feature, the difference in booking patterns among cargo groups is another important factor of market segmentation from the viewpoint of yield management application. Considering that yield management techniques determine whether to accept early booking requests of low paying customers or to reserve the capacity for late booking high paying customers, good candidates for yield management application are the markets in which high paying customers tend to book later than low paying customers. Therefore, the first phase of this research focuses on examining the booking patterns to identify significant differences in booking patterns among commodity groups. This provides the basis of market segmentation in the second phase of the research.

Due to the complexity of the tariff schedule, a few commodity groups were selected based on the average freight rates and the proportion of the cargo in total quantity. The booking patterns were investigated by commodity groups of different freight rate levels. This included the graphical analysis and the hypothesis test.

Graphical analysis

Using detailed booking data, the booking curves were derived and compared with those of the airlines in Figure 2-1. The booking curves were drawn by commodities of different freight rates and the groups of the commodities.

Hypothesis test

This part is to test if there exist significant differences in the booking patterns among market segments. For each commodity group, the actual booking data of each voyage were compiled to obtain the average of booking days before departure, the first quartile, and the third quartile, which are considered to represent the booking patterns (see Table 3-2).

Since the properties of a frequency distribution can be summarized by measurements of central location and variation, the average booking days before departure was chosen as a measurement of where the center of distribution lies, and the first and the third quartiles were chosen as measurements of variation. The frequency distributions of booking data may probably be skewed right or left as shown in the airline's booking patterns in Figure 2-1. In this case, the quartiles are more appropriate measurements of variation than standard deviation or variance that measures only the magnitude of variation.

Each voyage was counted as an observation, and a total of 21 voyages of data provided were included in the analysis.

Table 3-2

Data Structure for Hypothesis Test

(Days before departure)

groups		1			2			....			g	
variables	avg	q1	q3	avg	q1	q3	.....	......	.....	avg	q1	q3
voyage 1												
voyage 2												
:												
:												
:												
:												
:												
:												
:												

Notes: Avg, q1 and q3 represent the average, the first quartile and the third quartile of days between booking dates and departure respectively.

The booking patterns are tested by comparing the mean vectors of average, the first quartile and the third quartile. The hypothesis tested is:

H: Lower freight cargoes are booked earlier than higher freight cargoes.

$$H_0: \quad \mu_1 = \mu_2 = \cdots\cdots\cdots = \mu_g$$

versus

H_a: All μ's are not equal

where μ is mean vector of the average, the first quartile, and the third quartile of the days between booking date and departure date

1, 2, ·········, g are commodity groups

If we reject the null hypothesis, in other words if low freight cargoes are booked earlier than high freight cargoes, we may conclude that container shipping has an good opportunity to apply yield management to increase revenue by reserving some slots for high freight cargoes. This is plausible in that high value cargoes are probably more time sensitive due to high inventory costs than low value cargoes.

Some drawbacks of traditional statistical methods

The data to be used in the first phase of the research have a multivariate structure that includes one independent variable (commodity groups) and more than two dependent variables (average, the first quartile, and third quartile) as shown in Figure 3-2. The commodity groups need to be compared to examine whether the mean vectors of the dependent variables are the same. If the mean vectors are not equal, further investigation is needed to identify which mean components differ significantly.

As the Analysis of Variance (ANOVA) model is widely used to compare two or more univariate samples, the Multivariate Analysis of Variance (MANOVA) model can be used to test the equality of mean vectors of different groups. In MANOVA, Wilks' lambda (or Wilks' Λ Criterion) is used as the test statistic, just like F-ratio statistic is used in ANOVA. However, these traditional ANOVA and MANOVA procedures have some drawbacks.

ANOVA and MANOVA provide the means of testing the overall "omnibus" null hypothesis

$$H_o: \quad \mu_1 = \mu_2 = \cdots\cdots\cdots = \mu_g$$

versus the alternative hypothesis

H_a: All μ's of g groups are not equal.

However, when the null hypothesis is rejected, both ANOVA and MANOVA do not pinpoint exactly which group means or mean vectors are different.[1] It cannot be determined whether the null hypothesis is rejected because $\mu_1 \neq \mu_2$, or because $\mu_1 \neq \mu_3$, or because all the mean vectors are different.

Many post hoc multiple comparison procedures have been developed to identify where the significant differences lie: (1) Bonferroni *t* test, (2) Scheffe S test, (3) Tukey's honestly significant difference (HSD) method, (4) Tukey's extension of the Fisher least significant difference (LSD) approach, (5) Duncan's multiple range test, (6) the Newman-Keuls test, and so on.[2]

Although a few of these multiple comparison procedures are available in practice in the multivariate case, they are not viewed as being appropriate. For example, although the Bonferroni *t* is the simplest statistical procedure being used for the multiple comparison in the MANOVA situations, statistical power is small with a large number of

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1 Hamparsum Bozdogan, "Multi-Sample Cluster Analysis as an Alternative to Multiple Comparison Procedures", *Bulletin of Informatics and Cybernetics*, vol. 22, no. 1-2, 1986, pp. 97-98.

2 Joseph F. Hair, Jr., Rolph E. Anderson, Ronald L. Tatham, and Bernie J. Grablowsky, *Multivariate Data Analysis with Readings*, Petroleum Publishing Company, Tulsa, Okla., 1979, pp. 135-136.

potential comparisons.[3] While the Scheffe procedure adequately controls Type I error for any number of comparisons involving ANOVA situations, there seems to be little to recommend it in a MANOVA context.[4]

Moreover, MANOVA relies on the assumption of equality or homogeneity of covariance. If the covariance matrices are not equal, a bias occurs in the test for equality of mean vectors.[5]

The other problems with the traditional MANOVA approach include:

- The decision to accept or reject a model depends on a significance level α, which is arbitrarily chosen.
- It is not known how to protect the overall level of significance as we cluster the groups.
- The existing multiple comparison procedures are only devised to handle pairwise comparisons.

<u>Information criteria</u>

As an effort to avoid the drawbacks associated with the traditional approaches, information theoretic statistics pioneered by Hirotugu Akaike has been advanced for the last twenty years. The information theoretic statistics is based on the concepts of entropy, information, and likelihood.

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3 Harry R. Barker and Barbara M. Barker, *Multivariate Analysis of Variance (MANOVA): A Practical Guide to Its Use in Scientific Decision Making*, The University of Alabama Press, Ala., 1984, p. 35.

4 Harry R. Barker and Barbara M. Barker, *Ibid.*, 1984, pp. 30-31.

5 Hamparsum Bozdogan and Stanley L. Sclove, "Multi-Sample Cluster Analysis Using Akaike's Information Criterion", *Annals of Institute of Statistical Mathematics*, vol. 36, Part B, 1984, p. 164.

The objective of statistical analysis is to choose an appropriate model using the information provided by the data. However, we try to fit the model without knowing what the "true" model is or might be. If we can measure the distance between the "fitted" model and the "true" model, we have to make this distance as small as possible to choose the best approximating model. One measure of this distance is entropy, or negentropy which is known as the Kullback-Leibler information quantity.

Suppose that **X** is a continuous random vector characterized by a probability density function $f(\mathbf{X}|\theta)$ with parameter vector θ. Then, the entropy of **X** is defined by

$$\begin{aligned} \mathbf{H(X)} &= \mathbf{E}[-\log f(\mathbf{X}|\theta)] \\ &= \int\{-\log f(\mathbf{X}|\theta)\} f(\mathbf{X}|\theta)\, d\mathbf{X} \\ &= -\int f(\mathbf{X}|\theta) \log f(\mathbf{X}|\theta)\, d\mathbf{X} \end{aligned}$$

Let $f(\mathbf{X}|\theta^*)$ denote true probability density function with a true parameter vector θ^*. It is required to select θ closest to θ^*. In this case, we will measure the "closeness' or the "goodness of fit" of $f(\mathbf{X}|\theta^*)$ with respect to the model $f(\mathbf{X}|\theta)$ through the generalized entropy **B** of Boltzmann, or Kullback-Leibler information quantity (or in short K-L information quantity) **I**:

$$\mathbf{B}[f(\mathbf{X}|\theta^*); f(\mathbf{X}|\theta)] = -\mathbf{I}[f(\mathbf{X}|\theta^*); f(\mathbf{X}|\theta)]$$

or in terms of parameters,

$$\mathbf{B}(\theta^*;\theta) = -\mathbf{I}(\theta^*;\theta)$$

We may maximize

$$
\begin{aligned}
\mathbf{B}(\theta^*;\theta) &= \mathbf{E}[\log f(\mathbf{X}|\theta) - \log f(\mathbf{X}|\theta^*)] \\
&= \int f(\mathbf{X}|\theta^*) \log f(\mathbf{X}|\theta) d\mathbf{X} - \int f(\mathbf{X}|\theta^*) \log f(\mathbf{X}|\theta^*) d\mathbf{X} \\
&= \mathbf{H}(\theta^*;\theta) - \mathbf{H}(\theta^*;\theta^*)
\end{aligned}
$$

where $\mathbf{H}(\theta^*;\theta) = \int f(\mathbf{X}|\theta^*) \log f(\mathbf{X}|\theta) d\mathbf{X}$ is the cross-entropy which determines the goodness of fit of $f(\mathbf{X}|\theta)$ to $f(\mathbf{X}|\theta^*)$

$\mathbf{H}(\theta^*;\theta^*) \equiv \mathbf{H}(\theta^*)$ is the usual Shannon negative entropy which is constant for a given $f(\mathbf{X}|\theta^*)$

log means natural logarithm

Or, we may minimize the K-L information quantity

$$
\begin{aligned}
\mathbf{I}(\theta^*;\theta) &= -\mathbf{B}(\theta^*;\theta) \\
&= \mathbf{H}(\theta^*;\theta^*) - \mathbf{H}(\theta^*;\theta)
\end{aligned}
$$

Since $\mathbf{H}(\theta^*;\theta^*) \equiv \mathbf{H}(\theta^*)$ is a constant, we only have to estimate the cross-entropy or the expected log likelihood:

$$
\mathbf{H}(\theta^*;\theta) = \int f(\mathbf{X}|\theta^*) \log f(\mathbf{X}|\theta) d\mathbf{X}
$$

However, the quantity $\mathbf{H}(\theta^*;\theta)$ is not directly observable, because it depends on the true distribution which is unknown. Since the mean log likelihood is a natural estimator of $\mathbf{H}(\theta^*;\theta)$, the expected log likelihood, we may estimate the quantity $\mathbf{H}(\theta^*;\theta)$ by maximization of the mean log likelihood. However, the bias introduced by the maximum likelihood estimates needs to be adjusted or corrected.

Akaike's Information Criterion (AIC) was developed to correct this bias by penalizing extra parameters. In a simple form, AIC is defined as follows:

$$\mathbf{AIC(k) = -2\log_e L(\hat{\theta}) + 2k}$$

or in words,

$$\mathbf{AIC = (-2)\log_e(Maximized\ Likelihood)}$$
$$\mathbf{+\ 2(Number\ of\ free\ parameters\ within\ the\ model).}$$

AIC can be interpreted as follows:[6] The first term is a measure of inaccuracy, or badness of fit when the maximum likelihood estimators (MLE) of the parameters of the model are used. The second term is a measure of complexity or the penalty which depends upon the number of parameters used to fit the model. In other words, AIC measures the goodness of fit of a model with consideration of the penalty of additional parameters used to achieve that fit. Inclusion of an additional parameter is appropriate if the goodness of fit of a model increases. The decision rule to determine the best model is to choose a model with minimum AIC, which is called the minimum AIC procedure.

Recently, to make AIC more consistent to penalize overparameterization more stringently, and to choose the simplest model whenever appropriate, Bozdogan (1987, 1990) extended AIC in several ways: Consistent Akaike's Information Criterion (CAIC),[7] Consistent AIC with Fisher Information (CAICF),[8] and Information-Theoretic Measure of Complexity (ICOMP),[9] ICOMP using the Estimated Inverse-Fisher Information

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6 Hamparsum Bozdogan, "Model Selection and Akaike's Information Criterion (AIC): The General Theory and its Analytical Extensions", *Psychometrika*, vol. 52, no. 3, September 1987, p. 356.

7 Hamparsum Bozdogan, *ibid.*, 1987, pp. 356-359.

8 Hamparsum Bozdogan, *ibid.*, 1987, pp. 359-363.

9 Hamparsum Bozdogan, "On the Information-Based Measure of Covariance Complexity and Its Application to the Evaluation of Multivariate Linear Models", *Communications in Statistics*, Part A: Theory and Methods, vol. 19, no. 1, 1990, pp. 221-278.

[ICOMP(I-FIM)].[10] These information criteria have the same form as AIC, but differ in the choice of the penalty or complexity term as follows:

$$\mathbf{CAIC} = -2\log_e \mathbf{L}(\hat{\theta}) + \mathbf{k}[\log_e(\mathbf{n}) + 1]$$

$$\mathbf{CAICF} = -2\log_e \mathbf{L}(\hat{\theta}) + \mathbf{k}[\log_e(\mathbf{n}) + 2] + \log_e |\hat{F}(\hat{\theta})|$$

$$\mathbf{ICOMP} = -2\log_e \mathbf{L}(\hat{\theta}) + 2\{\mathbf{C}_1[\hat{\mathbf{Cov}}(\hat{\theta})] + \mathbf{C}_1[\hat{\mathbf{Cov}}(\hat{\varepsilon})]\}$$

$$\mathbf{ICOMP(I\text{-}FIM)} = -2\log_e \mathbf{L}(\hat{\theta}) + 2\,\mathbf{C}_1[\hat{F}^{-1}(\hat{\theta})]$$

where $\mathbf{L}(\hat{\theta})$ is the maximized likelihood
k is the number of free parameters
n is the sample size
$\hat{F}(\hat{\theta})$ is the estimated Fisher information matrix
$\hat{F}^{-1}(\hat{\theta})$ is the inverse-Fisher information matrix
$\mathbf{C}_1(\Sigma) = (2/\mathbf{p})\log[\mathbf{tr}(\Sigma)/\mathbf{p}] - (1/2)\log|\Sigma|$
$\hat{\mathbf{Cov}}(\hat{\theta})$ is the covariance matrix of the parameter estimates
$\hat{\mathbf{Cov}}(\hat{\varepsilon})$ is the covariance matrix of the residuals

Multi-sample cluster analysis using information theoretic statistics

In this research, the Multi-Sample Cluster Analysis developed by Bozdogan and Sclove (1984), Bozdogan (1986), and Bozdogan et. al. (1994)[11] was used. The multi-sample cluster analysis are carried out in the following three steps.

10 Hamparsum Bozdogan, *ibid.*, 1990, pp. 221-278.

11 Hamparsum Bozdogan, Stanley L. Sclove, and Arjun K. Gupta, "AIC: Replacement for Some Multivariate Tests of Homogeneity with Applications in Multisample Clustering and Variable Selection", in H. Bozdogan ed., *Proceedings of the First US/Japan Conference on the Frontiers of Statistical Modeling: An Informational Approach, Volume 2, Multivariate Statistical Modeling,* Kluwer Academic Publishers, Norwell, Mass., 1994, pp. 199-232.

(1) Identification of the best fitting model.

We can consider the following three models for the data matrix.

M_1: g groups with different mean vectors $(\mu_1, \mu_2, \cdots\cdots, \mu_g)$ and different covariance matrix $(\Sigma_1, \Sigma_2, \cdots\cdots, \Sigma_g)$

M_2: g groups with different mean vectors $(\mu_1, \mu_2, \cdots\cdots, \mu_g)$ and common covariance matrix $(\Sigma, \Sigma, \cdots\cdots, \Sigma)$

M_3: g groups with common mean vectors $(\mu, \mu, \cdots\cdots, \mu)$ and common covariance matrix $(\Sigma, \Sigma, \cdots\cdots, \Sigma)$

To find the best model that fits the data, values of information criteria for each model are computed and compared. The model with minimum value of information criteria is chosen to be the best model.

(2) Multi-sample cluster analysis under the best model

Under the best model, multi-sample cluster analysis is performed to determine the optimal multi-sample clustering structure. For all possible clustering alternatives, the information criteria are compared. The clustering alternative with minimum information criteria is chosen to be the best clustering structure.

If two or more groups are classified into the same cluster in the best structure, we may conclude the mean vectors of these groups are same. The groups classified into different clusters are considered to have different mean vectors. Therefore, multi-sample cluster analysis not only tests the overall hypotheses (say, H_0: $\mu_1 = \mu_2 = \cdots\cdots\cdots = \mu_g$

versus H_a: All μ's of g groups are not equal) but also tells us which group mean vectors are different at the same time.

For example, if there are g=3 samples or groups as in Table 3-3, multi-sample cluster analysis compares all of five clustering alternatives, and chooses the best one. If the best structure has all the groups in the same cluster, the null hypothesis is accepted. If only group 1 and 2 are in the same cluster, we reject the null hypothesis, and conclude the mean vector of group 3 is different from those of group 1 and 2 (see Table 3-3).

Table 3-3

Clustering Alternatives

Clustering Structures		If it is the best structure	
Alternative	Clustering	H_0: equal μ's	Multiple comparison
1	(1, 2, 3)	Accept	$\mu_1 = \mu_2 = \mu_3$
2	(1) (2, 3)	Reject	$\mu_1 \neq \mu_2 = \mu_3$
3	(2) (1, 3)	Reject	$\mu_2 \neq \mu_1 = \mu_3$
4	(3) (1, 2)	Reject	$\mu_1 = \mu_2 \neq \mu_3$
5	(1) (2) (3)	Reject	$\mu_1 \neq \mu_2 \neq \mu_3$

(3) Determination of the relevant variables

Under the best clustering structure, further investigation may be needed to identify which variable or variables are contributing most to the difference among groups. For all the possible subsets of variables, the information criteria are obtained and compared. Again, the subset of variables with minimum value of information criteria is considered most important.

In summary, by using the information criteria, the multi-sample cluster analysis can overcome the drawbacks associated with the traditional approaches:

- It can avoid an arbitrary choice of the significance level α, while decision in the traditional approach depends on a given α.
- It can handle the heterogeneous structures of different groups. while the traditional approaches assume homogeneity of covariance.
- It evaluates all possible cluster alternatives of groups combinatorially, while the traditional approaches handle only pairwise comparison.
- It allows parsimonious model selection due to the penalty factor, while the traditional approaches automatically rate more complex models better.

PHASE 2: Clustering the Tariff Schedule

The number of variables of the yield management model is largely determined by the number of market segments. The large number of tariff classes in the major international routes may cause severe complexity in applying yield management techniques.

The complicated tariff schedule in the major international container shipping routes would be an obstacle to the application of yield management due to an increasing number of decision variables. Cluster analysis using booking data was performed to identify the possibility of reducing the number of commodity groups to a manageable size.

The booking data of each voyage were compiled to obtain the average, the first quartile, and the third quartile of the booking days before departure and average freight rates (see Table 3-4). Applicability of yield management techniques can be verified if the commodity groups can be reduced to a manageable number in terms of these four variables, because the booking patterns and freight revenues are considered to be important factors to segment the market.

Table 3-4

Data Structure for Cluster Analysis

(Days before departure; average freight rates)

groups	1				2				.....	g			
variables	avg	q1	q3	fgt	avg	q1	q3	fgt	.....	avg	q1	q3	fgt
voyage 1													
voyage 2													
:													
:													
:													
:													
:													
:													
:													

Notes: Avg, q1 and q3 represent the average, the first quartile and the third quartile of days between booking dates and departure respectively. Fgt represents the average freight rate.

The multi-sample cluster analysis is used again. As already mentioned, the multi-sample cluster analysis evaluates all possible clustering alternatives of groups combinatorially. The number of alternatives of clustering g groups into m subset, denoted by S(g,m), is a Stirling's number of the second kind and can be computed by

$$S(g,m) = \frac{1}{g!}\sum_{j=0}^{m}(-1)^j \binom{m}{j}(m-j)^g$$

and the total number of clustering alternatives is given by

$$\sum_{m=1}^{g} S(g,m).$$

This procedure, so called clustering by complete enumeration, is not practical and is virtually impossible when the number of groups is large. As summarized in Table 3-5, if we have three groups to cluster, we need to compare only five alternatives to choose the best clustering structure. For ten groups, however, there are almost 116,000 alternatives.

Therefore, the tariff schedule was heuristically broken down to about 10 groups taking their freight rate levels, the proportion of total quantity and booking patterns into account. To reduce the number of groups further, the minimum AIC procedure was performed for the 45 alternatives of clustering 10 groups into 9 subsets. The same procedure was repeated until the number of groups is reduced to 5. Then, as in the first phase, the multi-sample cluster analysis by complete enumeration was performed to examine the possibility of further clustering.

Table 3-5

The Number of Clustering Alternatives

(g = the number of groups; m = the number of clusters)

	S(g, m) for each m										ΣS(g, m)
g	1	2	3	4	5	6	7	8	9	10	Total
1	1										1
2	1	1									2
3	1	3	1								5
4	1	7	6	1							15
5	1	15	25	10	1						52
6	1	31	90	65	15	1					203
7	1	63	301	350	140	21	1				877
8	1	127	966	1701	1050	266	28	1			4140
9	1	255	3025	7770	6951	2646	462	36	1		21147
10	1	511	9330	34105	42525	22827	5880	750	45	1	115975

PHASE 3: Application and Evaluation

The third phase of the research is to apply the yield management techniques to the container shipping industry and to evaluate their revenue impacts. The major purpose of this phase is to detect favorable and unfavorable environments for yield management application.

Limitations

Due to limits of data availability, this research excluded the following two points from consideration in developing the models.

(1) Service contract cargoes

Managing booking of the contract cargoes is beyond of the firm's control in immediate run decision making. Therefore, the first step of yield management application in the container shipping industry should be to forecast the booking of contract cargoes accurately to determine the capacity to be used for non-contract cargoes. The booking forecast can be based on the past booking curve, and can be dynamically adjusted as departure time approaches using actual booking data accepted to date.

However, the past booking data of contract cargoes were not provided for this research. Although the booking data provided included the contract cargoes, it was impossible to distinguish them from non-contract cargoes. Therefore, this research assumes that all the bookings are from non-contract cargoes.

(2) Overbooking problems

The overbooking problem was not included in this research due to the data limitation. Most routes of the international container shipping are troubled today by excess supply. Since overbooking is frequent especially in the excess demand situation, collecting cancellation and no-shows data is difficult in the current excess capacity market.

However, the booking data from an excess capacity market has an advantage in that it represents the actual demand. The booking data from an excess demand market may not be able to indicate the actual demand because the booking would have been limited by lack of capacity.

Application

As described in the previous chapter, there are three basic approaches to yield management decision making: mathematical programming, marginal analysis approach, and threshold curve method. Considering the probabilistic and dynamic nature of the yield management, the mathematical programming approach is too complicated to be applied to the actual problems.

Therefore, this research focuses on application of the marginal revenue approach and the threshold curve method to the actual container shipping environment. Implementing the marginal revenue approach is based on the expected marginal seat revenue (EMSR) model developed by Belobaba (1987).[12] The threshold curve method is based on Cross (1986).[13] Both approaches are explained in detail with examples in Chapter 5. The actual booking data from the North America-Asia route are treated as booking requests. Acceptance or rejection of the booking requests is determined by the capacity allocated or the threshold curves.

Evaluation

To evaluate the performance of the yield management techniques in the container shipping industry, the revenue impacts of both approaches were examined. The assessment of the revenue impact is based on the difference between the revenue earned when the cargoes are booked in the order of the booking requests and the revenue that would be earned when the cargo booking is controlled by yield management techniques.

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12 Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987.

13 Robert G. Cross, "Strategic Selling: Yield Management Techniques to Enhance Revenue", presented to Shearson-Lehman Brothers, Inc. 1986 Airline Industry Seminar, Key Largo, Fla., February 14, 1986.

Evaluation of revenue impacts focuses on answering the following research questions:

- Is yield management effective even if freight rates cannot be changed immediately due to the tariff filing system, and the only way to control the demand is to decide whether to accept a certain cargo or not?
- Does the shipping demand really fluctuate substantially so that the yield management techniques can be effective?
- At what level of demand per capacity ratio is yield management most effective or least effective?

Although yield management involves both pricing and capacity control, this research assumes that the freight rates cannot be changed in the immediate run. Therefore, the first question can be answered by examining the overall revenue impacts generated by the two models applied here. The revenue impacts are also evaluated in terms of the demand per capacity ratio to find the level of demand per capacity, at which yield management is most effective or least effective. Comparing the revenue impacts by the demand per capacity ratios may also assess if the container shipping satisfies a necessary condition of substantial demand fluctuation for yield management application. The revenue impact is also evaluated in terms of the techniques applied to compare these two models.

Finally, if yield management is found to be applicable to the container shipping industry, the next questions will be:

- What are the managerial implications for developing yield management systems?
- What are the directions for future research?

The concluding chapter answers these questions on the basis of the findings from application and evaluations.

SUMMARY OF THE METHODOLOGY

The research methodology and procedures are summarized in Table 3-6. The data were collected from the North America-Asia route. The detailed booking data were used to investigate the booking patterns, and to examine possibility of clustering the tariff schedule to a manageable number of commodity groups.

The research consisted of three phases: (1) examination of the booking patterns, (2) clustering the tariff schedule, and (3) application and evaluation. In the first two phases, the Multi-Sample Cluster Analysis based on the Information Criteria were performed instead of the traditional MANOVA approach. In the third phase, the capacity allocation techniques of yield management were applied to the actual booking data. The impacts of the yield management on revenue were evaluated.

Table 3-6

Summary of Research Methodology

Phase	1	2	3
Research	Examination of Booking Patterns	Clustering Tariff Schedule	Application and Evaluation
Methodology and Procedures	· Multi-Sample Cluster Analysis · Variable Subset Selection · Minimum AIC procedure	· Multi-Sample Cluster Analysis · Minimum AIC procedure	· Marginal Revenue Approach, · Threshold Curve Method
Objective	· To test the possibility of market segmentation according to the booking patterns	· To examine the possibility of reducing the number of tariff schedule to a manageable size in the yield management environment	· To investigate the applicability of yield management techniques and to evaluate their revenue impacts. · To find out the conditions that are favorable or unfavorable to yield management application

CHAPTER 4

MARKET SEGMENTATION

As discussed in Chapter 1, yield management in the container shipping industry deals with two basic tasks: (1) develop a discriminatory price structure by dividing commodities into several distinct cargo groups, and (2) decide which group or groups of cargoes should be accepted on the immediate run basis. This chapter is devoted to the first task, and the following chapter goes on to perform the second task.

This chapter is split into two sections. The first section examines the characteristics of the market segmentation in container shipping. Since segmented pricing is a common practice in the container shipping market through its "value of service pricing" or "charging what the traffic can bear" principle, the major focus is upon examining if the booking patterns are different among commodities of different freight rates.

In the second section, the container shipping market is segmented to provide basis for yield management application. Hundreds of commodities carried on container ships are clustered into several distinct groups based on booking patterns as well as freight revenues.

EXAMINATION OF BOOKING PATTERNS

With regard to the market segmentation, the following research questions should be answered to confirm the discriminatory price structure of the container shipping market:

What are the characteristics of the market segmentation of the container shipping industry? What are the major factors that discriminate among different cargo groups? Are the booking patterns different between high freight cargoes and low freight cargoes?

The literature review in Chapter 2 confirmed the principle of "value of service pricing" or "charging what the traffic can bear" in the liner shipping industry. Many studies figured out that commodity value and stowage factor were major factors that discriminated among cargo groups. However, from the viewpoint of yield management, booking pattern is also an important factor, on which market segmentation should be based. Therefore, the major intention of this section is to answer the third question: Are the booking patterns different between high value cargoes and low value cargoes? More specifically, do high freight cargoes tend to book later than low freight cargoes?

Graphical analysis

Actual booking data were provided by a container shipping company. A total of 21 trans-Pacific westbound voyages of data from November 1993 to April 1994 were used for analysis. Five container ships with carrying capacity of 4,000 TEU fulfilled 17 voyages out of 21, and three 1,660 TEU ships were deployed to the other 4 voyages.[1]

The company uses its own 3-digit codes to categorize the commodities carried. Almost 100 different codes are used to represent the commodities carried from the west coast of the United States to Asian countries. Freight tariffs[2] are also determined by

1 The firm was in transition of upgrading carrying capacity on the trans-Pacific route.

2 The provided data included the expected freight revenue for some bookings. Freight revenue for the other bookings were estimated based on the given data, since the complete freight revenue

origin, destination, types of container used (20-foot, 40-foot, or high cube container, etc.), and such terms as door to door, port to port, yard to yard, or any other combinations, in addition to the types of commodities.

To examine if low freight commodities are booked earlier than high freight cargoes, the commodities were roughly categorized into three groups based on the 20-foot equivalent freight levels: high, medium, and low level of freight groups.[3] Three commodities from each cargo group were chosen to represent each group. For each commodity, total quantity carried during the 21 voyages was calculated across the booking dates in the form of the days before departure. Then, the cumulative percentage of quantity on each day was obtained to draw a booking curve of the commodity. Since the booking curve can be drawn using composition data, all the 21 voyages of data were used, even though the amount of cargoes carried by 1,660 TEU ships were significantly lower than that of 4,000 TEU ships.

The results are presented in Figure 4-1. The different cargo groups are distinguished by the thickness of curves. The thicker curves represent higher freight commodities. In general, it shows that higher freight cargoes are booked later than lower freight cargoes. However, commodity C-201 (hides) in the highest freight group tends to book very early, probably earlier than the lowest freight commodities. The possible reason for this is in its low stowage factor. In other words, this commodity is charged

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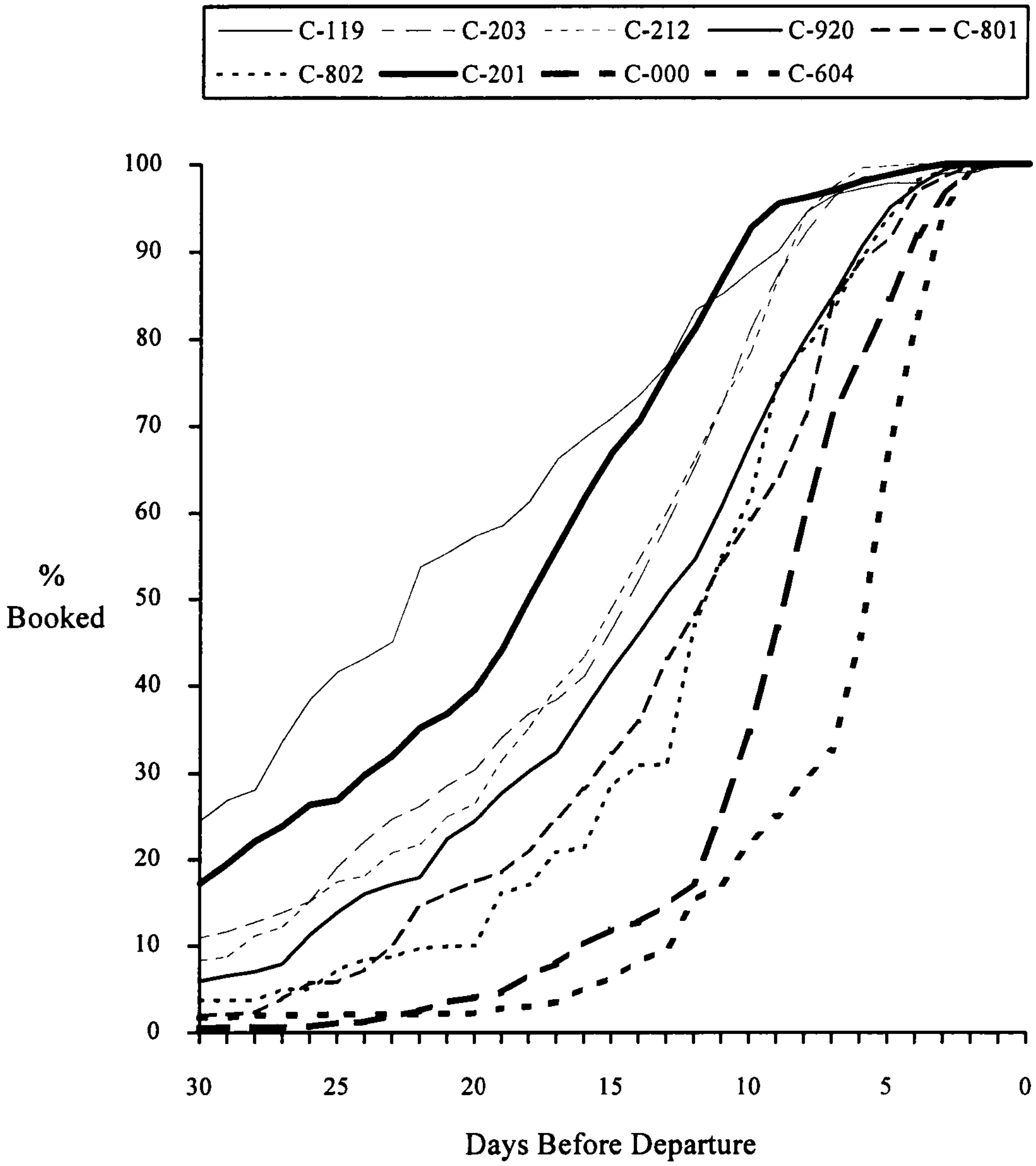
data for all of each booking were not available. Although this may not reflect the exact amount of freight revenue the company actually earned, it can meet the data needs for this research by representing the general freight level of each commodity.

3 The 20-foot equivalent freight rates here does not mean the freight rates per TEU in the tariff. They are average freight rates obtained by dividing total freight revenue by total quantity calculated in terms of TEU. To calculate the TEU equivalent quantities, 40-foot containers were multiplied by 2, and high cube containers were multiplied by 2.2, which were suggested by Jeffrey F. Hudson, "Capacity Measurement for the High Cube Fleet", *Journal of Transportation Research Forum*, vol. 30, no. 2, p. 520.

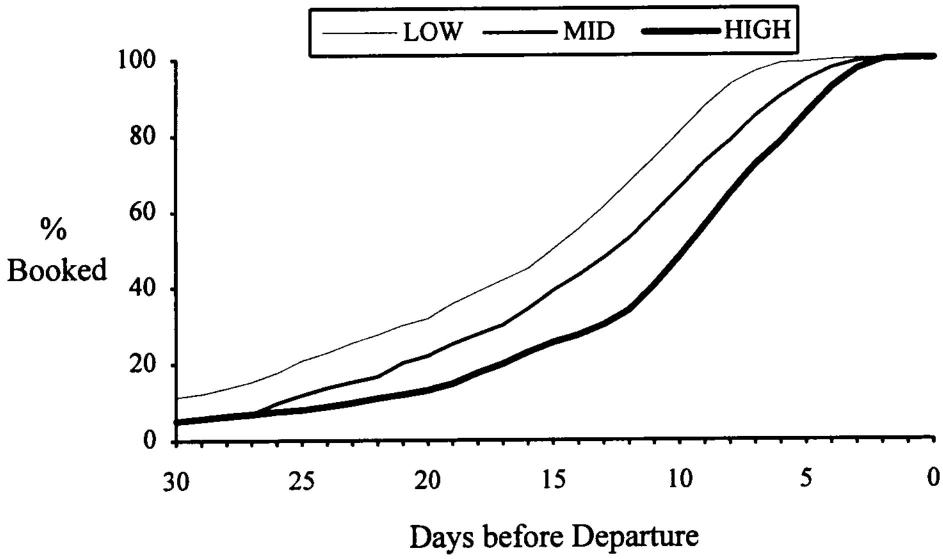


Booking Patterns of Container Cargoes

Figure 4-1

high freight because it occupies much weight capacity of the vessel due to its heavy weight. Commodity C-119 (hay cubes) is another exception. It tends to book earlier than the other two commodities in the low freight level group.

Figure 4-2 shows that the different booking patterns of the three cargo groups in terms of total quantity of three commodities of each group. Obviously high freight cargoes are booked later than lower freight cargoes. Although the difference in the booking patterns is not so obvious as in the passenger airline cases in Figure 2-1, it implies a positive conclusion for applicability of yield management techniques to the container shipping industry.



Booking Patterns by Freight Level Groups

Figure 4-2

Hypothesis test

To examine if the difference in the booking patterns among cargo groups is significant, the hypothesis that lower freight cargoes are booked earlier than higher freight cargoes was statistically tested. For each of nine commodities chosen, the booking data of each voyage were rearranged by booking dates to see how many days before departure 25 percent and 75 percent of total quantity were booked. The data were also manipulated to obtain the average booking days before departure. These three variables, the average, the first quartile, and the third quartile of booking days before departure are considered to represent booking patterns.

The hypothesis tested is:

$$H_o: \quad \mu_1 = \mu_2 = \cdots\cdots\cdots = \mu_g$$

versus

H_a: All μ's are not equal

where μ is mean vector of the average, the first quartile, and the third quartile of the days between booking date and departure date

1, 2, ..., g are commodity groups

In this research, instead of traditional hypothesis testing procedures, the multi-sample cluster analysis based on information theoretic statistics was performed. Two types of information criteria, Akaike's Information Criterion (AIC)[4] and Information Theoretic Measure of Complexity using the Estimated Inverse-Fisher Information

4 Hamparsum Bozdogan, "Model Selection and Akaike's Information Criterion (AIC): The General Theory and its Analytical Extensions", *Psychometrika*, vol. 52, no. 3, September 1987, p. 356.

[ICOMP(I-FIM)][5], were used as decision criteria. These information criteria are defined as follows.

$$\mathbf{AIC(k)} = -2\log_e \mathbf{L}(\hat{\theta}) + 2\mathbf{k}$$

$$\mathbf{ICOMP(I\text{-}FIM)} = -2\log_e \mathbf{L}(\hat{\theta}) + 2\,\mathbf{C}_1[\hat{F}^{-1}(\hat{\theta})]$$

where $\mathbf{L}(\hat{\theta})$ is the maximized likelihood

k is the number of free parameters

$\hat{F}^{-1}(\hat{\theta})$ is the inverse-Fisher information matrix

$\mathbf{C}_1(\Sigma) = (2/\mathbf{p})\log[\mathbf{tr}(\Sigma)/\mathbf{p}] - (1/2)\log|\Sigma|$

(1) Identification of the best fitting model

The first step of the multi-sample cluster analysis is to examine to which of the following models the data matrix fits most:

M_1: g groups with different mean vectors ($\mu_1, \mu_2, \cdots\cdots, \mu_g$) and different covariance matrix ($\Sigma_1, \Sigma_2, \cdots\cdots, \Sigma_g$)

M_2: g groups with different mean vectors ($\mu_1, \mu_2, \cdots\cdots, \mu_g$) and common covariance matrix ($\Sigma, \Sigma, \cdots\cdots, \Sigma$)

M_3: g groups with common mean vectors ($\mu, \mu, \cdots\cdots, \mu$) and common covariance matrix ($\Sigma, \Sigma, \cdots\cdots, \Sigma$)

5 Hamparsum Bozdogan, "On the Information-Based Measure of Covariance Complexity and Its Application to the Evaluation of Multivariate Linear Models", *Communications in Statistics*, Part A: Theory and Methods, vol. 19, no. 1, 1990, pp. 221-278.

Values of information criteria for each model were computed and compared. Because information criterion measures badness of fit and complexity of a model, the model with minimum value of the criterion is the best fitting model with the least complexity. The summary of the values of AIC and ICOMP(I-FIM) under the three models is presented in Table 4-1, where "*" denotes the minimum value of each information criterion.

Table 4-1

The Best Fitting Model for Hypothesis Test Data

Model	AIC	ICOMP(I-FIM)
M_1: Different μ_g and Σ_g	798.2003	792.9773
M_2: Different μ_g and Common Σ	786.9174*	746.6979*
M_3: Common μ and Σ	834.3601	826.1645

Since M_2 with different μ_g and common Σ has the minimum values of AIC and ICOMP(I-FIM), we can entertain the MANOVA (multivariate analysis of variance) model indicating that mean vectors are different among cargo groups, but the covariances are the same across the three cargo groups. More specifically, we can assume that the covariances are equal because the values of AIC and ICOMP(I-FIM) for M_1 with different μ_g and Σ_g are greater than those for M_2 with different μ_g and common Σ. However, we reject the null hypothesis

$$H_o: \quad \mu_1 = \mu_2 = \cdots\cdots = \mu_g \text{ given that } \Sigma_1 = \Sigma_2 = \cdots\cdots = \Sigma_g = \Sigma$$

versus

$$H_a: \quad \text{All } \mu\text{'s are not equal,}$$

since the values of AIC and ICOMP(I-FIM) for M_3 with common μ and Σ are greater than those for M_2 with different μ_g and common Σ.

(2) Multi-sample cluster analysis under the best fitting model

To find out which group mean vectors are different, multi-sample cluster analysis was carried out under the best fitting model. The results are given in Table 4-2. Minimum values of AIC and ICOMP(I-FIM) were achieved at the clustering structure that treats each cargo group separately. This means that the mean vectors of three groups differ significantly from each other. As a result, we can conclude that high freight cargoes are booked later than low freight cargoes, which implies applicability of yield management techniques to container shipping.

Table 4-2

The Best Clustering Structure for the Hypothesis Data

Alternative	Clustering Structure	AIC	ICOMP(I-FIM)
1	(1, 2, 3)	834.3601	840.2109
2	(1) (2, 3)	797.7394	778.5842
3	(2) (1, 3)	839.6552	824.1405
4	(3) (1,2)	805.9356	787.2091
5	(1) (2) (3)	786.9174*	746.6979*

Table 4-2 also suggests the possibility of clustering cargo groups. If we need to cluster any two cargo groups for any reason, we should cluster groups 2 and 3 or groups 1 and 2 together based on their low values of AIC and ICOMP(I-FIM). However, we should not cluster groups 1 and 3 together because the clustering structure has the highest value of AIC and ICOMP(I-FIM) among the 2 group structures. The clustering problem is discussed in detail in the next section.

(3) Determination of the relevant variables

Since the data are multivariate we need to identify which variable or variables are contributing most to the difference in mean vectors among groups. For all possible subsets of variables, the values of AIC and ICOMP(I-FIM) were computed, and the same procedure was repeated for optimal clusters for each number of groups, (1, 2, 3), (1) (2, 3), and (1) (2) (3) in this case. The summary of the results is presented in Table 4-3 and Table 4-4.

Table 4-3

The AIC Values for All Subsets of Variables across the Multi-Sample Clustering Structures

Subset	p	Clustering Structure (1, 2, 3)	(1) (2,3)	(1) (2) (3)	Ordering of Variables Best to Worst
(X_1)	1	321.3296	286.8813	277.9618	
(X_2)	1	380.5123	357.6282	351.3771	(X_3) (X_1) (X_2)
(X_3)	1	278.4872	246.4620	234.1516	
(X_1, X_2)	2	604.2239	571.5686	564.5724	
(X_1, X_3)	2	549.4696	511.0957	498.3243	(X_1, X_3) (X_1, X_2) (X_2, X_3)
(X_2, X_3)	2	623.1726	589.3231	577.1759	
(X_1, X_2, X_3)	3	834.3601	797.7394	786.9174	

X_1 = average of days before departure; X_2 = the first quartile of days before departure; X_3 = the third quartile of days before departure

Table 4-4

The ICOMP(I-FIM) Values for All Subsets of Variables across the Multi-Sample Clustering Structures

		Clustering Structure			Ordering of Variables
Subset	**p**	**(1, 2, 3)**	**(1) (2,3)**	**(1) (2) (3)**	**Best to Worst**
(X_1)	1	318.9435	277.8789	263.2546	
(X_2)	1	379.0006	347.9270	333.7575	$(X_3)\ (X_1)\ (X_2)$
(X_3)	1	275.5209	238.1931	221.8055	
(X_1, X_2)	2	606.7538	559.2046	538.5411	
(X_1, X_3)	2	546.7030	493.3581	469.0044	$(X_1, X_3)\ (X_1, X_2)\ (X_2, X_3)$
(X_2, X_3)	2	623.3098	573.3924	547.1341	
(X_1, X_2, X_3)	3	840.2109	778.5842	746.6979	

X_1 = average of days before departure; X_2 = the first quartile of days before departure;
X_3 = the third quartile of days before departure

We note that the best subset of variables is $\{X_3\}$, which means that the day before departure when 75 percent of total quantity are booked is the most important variable that discriminates among cargo groups. Variable X_1, which is the average of booking days before departure, is considered to be the next important variable. In other words, the first quartile of booking days before is not so different among cargo groups as the third quartile and average of booking days. This result implies that yield management techniques may be effective especially when the departure time is approaching.

CLUSTERING TARIFF SCHEDULES

The second phase of this research was to cluster container tariff schedules into several groups for yield management implication. Since the freight rates of container cargoes depend on the commodities, origin, destination, type of container used (20-foot, 40-foot, or high cube container, etc.), and such terms as door to door, port to port, yard to yard, or any other combination, the tariff schedule of the container shipping usually has hundreds of rate classes. However, as mentioned in Chapter 2, the number of decision variables in a yield management model depends on the number of rate classes. It is almost impossible to treat each of hundreds of rate classes in the tariff schedule separately. Instead, we need to cluster the rate classes into a smaller and more manageable number of cargo groups. Furthermore, for the purpose of yield management application, the commodities should be grouped not only by their freight rates but also booking patterns, in the light of the fact that yield management basically determines whether to accept or to deny the booking requests during the course of booking process.

First, the commodities of the actual booking data were heuristically broken down to 10 groups based on the firm's commodity code system,[6] the freight rate level, and the proportion of total quantity. The classifications of 10 groups are shown in Table 4-5. However, since some of the groups account for only a small amount of cargo quantity, further clustering was needed.

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6 In the case of the booking data used in this research, the commodities can be categorized based on the firm's 3-digit commodity code system. However, the quantity of C-200's account for more than half of total quantity, while some commodity groups represent less than 5 percent of the total quantity. Therefore, C-200's were classified into 4 groups on the basis of freight level. Instead, C-300's, C-400's, C-500's, and C-700's are grouped together because these commodities form a minimal portion of the firm's business.

Table 4-5
Ten Major Container Cargo Groups

Group	Commodity Codes	Average Freight Rate ($/TEU)	% of Total Quantity	Average Booking Days (Days)	First Quartile (Days)	Third Quartile (Days)
1	100's	911	8.7	23.6	31.4	14.6
2	212	760	14.4	16.8	21.0	10.6
3	203	626	21.6	17.0	22.8	10.7
4	201, 211, 215	2,194	6.3	19.4	24.4	12.0
5	Other 200's	940	14.6	15.7	20.6	9.9
6	600's	1,573	4.9	12.6	16.9	5.7
7	300's, 400's, 500's, 700's	1,371	2.6	19.0	27.2	8.7
8	800's	1,339	4.8	13.3	17.1	8.3
9	900's	1,466	12.6	13.9	19.1	8.1
10	000's	1,706	9.5	9.3	11.4	6.7

C-000's: Special commodities such as dangerous cargoes, refrigerated cargoes, etc.

C-100's: Goods made of materials such as metal products, aluminum ware, plastic goods, leather goods, etc.

C-200's: Raw materials.

C-212: Resin;

C-203: Waste paper;

C-201: Hides; C-211: Chemicals; C-215: Borax.

C-300's: Electrical goods such as audio/video equipment, microwave ovens, refrigerators, light bulbs, etc.

C-400's: Volume cargoes such as fibers, yarns, leather garments footwear, gloves, etc.

C-500's: Volume cargoes such as toys, musical instruments, furniture, etc.

C-600's: Tools including hand tools, transport equipment, automobile, auto parts, tires and tubes, bicycles, etc.

C-700's: Miscellaneous goods such as stationary, albums, wall ornaments, optical goods, etc.

C-800's: Miscellaneous goods such as foodstuff, beverages, drug and medicines, etc.

C-900's: Other goods including freight all kinds, mixed commodities, etc.

Multi-sample cluster analysis was performed again for further clustering. The average freight rate of each group is included in the variables as well as the average, the first quartile, and the third quartile of days before departure. This enables market segmentation not only based on revenue but also on booking patterns.

Identification of the best fitting model

The summary of the ICOMP(I-FIM) values under the three possible models is presented in Table 4-6, which shows that minimum value occurs at M_2 with different μ_g and common Σ. As in the hypothesis test case, we can entertain the MANOVA model indicating that mean vectors are different among cargo groups, but the covariances are the same across the three cargo groups.

Table 4-6

The Best Fitting Model for Clustering Tariff Schedule

Model	ICOMP(I-FIM)
M_1: Different μ_g and Σ_g	6,566.9
M_2: Different μ_g and Common Σ	5,318.6*
M_3: Common μ and Σ	6589.3

Multi-sample cluster analysis

To reduce the number of groups further, the multi-sample cluster analysis was carried out once again. However, as already mentioned in Chapter 3, the number of clustering alternatives is almost 116,000 for 10 groups, which makes clustering by complete enumeration virtually impossible. Therefore, the clustering procedure was performed for 45 alternatives that cluster 10 groups into 9 sub-groups to find the best clustering structure among 9 group structures. This procedure was repeated until the number of groups was reduced to 5. Then clustering by complete enumeration was performed for all of the 52 clustering alternatives.

The complete lists of the ICOMP(I-FIM) values obtained from this series of the clustering procedure are given in the tables in the Appendix. Table 4-7 summarizes the results, presenting the best clustering structure at each number of groups. The minimum value of ICOMP(I-FIM) was achieved at the 10 group structure that treats each commodity group separately. However, the other clustering structures in Table 4-7 suggest the further clustering possibilities, since each represents the best clustering structure at each number of groups.

Table 4-7

The Best Clustering Structure at Each Number of Groups

# of Groups	Clustering Structure	ICOMP(I-FIM)
10	(1) (2) (3) (4) (5) (6) (7) (8) (9) (10)	5,318.6*
9	(1) (2) (3) (4) (5) (6) (7) (8, 9) (10)	5,387.6
8	(1) (2) (3) (4) (5) (6, 10) (7) (8, 9)	5,472.3
7	(1) (2, 3) (4) (5) (6, 10) (7) (8, 9)	5,554.3
6	(1) (2, 3) (4) (5) (6, 10) (7, 8, 9)	5,647.2
5	(1, 5) (2, 3) (4) (6, 10) (7, 8, 9)	5,743.6
4	(1, 5, 2, 3) (4) (6, 10) (7, 8, 9)	5,893.0
3	(1, 5, 2, 3) (4) (6, 10, 7, 8, 9)	6,049.7
2	(1, 5, 2, 3) (4, 6, 10, 7, 8, 9)	6,352.4
1	(1, 5, 2, 3, 4, 6, 10, 7, 8, 9)	6,706.3

* Minimum value of ICOMP(I-FIM)

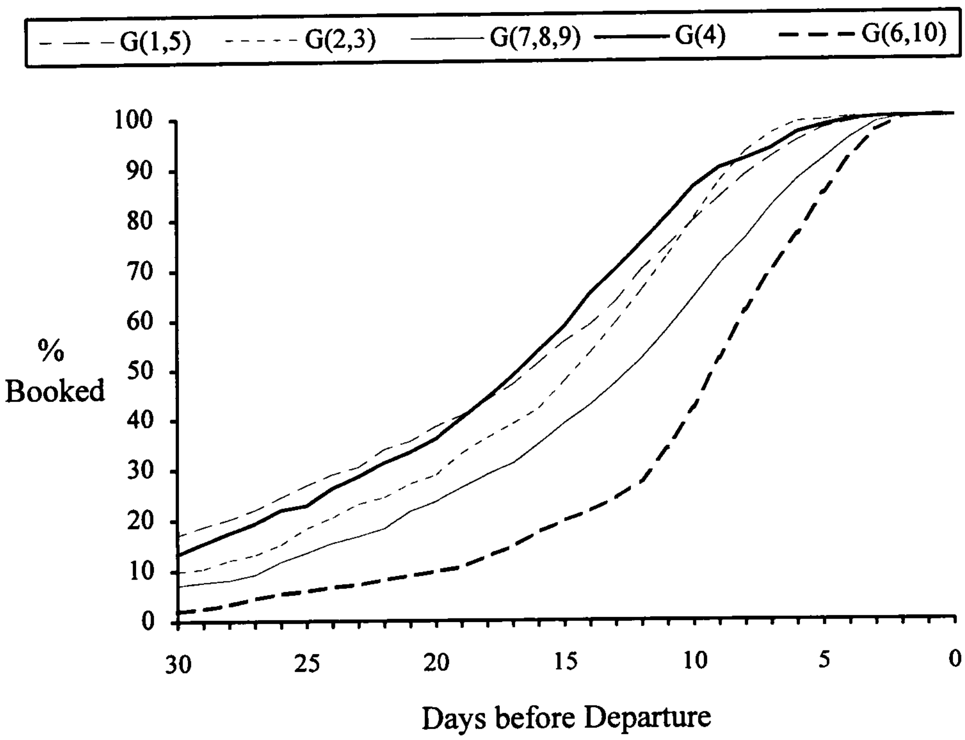
To examine these possibilities, the average freight rates, the portions of total quantity and the booking patterns (see Table 4-5) can be taken into consideration. Above all, however, managerial judgment eventually determines the number of groups in the yield management models. In this research, for simplicity, the further clustering was stopped at the 5-group structure.

To see if this five group structure represents appropriate market segments from the viewpoint of yield management application, the average freight rates, the proportions of total quantity and booking patterns of the five cargo groups were examined in Table 4-8 and Figure 4-3. Since group (4) accounts for only a small portion of the total quantity, the possibility of clustering the group into one of the other groups was examined. The commodities in group (4) tend to book very early, although the average freight rate is the highest among the five groups, while other high freight cargoes in group (6, 10) are booked late. This is consistent with the fact that C-201 in group (4) was found to be booked very early in spite of its high freight rate in the first section of this chapter. In reality, since the commodities in group (4) are booked early, there is no need to control booking requests to reserve capacity for them. Therefore, group (4) can be combined with group (6, 10). In other words, because the commodities in group (4) generate higher freight revenue and tend to book earlier than commodities in group (6, 10), there is no risk of rejecting booking requests of higher revenue from group (4) in favor of reserving that capacity for later booking group (6, 10) of lower revenue, even if both groups are combined into the same market segment.

Table 4-8

Freight Rates and Booking Patterns of Five Cargo Groups

Group	(1, 5)	(2, 3)	(4)	(6, 10)	(7, 8, 9)
Average Freight Rate ($/TEU)	929	679	2,194	1,661	1,416
Proportion of Total Quantity (%)	23.3	36.0	6.3	14.4	20.0
Average of Days before Departure	18.6	16.9	19.4	10.4	14.4
1st Quartile of Days before Departure	25	21	24	12	19
3rd Quartile of Days before Departure	10	10	12	6	8



Booking Patterns of Five Cargo Groups

Figure 4-3

In that the minimum value of ICOMP(I-FIM) among four groups structures occurred when the group (1, 5) and (2, 3) were clustered together, they are another pair of groups that may probably be clustered in a segment. In spite of their similarity of booking patterns, the booking pace of commodities in group (1, 5) slows down within two weeks before departure compared to that of group (2, 3) commodities. If group (1, 5) and (2, 3) are combined into a segment, group (2, 3) commodities with lower average freight would probably be booked first without reserving capacity for higher freight group (1, 5) commodities. It is not considered appropriate to cluster group (1, 5) and (2, 3) together also in that it will make an unbalanced big commodity group that accounts for nearly 60 percent of total quantity.

In conclusion, almost 100 commodity types carried by container ships from the United States to the Asia region were clustered to four cargo groups for yield management application. These four groups are arranged in the order of average freight level in Table 4-9. On the basis of this segmentation, yield management techniques are applied to actual booking data, and their revenue impacts are evaluated in the next chapter.

Table 4-9

Segmentation of Container Shipping Market

$/TEU, %

Group	Commodities	Average Freight	% of Total Demand
1	Refrigerated cargoes, hides, chemicals, borax	1,822	21
2	Mixed commodities, stationary, foodstuff, etc.	1,416	20
3	Products made of materials, other raw materials	929	23
4	Waste paper, resin	679	36

CHAPTER 5
APPLICATION AND EVALUATION

The third phase of this research is to apply yield management techniques to actual container cargo booking data and assess the effectiveness of yield management in the container shipping industry. On the basis of four groups of market segments developed in the previous chapter, two types of capacity allocation techniques are applied: (1) marginal analysis approach and (2) threshold curve method. Some details of both approaches are presented with examples.

The major intention of this chapter is to answer a set of following research questions. Does the shipping demand really fluctuate substantially so that the yield management techniques can be effective? Will yield management be effective even if freight rates cannot be changed immediately due to the tariff filing system, and the only way to control the demand is to decide whether to accept a certain booking request or not? At what level of demand per capacity ratio is yield management most effective or least effective? Answering these questions may identify the favorable and unfavorable environment for yield management application. The effectiveness of yield management application is assessed by examining revenue impacts. The revenue impacts are compared by the models applied and by various demand per capacity ratios to evaluate performance in various situations.

MARGINAL ANALYSIS APPROACH

Distinct fare class model[1]

The basic idea of marginal analysis approach is that the optimal seat allocation is achieved when the marginal revenue for the last unit sold in one group is the same as for another group.[2] In this research, the Expected Marginal Seat Revenue (EMSR) model developed by Belobaba (1987) was applied. The expected marginal revenue of the S_ith seat in fare class i, EMSR$_i(S_i)$, is the average fare level in that class multiplied by the probability of selling S_i or more seats. That is,

$$\text{EMSR}_i(S_i) = f_i \cdot P[r_i > S_i]$$

where f_i = the average fare in rate class i
r_i = total number of requests for reservation in rate class i
S_i = the seats allocated to rate class i.

Normal probability density functions are assumed for booking requests of each class, and the relationship between probability distribution of booking requests (P_i) and the probability of denied booking requests ($P[r_i > S_i]$) is illustrated in Figure 5-1.

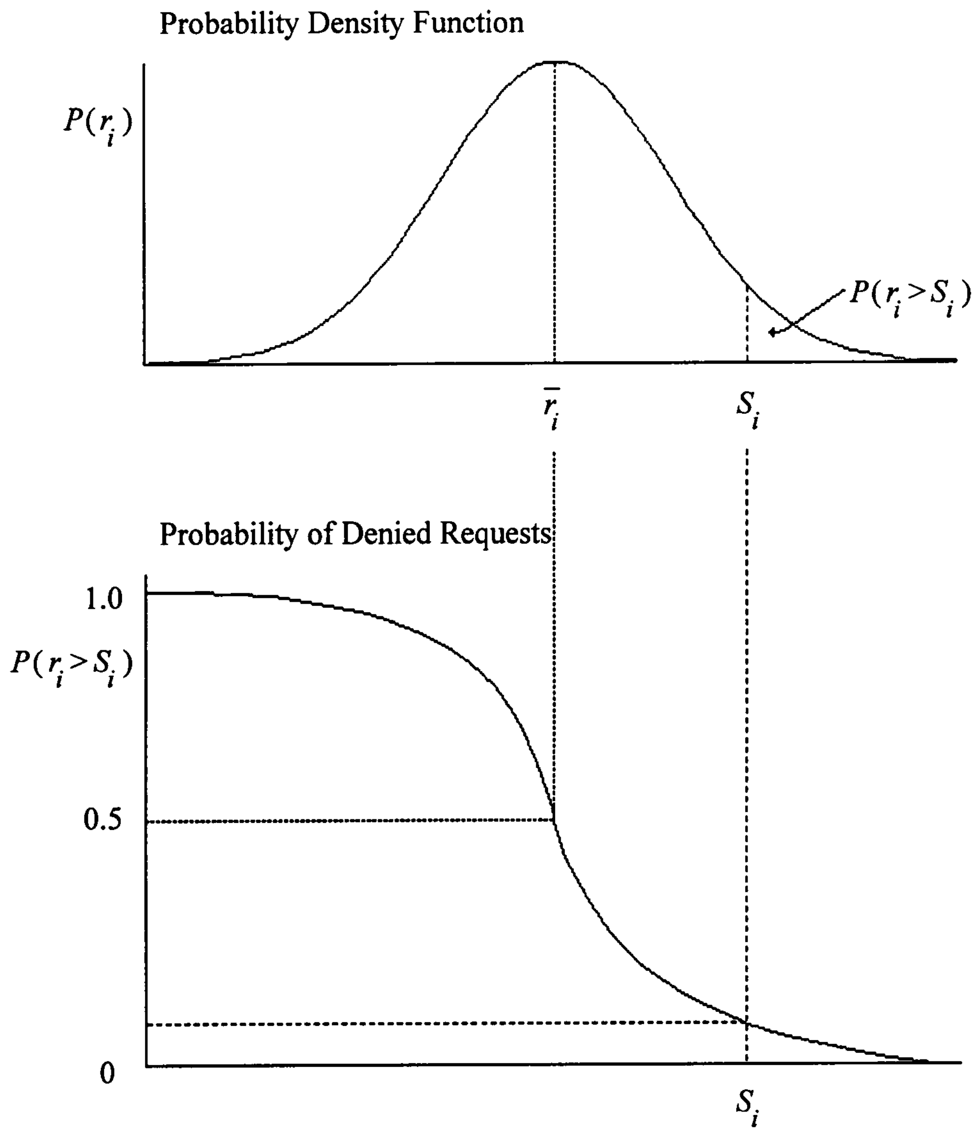
The optimal allocation can be achieved when

$$\text{EMSR}_i(S_i) = \text{EMSR}_j(S_j) = \lambda, \qquad \text{for all } i \neq j$$

where $\lambda = f_i \cdot P\left[r_i > S_i^*\right]$ for all i

1 Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987, pp. 101-107.

2 Sheryl E. Kimes, "Yield Management: A Tool for Capacity-Constrained Service Firms", *Journal of Operations Management*, vol. 8, no. 4, October 1989, p. 356.



Source: Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987, p. 104.

Probability Distribution of Booking Requests

Figure 5-1

where $S_i{}^*$ is the seats allocated at optimality.

An example of optimal allocation in the 2-class case is given in Figure 5-2. In this case, the EMSR of the final seat allocated to class 1 could be lower than the average rate of class 2 (f_2). That is, an unexpectedly high demand of class 2 would be refused in favor of reserving the seat for class 1 demand in spite of its low probability to be materialized.[3] In addition, an unexpectedly high demand of class 1 would be rejected to keep the seat for lower fare class 2 demand.

Nested fare class model[4]

To avoid these shortfalls of the distinct fare class model, Belobaba (1987) developed a nested fare class model, which determines how many seats should be protected from lower fare classes. As illustrated in Figure 5-2, in the two fare classes case, the revenue maximizing protection level for class 1 from class 2 (S_2^1) is determined where

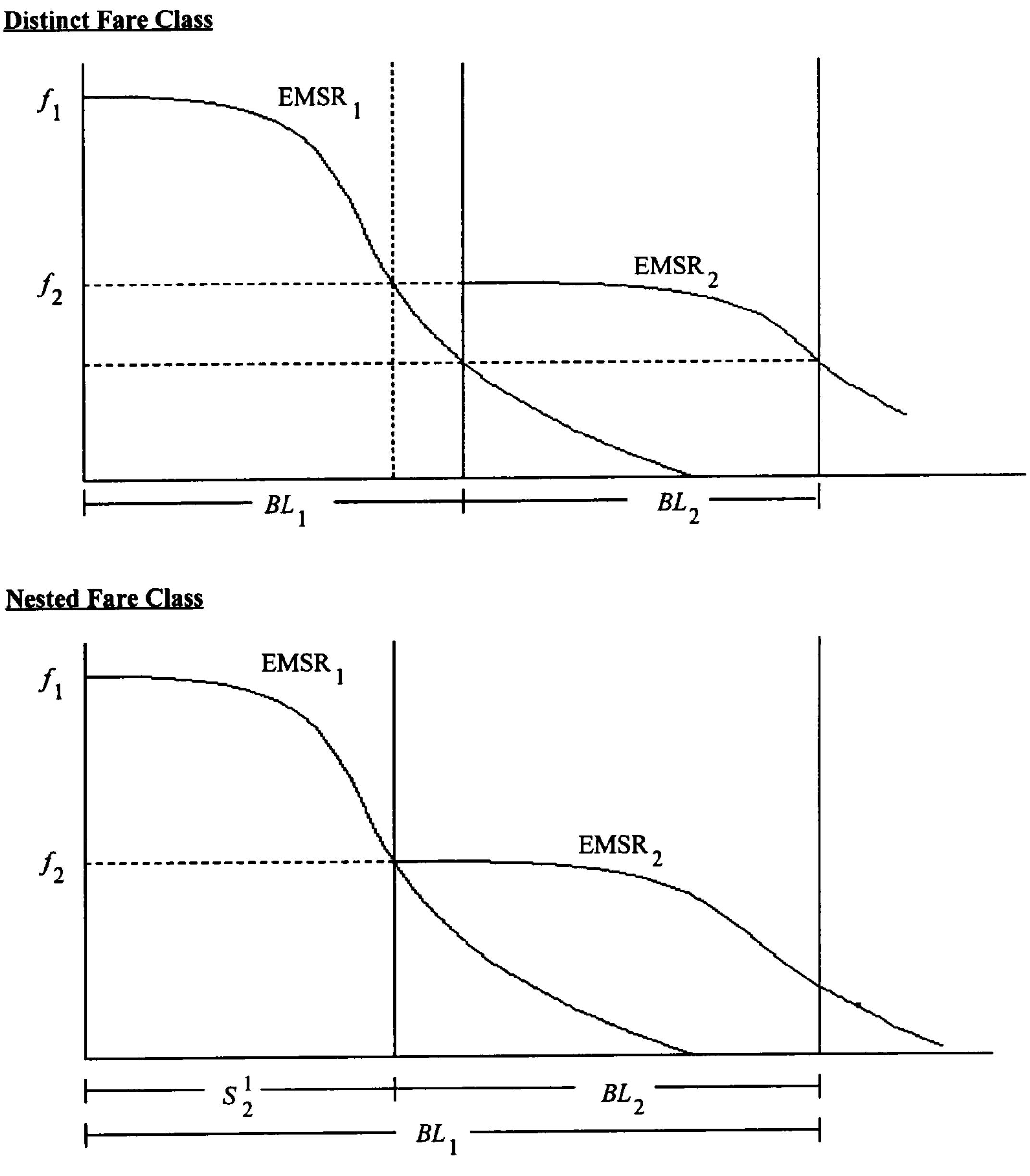
$$\text{EMSR}_1(S_2^1) = f_1 \cdot P(r_1 > S_2^1) = f_2.$$

Each of S_2^1 seats has an expected revenue greater than average fare of class 2 (f_2). Therefore, at least S_2^1 seats should be protected from class 2, and remaining seats may be available to class 2. The optimal booking limit of class 2 (BL_2) thus can be

$$BL_2 = C - S_2^1 \qquad \text{where } C \text{ is total capacity}$$

3 Peter Paul Belobaba, *ibid.,* 1987, p. 112.

4 Peter Paul Belobaba, *ibid.,* 1987, pp. 107-118.



Source: Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987, p. 111.

Maximization of Expected Marginal Revenue

Figure 5-2

In the nested fare class model, booking limits are binding only for lower rate classes. Since the booking requests of the higher fare class 1 should be accepted as long as seats are available, the booking limit of the class 1 is total capacity (C).

This nested model can be expanded to the cases of more than two fare classes, and the optimal values of protection levels must satisfy:

$$\mathrm{EMSR}_i(S_j^i) = f_i \cdot P(r_i > S_j^i) = f_j$$

In the nested 4-class problem, as our container cargo booking case, the following six protection levels are required.

$$\begin{aligned}
\mathrm{EMSR}_1(S_2^1) &= f_1 \cdot P(r_1 > S_2^1) = f_2 \\
\mathrm{EMSR}_1(S_3^1) &= f_1 \cdot P(r_1 > S_3^1) = f_3 \\
\mathrm{EMSR}_1(S_4^1) &= f_1 \cdot P(r_1 > S_4^1) = f_4 \\
\mathrm{EMSR}_2(S_3^2) &= f_2 \cdot P(r_2 > S_3^2) = f_3 \\
\mathrm{EMSR}_2(S_4^2) &= f_2 \cdot P(r_2 > S_4^2) = f_4 \\
\mathrm{EMSR}_3(S_4^3) &= f_3 \cdot P(r_3 > S_4^3) = f_4
\end{aligned}$$

These optimal protection levels in turn determine the optimal booking limits on each fare class:

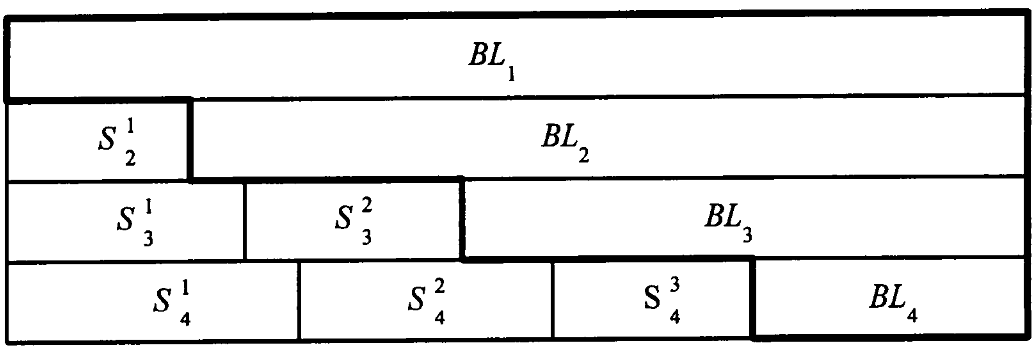
$$\begin{aligned}
BL_1 &= C \\
BL_2 &= C - S_2^1 \\
BL_3 &= C - S_3^1 - S_3^2 \\
BL_4 &= C - S_4^1 - S_4^2 - S_4^3
\end{aligned}$$

or, in generalized terms,

$$BL_j = C - \sum_{i<j} S_j^i$$

That is, all capacity with an expected marginal revenue greater than f_j should not be sold to class j.

The relationship between S_j^i and BL_j in the 4-class case is illustrated in Figure 5-3. Booking limits are set to protect a certain amount of capacity for higher fare classes. For example, BL_2 is determined by subtracting S_2^1 reserved for class 1 from total capacity, and BL_3 is determined by reserving S_3^1 for class 1 and S_3^2 for class 2. The incremental seats protected for class 1 (S_3^1) and 2 (S_3^2) above the protection level for class 1 alone (S_2^1) is equal to $BL_2 - BL_3$. This is referred to as the nested protection level for class 2 (NP_2) and equals $S_3^1 - S_2^1 + S_3^2$. In a generalized expression, using nested protection levels, the booking limits are determined by:



The Protection Levels and Booking Limits

Figure 5-3

$$BL_{j+1} = BL_j - NP_j$$

where $$NP_j = \sum_{i \le j} S^i_{j+1} - \sum_{i<j} S^i_j$$

Dynamic model[5]

The EMSR model outlined above provides a static capacity control solution by setting the booking limits at a certain point in time prior to departure. However, this EMSR framework can be repeatedly applied to determine the optimal booking limit at any time period remaining to departure. In this case, the booking limits are dynamically adjusted at various times before departure.

The optimal protection level for each fare class can be determined, just like previous static cases, where

$$\text{EMSR}_i[S^i_j(t)] = f_i \cdot P^t(r^t_i > S^i_j) = f_j$$

where r^t_i is the number of requests for class i during the period between day t before departure and the day of departure

$P^t(r^t_i > S^i_j)$ is the probability of receiving S^i_j or more requests for class i between day t before departure and the day of departure.

To determine the revised booking limits at the time t, actual bookings already accepted are taken into consideration as follows:

$$BL_j(t) = C - \sum_{i<j} S^i_j(t) - \sum_{i<j} b^t_i$$

5 Peter Paul Belobaba, *ibid.*, 1987, p. 119-122.

where b_i^t is the number of bookings already accepted in class i until day t before departure.

Or, using the nested protection levels:

$$BL_{j+1}(t) = BL_j(t) - NP_j(t)$$

where $$NP_j(t) = \sum_{i \le j} S_{j+1}^i(t) - \sum_{i<j} S_j^i(t) + b_j^i$$

An example of the expected marginal revenue model application

The protection levels and booking limits are set using historical demand data and average freight rates of each group. The average freight rate of each cargo group was obtained based on the actual freight revenue from a total of 21 voyages. For calculation of average and standard deviation of booking requests of each cargo group, only 17 voyages to which 4,000 TEU vessels were deployed were used. The other 4 voyages were excluded because the booking quantities were probably affected due to the capacity limitation.

Under the assumption of normal distribution of booking requests, the initial protection level and corresponding booking limit on each group were computed on 60 days (12 weeks in calendar days) before departure. On day 20 before departure (4 weeks in calendar days), the first revision of booking limits was made based on the future demand expected (historical mean of booking requests to the time of departure) and actual booking amount already accepted. Thereafter, the booking limits were adjusted every 5 days (every week in calendar days).

Actual booking data of a voyage were arranged in the order of the booking dates and were treated as booking requests. An example is presented in Table 5-1 and Figure

5-4 to show how the booking limits of four cargo groups are adjusted and how the bookings are controlled by cargo groups through the course of the booking process.

Higher than expected group 3 bookings in each period led to successive increases in the total group 3 protection level. After day 20, group 1 and 2 bookings were increased to above expected levels, which increased the total group 1 and 2 protection levels and in turn lowered booking limits of the other groups to reserve some slots for later booking group 1 and 2 cargoes.

However, the expected marginal revenue model does not guarantee the optimal result. In Table 5-1, the booking limit of group 4 was lowered from 851.6 TEU to 604.2 TEU on day 10, but 743.8 TEU of group 4 bookings were already accepted. Many of the later booking requests from higher paying group 1 and 2 had to be rejected because capacity was already filled. This can be mitigated by revising the booking limits more frequently than 5 days, although it is still possible that too many lower freight cargoes are booked early in the booking process.

Although the result is not optimal, the model controls the booking levels of each cargo group quite well. No more bookings from group 4 were accepted after day 10. Out of total booking requests of 60.2 TEU from group 3 only 7 TEU were accepted after day 10. After day 5, only group 1 cargoes were booked. This certainly saves more capacity for group higher freight groups and generates more freight revenue than earned when the booking process is not controlled and every booking is accepted in the order of request as discussed in the final section of this chapter.

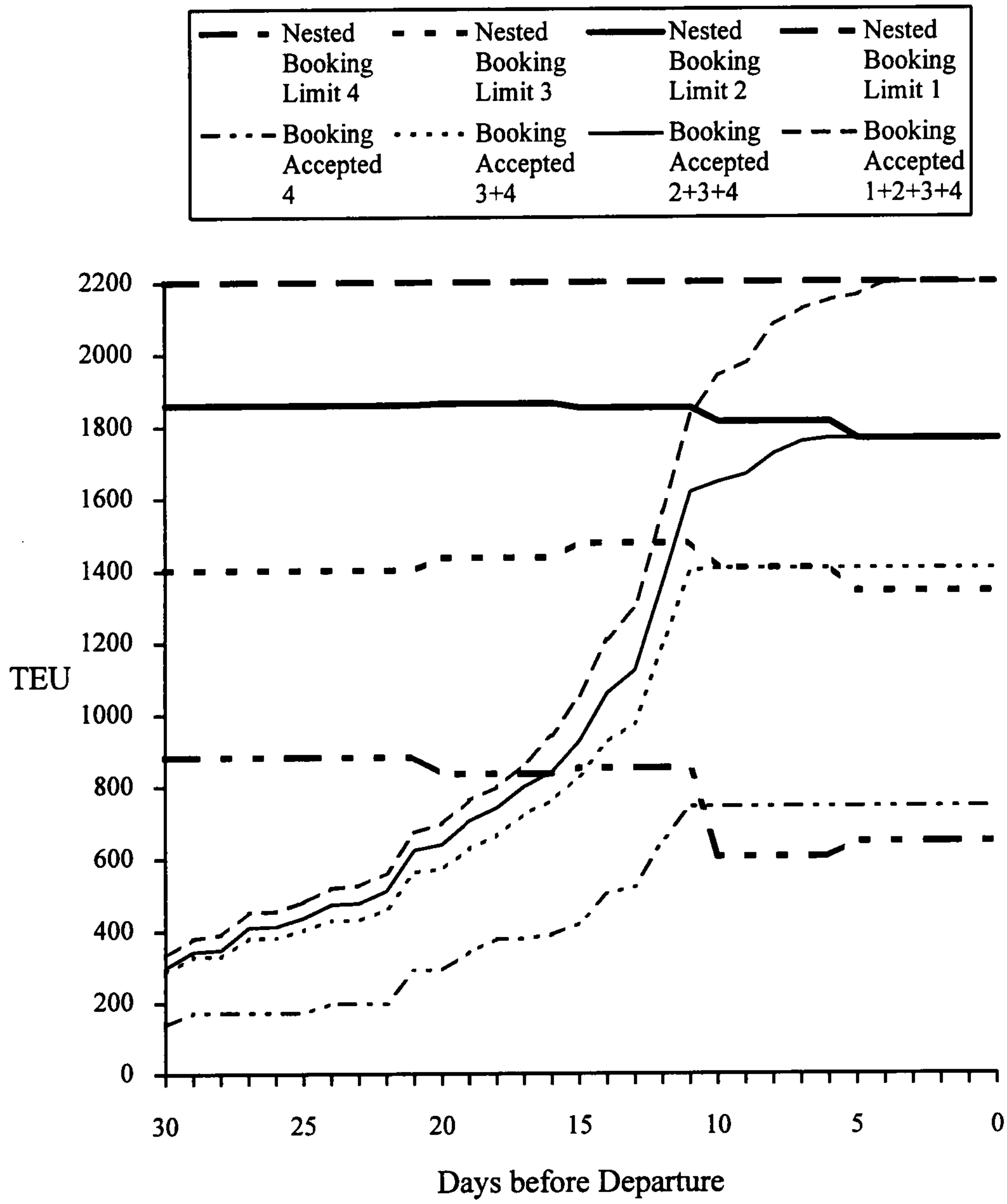
Table 5-1

An Example of Dynamic Nested Class Expected Marginal Revenue Model

unit: TEU

Cargo Groups	1	2	3	4
Initial Booking Limits				
Expected Requests to departure	440.5	409.3	512.6	787.6
Nested Protection Levels (*NP*)	341.1	457.7	519.9	
Nested Booking Limits (*BL*)	2200.0	1858.9	1401.2	881.3
Booking Requests through day 21	48.4	61.2	270.4	291.2
Accepted Bookings through day 21 (*b*)	48.4	61.2	270.4	291.2
Day 20 Booking Limits				
Expected Requests day 20 to departure	365.8	326.1	326.6	568.6
Nested Protection Levels for future request	288.2	366.5	330.4	
Total Nested Protection Levels (*NP*)	336.6	427.7	600.8	
Nested Booking Limits (*BL*)	2200.0	1863.4	1435.7	834.9
Booking Requests during day 20 to 16	51.4	19.0	100.2	98.0
Accepted Bookings during day 20 to 16	51.4	19.0	100.2	98.0
Accepted Bookings through day 16 (*b*)	99.8	80.2	370.6	389.2
Day 15 Booking Limits				
Expected Requests day 15 to departure	310.0	270.2	244.5	445.6
Nested Protection Levels for future request	249.0	295.3	253.5	
Total Nested Protection Levels (*NP*)	348.8	375.5	624.1	
Nested Booking Limits (*BL*)	2200.0	1851.2	1475.7	851.6
Booking Requests during day 15 to 11	114.2	137.2	284.6	354.6
Accepted Bookings during day 15 to 11	114.2	137.2	284.6	354.6
Accepted Bookings through day 11 (*b*)	214.0	217.4	655.2	743.8
Day 10 Booking Limits				
Expected Requests day 10 to departure	220.5	172.4	125.6	20.4
Nested Protection Levels for future request	173.3	188.8	147.1	
Total Nested Protection Levels (*NP*)	387.3	406.2	802.3	
Nested Booking Limits (*BL*)	2200.0	1812.7	1406.5	604.2
Booking Requests during day 10 to 6	168.6	143.0	60.2	187.0
Accepted Bookings during day 10 to 6	168.6	143.0	7.0	0.0
Accepted Bookings through day 6 (*b*)	382.6	360.4	662.2	743.8
Day 5 Booking Limits				
Expected Requests day 5 to departure	74.6	50.2	22.6	8.1
Nested Protection Levels for future request	51.3	63.9	34.4	
Total Nested Protection Levels (*NP*)	433.9	424.3	696.6	
Nested Booking Limits (*BL*)	2200.0	1766.1	1341.8	645.2
Booking Requests during day 5 to 0	93.2	36.2	32.0	18.6
Accepted Bookings during day 5 to 0	50.2	0.0	0.0	0.0
Accepted Bookings through day 0 (*b*)	432.8	360.4	662.2	743.8

Note: Based on the actual booking data of a trans-Pacific westbound voyage.



Note: Based on the actual booking data of a trans-Pacific westbound voyage.

Illustration of Dynamic Nested Class Expected Marginal Revenue Model

Figure 5-4

THRESHOLD CURVE METHOD

The threshold curve method, presented by Cross (1986),[6] is a statistical approach to control booking levels within optimized booking ranges. Using historical booking data, a set of optimal booking paths (threshold curves) is constructed. Simple threshold curves can be drawn using mean and standard deviation of actual booking of each day, although many of the commercial applications use cubic spline methodology to smooth out the threshold curves.[7]

Then, actual bookings are plotted against the optimal paths throughout the booking process. Booking levels are controlled to remain within the optimized range by opening or closing lower fare classes.

An example of the threshold curve method application

Using actual booking data of 21 voyages, threshold curves were constructed. Mean and standard deviation of the percentage booked on each day before departure were computed. Three threshold curves were built using one, one and half, and two standard deviations above mean, and each of them was used as a guideline to accept or reject booking requests from group 4, group 3, or group 2. For example, if total booking level went beyond the curve of one standard deviation above mean, booking requests of the lowest freight rate cargo group 4 were rejected, and vice versa. Since booking requests from the highest level group 1 should always be accepted as long as capacity is available, we do not need a threshold curve for group 1.

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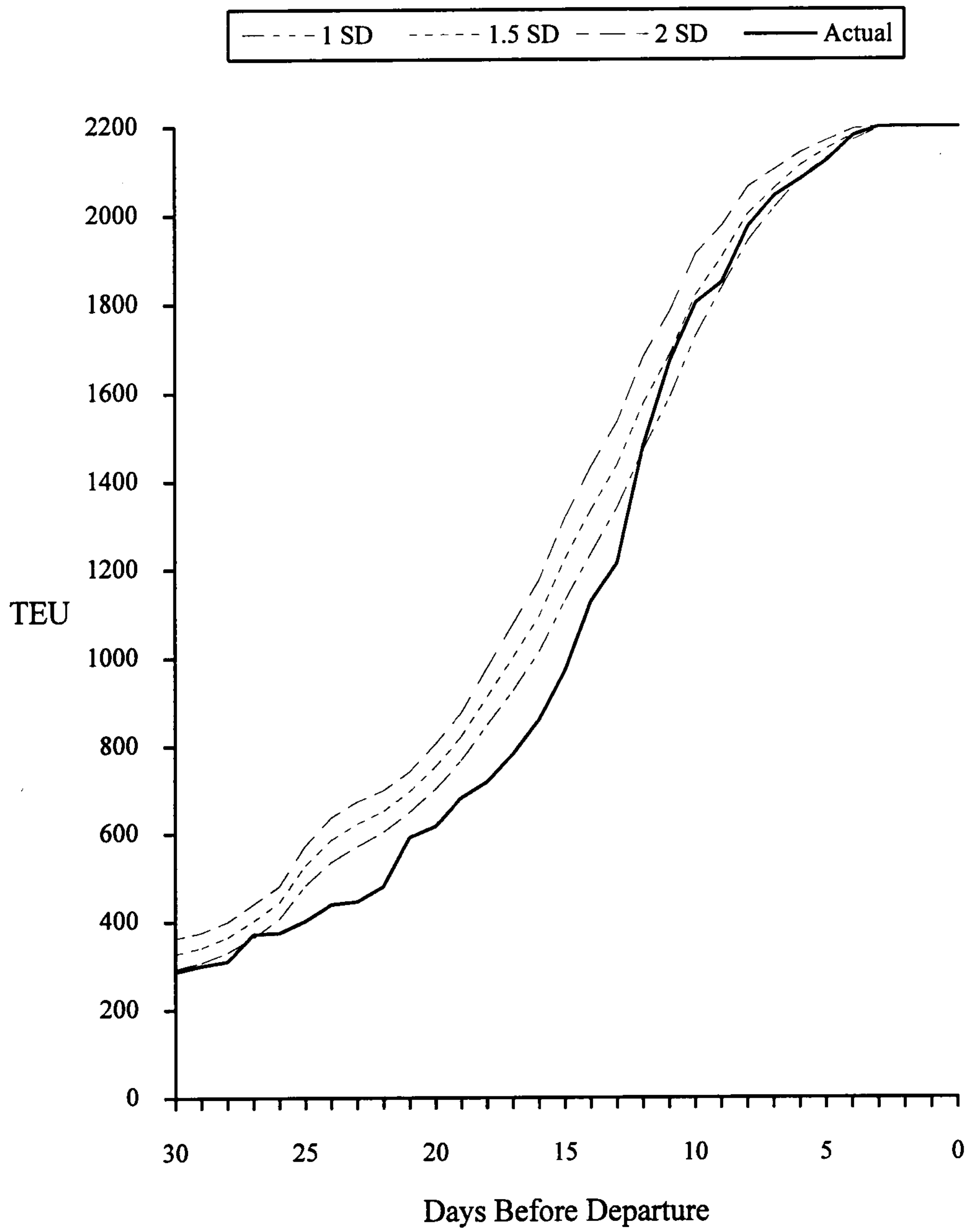
6 Robert G. Cross, "Strategic Selling: Yield Management Techniques to Enhance Revenue", presented to Shearson-Lehman Brothers, Inc. 1986 Airline Industry Seminar, Key Largo, Fla., February 14, 1986.

7 Sheryl E. Kimes, *op. cit.*, 1989, p. 359.

Figure 5-5 illustrates how bookings are controlled by these threshold curves during the booking process. The same data used in the example of expected marginal revenue model was used again for comparison purposes. On day 30 before departure, since the booking level exceeded the historical mean plus a standard deviation, the requests from group 4 were accepted only within the range. On day 26, the booking level returned to below the first threshold curve, and all the booking requests from group 4 were again accepted. On day 12, the booking level went beyond the first threshold curve again. After that, out of total requests 428.2 TEU, only 187.8 TEU were accepted. In this case, the actual booking level never exceeded the second threshold curve. Therefore, the booking requests from group 1, 2, and 3 were always accepted in the order of requests until the capacity was filled on day 3.

The threshold curve method does not intend to produce optimal results. Booking requests from group 1 were always accepted, but the requests of 20.8 TEU during the last 3 days before departure could not be accepted because the total capacity had been already filled. Capacity may be saved for higher freight cargo groups more aggressively with lower threshold curves (i.e., 0.5 standard deviations above mean for group 4 control instead of 1 standard deviation used here). However, this may increase the risk of having empty capacity at the time of departure if the demand is not so vivid as in the beginning of the booking process.



An Example of Threshold Curve Model

Figure 5-5

APPLICATION AND EVALUATION

Application

A dynamic nested 4-class expected marginal revenue model and a threshold curve method were applied to the actual booking data. Out of a total of 21 voyages, 17 voyages were simulated. The other 4 voyages, for which 1,600 TEU vessels were deployed, were excluded from the simulation. Simulation programs for the two approaches were developed using QBasic and were executed on a 486 PC.

Three scenarios of scheduled capacity

Actual booking data from a container shipping firm shows wide demand fluctuation ranging from about 1,100 TEU's to over 3,000 TEU's per each of 17 voyages. Figure 5-6 shows that the shipping demand fluctuates voyage by voyage, while it also indicates seasonal demand increases. However, it is very difficult for a container shipping firm to adjust capacity on an every voyage basis in order to meet demand fluctuations. The booking patterns show that more than 50 percent of total cargoes are booked within 3 weeks before departure. Forecasting demand of a particular voyage in advance is extremely difficult. It is almost impossible to reposition vessels from one route to another according to the demand situation while meeting a predetermined schedule. To provide fixed-day service,[8] which is a very common practice in today's market for better customer service, vessels of the same type are usually deployed on a particular route.

Considering the inflexibility in scheduling capacity, three scenarios of scheduled capacity were simulated for comparison: 1,900 TEU, 2,200 TEU, and 2,500 TEU. The

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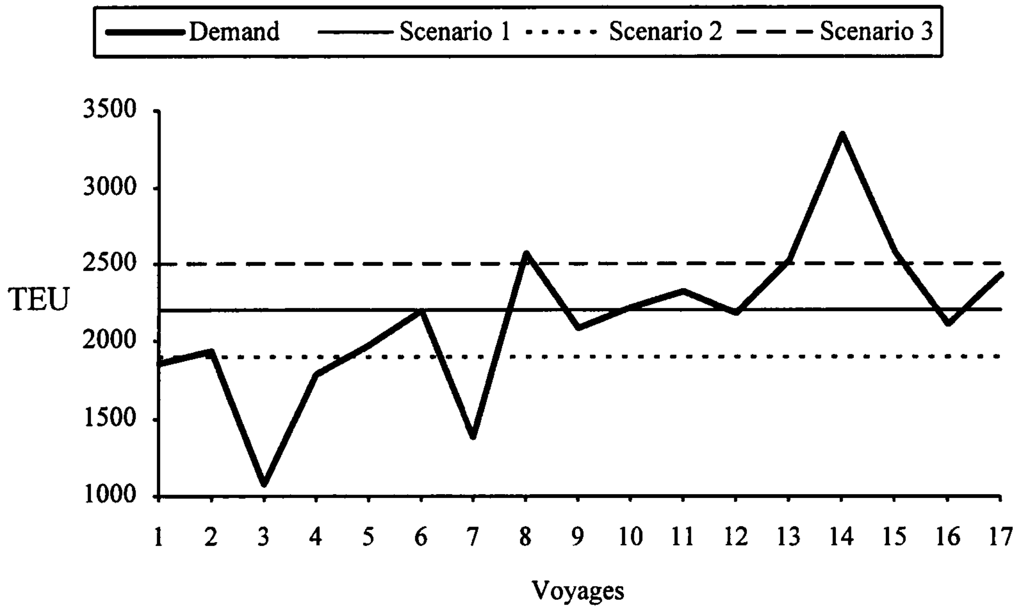
8 For example, vessels depart Long Beach on every Tuesday and Oakland every Thursday, and arrive in Hong Kong on every Monday, etc.

case of 2,200 TEU capacity vessel, the average of the 17 voyages, represents a balanced demand per capacity situation. Each of the 1,900 TEU and 2,500 TEU scenarios represents an excess demand and excess capacity situation respectively.



Demand Fluctuation and Three Scenarios of Scheduled Capacity

Figure 5-6

Overall performance of yield management models

The revenue impacts were examined to evaluate performance of yield management techniques. The assessment of the revenue impacts was based on the difference between the revenue earned, when the cargoes were booked in the order of the booking requests, and the revenue that would be earned when the cargo booking was controlled by yield management techniques.

Table 5-2 presents a summary of the results of a total of 102 simulations (17 voyages × 3 scenarios × 2 models). In the balanced demand per capacity case, yield management models produced 760,000 dollars or 2 percent more revenues for the total of 17 voyages than the revenue earned when bookings were not controlled. This may be translated into 2 million dollars of revenue increase a year (52 weeks). The value of yield also increased from 55.1 percent to 56.2 percent. This result is not surprising in the light of wide fluctuations of the container shipping demand (see Figure 5-5).

Table 5-2

Overall Revenue Impacts of Yield Management Application

		Total of 17 voyages	
Scheduled Capacity (TEU)	**1,900**	**2,200**	**2,500**
Total Demand			
(TEU)	36,549	36,549	36,549
($ in thousand)	40,746	40,746	40,746
No Yield Management Application			
Cargo Carried (TEU)	30,797	33,962	35,527
Revenue Earned ($ in thousand)	33,521	37,480	39,405
Yield (%)*	57.0	55.1	50.9
Expected Marginal Revenue Model			
Cargo Carried (TEU)	30,416	33,902	35,526
Revenue Earned ($ in thousand)	35,553	38,243	39,667
Yield (%)*	60.5	56.2	51.3
Revenue Increase ($ in thousand)	2,032	763	262
(%)	6.1	2.0	0.7
Threshold Curves Model			
Cargo Carried (TEU)	30,558	33,727	35,407
Revenue Earned ($ in thousand)	35,447	38,240	39,666
Yield (%)*	60.3	56.2	51.3
Revenue Increase ($ in thousand)	1,926	760	261
(%)	5.8	2.0	0.7

* Yield = Revenue Earned / Revenue Potential

Revenue Potential = Total Capacity × Average Freight of Group 1 ($1,820/TEU)

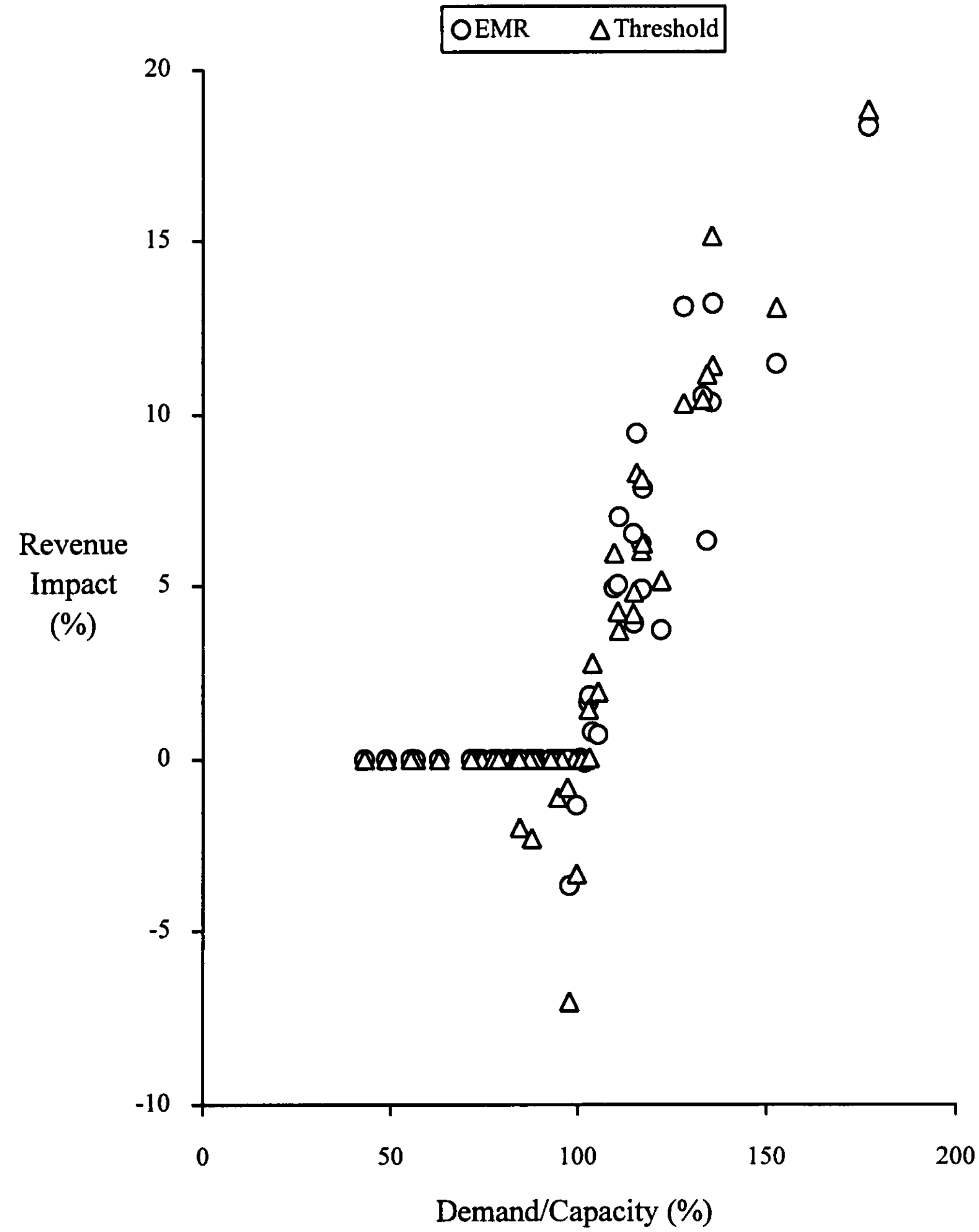
In the excess demand situation, the revenue impacts were even higher, while yield management models generated minimal impact in the excess capacity scenario.

However, higher revenue impacts of the excess demand case do not necessarily imply that scheduling 1,900 TEU vessels to this route is the best strategy. It certainly cannot meet the total demand, which may result in loss of market share. Yield management models intend to maximize revenue with given capacity already scheduled.

Even scheduling the 2,200 TEU capacity met only 93 percent of total demand. This is due to the assumption of no demand shift between voyages that was made in Chapter 1. Due to conferences and tariff filing systems, it is difficult for an individual firm to affect demand patterns by pricing strategy. The positive revenue impacts obtained here implies that yield management techniques are effective even when they only allocate the scheduled capacity to various market segments without control over demand. However, if the firm was able to shift demand from peak to valley, the revenue impacts would have been much higher.

Demand per capacity situations

The revenue impacts were evaluated in terms of the demand per capacity ratio to find a situation at which yield management is most effective or least effective. Table 5-2 already indicated that yield management models perform best in the excess demand situation. To show detail, the revenue impacts of a total of 102 simulations are condensed into Figure 5-7. It is obvious that the revenue impacts of yield management application vary greatly depending upon demand per capacity situations for individual voyages: the higher the demand per capacity ratio, the greater the revenue impacts of yield management.



Revenue Impacts of Yield Management Application

Figure 5-7

It is also worthwhile to note that yield management may result in lower revenue than when bookings are accepted simply in the order of requests. The negative revenue impacts are most evident when the demand level is a little below the scheduled capacity. The yield management system rejects booking requests from low freight groups when the pace of booking is faster than expected. If the demand is much lower than scheduled capacity, there is no chance to reject any booking requests, which may result in no revenue impact. Therefore, yield management is not appropriate when demand is stable or can be predicted quite easily, on the basis of which capacity can be scheduled adequately. This confirms one of the necessary conditions for the yield management application mentioned in Chapter 1. That is, yield management is appropriate when demand fluctuates substantially and cannot be forecasted accurately.

Even though it is possible to get negative results from the yield management application, it is minimal compared to the positive results. As in Table 5-3, only 8 cases out of a total of 54 cases when the demand is below scheduled capacity turned out negative revenue impacts. The negative impacts of a case was less than 1 percent. On the other hand, 43 out of 48 cases when the demand exceeded the scheduled capacity produced positive revenue impacts. Of these cases, 39 had revenue impacts higher than 1 percent.

The negative revenue impacts can be reduced by recapturing denied booking requests. The yield management models applied here overlooked the possibility that refused booking requests from low freight groups may be recaptured when the demand expected from high freight groups does not materialize. Revenue impacts and capacity utilization ratios can be increased by recapturing denied requests. This is especially true when if not recovered, yield management produces a negative revenue impact.

Table 5-3

Positive or Negative Revenue Impacts of Yield Management

Number of cases

	Model	Total	Positive Impact (more than 1%)	Negative Impact (less than 1%)	No Impact
Demand > Capacity	EMR	24	22 (19)	1 (1)	1
	Threshold	24	21 (20)	-	3
Demand < Capacity	EMR	27	-	2 (0)	25
	Threshold	27	-	6 (1)	21
Total	EMR	51	22 (19)	3 (1)	26
	Threshold	51	21 (20)	6 (1)	24
Total		102	43 (39)	9 (2)	50

Yield management models applied

As shown in Table 5-2, the threshold curve model, in spite of its simplicity, produced almost the same revenue impacts as the expected marginal revenue model. However, looking at the detail in Figure 5-6, the revenue impacts of the threshold curve method were a little higher than those of the expected marginal revenue model when demand exceeds scheduled capacity. The reason for this difference is in the way that the two models set the booking limits to control capacity. The expected marginal revenue model determines the protection level for each cargo group first, and booking limits are determined by subtracting protection levels of higher freight rate groups and their actual booking already accepted from total capacity. Therefore, bookings are not controlled until the actual booking level reaches a substantial amount, which may allow early booking requests from low freight groups to be accepted without control.

On the other hand, the threshold curves are determined by the booking patterns of each day before departure and can control booking requests from the earliest stage of the booking process. This certainly reserves capacity for high freight cargoes more aggressively than marginal revenue approach. In previous examples, the threshold curve model began to reject booking requests from group 4 from day 30, while booking control in the expected marginal revenue model began on day 10 before departure. However, reserving capacity too early could increase the risk of having empty capacity at the time of departure if the demand from higher freight cargoes does not materialize as expected. As shown in Figure 5-6 and Table 5-3, the threshold curve approach resulted in negative revenue impacts more frequently than the expected marginal revenue model due to empty space at the time of departure.

CHAPTER 6

SUMMARY AND CONCLUSION

The objectives of this dissertation were to investigate the applicability of yield management techniques to the international container shipping industry, and to provide the basis for future research and development of yield management systems for container shipping firms. On the basis of the literature review, two basic tasks of yield management in the container shipping environment were identified: (1) market segmentation, and (2) capacity allocation to each segment of the market.

In the first phase of the research (the first section of chapter 4), using actual booking data from the trans-Pacific westbound route provided by a container shipping firm, the booking patterns of major commodities were examined to see if market segmentation is possible by different booking patterns. In the second phase (the second section of chapter 4), hundreds of rate classes of container tariffs were clustered into 4 cargo groups on the basis of booking patterns as well as average freight revenues. During the first two phases, multi-sample cluster analysis using information theoretic statistics was performed to avoid drawbacks of traditional statistical approaches. In the third phase of the research (chapter 5), the expected marginal revenue model and the threshold curve method were applied to the actual booking data. Some details of each model were presented. To evaluate the performance of yield management in container shipping, the revenue impacts were examined. The revenue impacts were assessed in terms of the model applied and demand per capacity ratio.

In this final chapter, the summary of major findings is presented. Managerial implications and directions for further studies are discussed with a view to practical application of yield management in the container shipping environment. Finally, the usefulness of this research is summarized to conclude the dissertation.

SUMMARY OF MAJOR FINDINGS

Booking patterns and market segmentation

The booking patterns of major container cargoes were found to be different according to their freight levels. High freight cargoes tend to book later than low freight cargoes, although a few commodities are exceptions. This certainly implies that booking requests should be controlled during the booking process to maximize freight revenue on each voyage.

Current container shipping tariffs reflect value of service pricing, in which high value cargoes are charged higher freight rates than low value cargoes. By charging what the traffic can bear, the market is segmented based upon the price sensitivity of shipping demand. In this research, the market was segmented on the basis of booking patterns as well as freight rate levels. It added another dimension of the time sensitivity of shipping demand to market segmentation. Differentiating time sensitivity of demand among cargo groups is important to yield management application because yield management controls capacity during the course of the booking process.

Revenue impacts of yield management

Two yield management models, the expected marginal revenue model and the threshold curve model, were applied using the actual booking data from a shipping firm. A total of 102 runs of simulation were executed. The results showed that the yield management model increased the freight revenue by controlling booking requests compared to when all bookings were accepted simply in the order of requests. Owing to the wide fluctuation of demand and the inflexibility of scheduling capacity, which are inherent in the container shipping business, container shipping is a good candidate for yield management applications.

The overall revenue impacts of the threshold curve method were almost the same as the expected marginal revenue model. However, the threshold curves had more chance to produce negative revenue impacts when demand is below the scheduled capacity, while the expected marginal revenue model generated stabler results.

Performance of yield management techniques varied greatly depending on the level of capacity scheduled. Revenue was increased by 760,000 dollars or 2 percent for a total of 17 voyages simulated when the capacity was scheduled at the average demand level. Revenue impact was even higher when 15 percent less capacity was scheduled, while it was minimal when 15 percent more capacity was scheduled. It is also noted that the techniques may result in negative revenue impacts when the demand level is below scheduled capacity.

The overall performance of the yield management model showed that yield management techniques can be applied to container shipping with considerable revenue increases. However, the big variance of revenue impacts also indicates the importance of capacity scheduling to successful yield management implementation.

MANAGERIAL IMPLICATIONS

A possible answer for increased profitability

For many years, the international container shipping industry has suffered an insufficient return on investment. Profitability has been minimal on the major world trade routes linking North America, Asia and Europe.

Traditionally, shipping firms concentrated their efforts on minimizing the shipping costs. Economies of scale have caused shipping firms, with high fixed costs relative to variable costs, to build bigger ships. However, unless those ships are filled with cargoes, shipping firms cannot benefit from the economies of scale. In order to fill those slots and contribute something to fixed costs, carriers are pressed to cut freight rates even to losing levels until some of them are forced to leave the market. This is a classical short run versus long run profitability strategy, and the result has been a cycle of feast and famine in the industry.[1]

Yield management is an approach to increase profitability through revenue maximization. The results of this dissertation suggest that yield management can be applied to container shipping as a possible answer to increase profitability.

Scheduling capacity

Shipping demand cannot be predicted with certainty, and capacity cannot be adjusted instantaneously. The traditional approach to cope with the uncertainties of demand has been to build sufficient reserve capacity. Liner shipping firms have feared

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1 Gary N. Dicer and Dong-Woo Ha, "The Application of Yield Management Techniques in the Container Shipping Industry: A Possible Answer for Increased Profitability", *Intermodal Distribution Education Academy (IDEA) Proceedings,* presented to 1994 Annual Meeting, April 19-21, 1994, p. 49.

that without such sufficient capacity, they would fail to satisfy every available demand, which may result in losing good will and in turn market share.[2]

Yield management models generate positive revenue impacts when demand exceeds the scheduled capacity. If capacities are scheduled to meet peak demand, the revenue impacts of a yield management application would be minimal. Unfortunately, the current capacity situation in the industry is sufficient to accommodate peak demand and so there is little room for yield management applications. Therefore, the successful implementation of yield management for a container line largely depends on how to reschedule this over-capacity. The success of capacity reduction program of the Trans-Pacific Stabilization Agreement (TSA), followed by the recent introduction of a similar program by the Trans-Atlantic Agreement (TAA), provides the possibility of downsizing existing capacity.

Shifting demand

Together with scheduling adequate capacity, shifting demand between voyages is critical for yield management success. Rather than scheduling capacity to meet peak demand, scheduling less capacity and shifting peak demands to voyages of low demand are key elements of yield management. This research has assumed the freight rates as given in the immediate run. However, the research results strongly indicate that a pricing strategy still needs to be incorporated in a yield management system to smooth out the demand fluctuation.

Although changing freight rates frequently is limited due to the conference and tariff filing system, it is still possible to adjust price to some extent. For example, waste

2 Bernard Gardner, "Some thoughts on normal-cost price theory and its application to liner shipping", *Maritime Policy and Management*, vol. 13, no. 3, 1986, p. 240.

paper, one of the major commodities in the trans-Pacific westbound trade, is exempted from tariff filing with FMC.[3] Since waste paper is one of the lowest freight commodities, it would be desirable to shift its demand from peak to low demand voyages by raising or lowering the freight rate level depending on the situation.

Shipper and carrier relationship

The response from shippers is one of the possible problems that a firm may face with yield management implementation. Despite the common practice of discriminatory pricing in container shipping, shippers may not want to see discrimination in the booking process as well. Shippers of high freight cargoes have always complained that they are cross-subsidizing the low freight cargoes. Yield management may alleviate those complaints by giving priority in the booking process to those high paying cargoes. However, yield management may also cause new complaints from low paying shippers because it discriminates against the low freight cargoes in the booking process.

In addition, any efforts by carriers to reschedule existing over-capacity may face severe opposition from shippers who fear that such rescheduling may lead to higher freight rates. Firms adopting a yield management system may need to educate their customers. Developing a sound relationship with shippers plays a critical role in yield management application. With support from shippers, scheduling capacity and shifting demand would become easier. Yield management is not merely a technique to maximize a carrier's freight revenue. It also reduces the shipping costs by scheduling adequate capacity and increasing capacity utilization. If the savings are passed along to shippers, yield management allows the shippers to enjoy a lower cost shipping service.

3 The Shipping Act of 1984, Sec. 8 (a) (1).

Loss of competitive focus

Implementing yield management techniques may result in the loss of competitive focus.[4] Since yield management aims at maximizing revenue in the immediate run, it may take managerial attention away from the long term goal of the firm. For example, a booking request from one of the major shippers should not be denied even though the yield management system indicates not to accept. The yield management system is merely a management support system still leaving many jobs to the judgment of managers.

Booking information system

Most yield management techniques use historical booking data to set booking limits. Data availability and accuracy are critical to successful yield management implementation. In the center of any yield management system is the booking system.

The booking system should be designed to provide all of the information needed. It should be possible to obtain data about demand and capacity availability from the booking system on a real time basis. It is also important to keep the booking records across the booking dates. Since yield management techniques determine whether to accept early booking requests of low paying customers, or to reserve the capacity for late booking high paying customers, the booking data across the booking dates are essential to the yield management system. Data concerning cancellation and no-shows are also necessary to improve the performance of yield management models. All the data should be kept for an extended period of time for detailed statistical analysis.

Significant advances in information technology with increasing capacity of hardware, commensurate capabilities of software and their decreasing costs make it easier

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4 Sheryl E. Kimes, "Yield Management: A Tool for Capacity-Constrained Service Firms", *Journal of Operations Management*, vol. 8, no. 4, October 1989, p. 357.

to develop a very large sophisticated yield management system. However, it would still be difficult for a shipping firm presently burdened with a great amount of accumulated losses to invest in a new yield management system.

DIRECTIONS FOR FURTHER STUDIES

This research made several assumptions to make yield management applications simple. Further studies which would release those assumptions are required

Service contract

In this research, due to data limitations, service contract cargoes were not classified separately. The booking requests of service contract cargoes must be accepted up to a certain limit specified in the contract regardless of their freight or marginal revenue level. This is contradictory to the basic concepts of yield management that controls the booking requests based on freight levels. A possible solution for this is to reserve adequate capacity for service contract cargoes from the beginning of the booking process. The initial level can be set by forecasting the expected requests of service contract cargoes using historical booking data. During the course of the booking process, this reserved level should be adjusted by comparing historical booking patterns and actual bookings accepted to date. An examination of the booking patterns of service contract cargoes is needed for an accurate forecast.

Service contract cargoes may limit the performance of a yield management system. To minimize this adverse effect, the carrier's commitment to assure space should be relaxed by incorporating flexibility clauses in such contracts. Shipper and carrier relationships again play an important role here.

Demand distribution

One of assumptions made for the expected marginal revenue model was the normal probability density function of demand. It was difficult to test the normality assumption with the limited number of observations available. Since the protection level for each rate group is determined by its demand distribution, improper assumptions for demand distribution may produce inaccurate results from the yield management application. Although the empirical evidence in passenger airline cases did not allow one to reject the assumption of a normal distribution of each fare class demand,[5] the examination of the demand density shape in container shipping is required to derive accurate optimal protection levels.

Incorporating pricing decision into yield management models

In this research, as in most current capacity allocation models like the marginal revenue approach, the freight rate's structure was assumed as a given. Since yield management consists of not only capacity control but also pricing, it would be desirable to develop a model that incorporates pricing decisions as well as capacity allocation. This is especially desirable when demand fluctuates widely as in the shipping business, because pricing can shift demand from peak to valley.

It would be important to study the effects of price changes on demand for various cargo groups. Changing prices based on demand elasticity will increase the potential benefits from yield management implementation.

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5 Peter Paul Belobaba, *Air Travel Demand and Airline Seat Inventory Management*, Doctoral Dissertation, Massachusetts Institute of Technology, Cambridge, Mass., 1987, pp. 142-143.

CONCLUSION

During the course of research, the main purpose of this dissertation to investigate the applicability of yield management to container shipping was accomplished. The research is especially useful in the following points.

First, by examining the booking patterns, this research added an additional dimension of time sensitivity of shipping demand to the market segmentation. Traditionally, the shipping market has been segmented based only upon the price sensitivity of the demand.

Second, from a methodological standpoint, this research illustrated the procedure of information theoretic statistics. The new informational approach eliminates the drawbacks of traditional statistics, and identifies the best fitting model instantaneously for a given complex data structure. It has potential applications in many areas, as traditional methodologies based on test theory have become inadequate to solve complex, large scale real-world problems.

Finally, the results of simulations indicate that the yield management techniques are indeed applicable, and that it can be an answer for increased profitability of the industry. For successful implementation of the yield management system in the container shipping business, further studies are awaited.

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APPENDIX

APPENDIX

ICOMP(I-FIM) VALUES FOR CLUSTERING ALTERNATIVES

Table A-1

Finding the Best Clustering Structure at Each Number of Groups

(1) The Clustering Structures of 9 Groups

Clustering Alternatives	ICOMP (I-FIM)	Clustering Alternatives	ICOMP (I-FIM)
(1 2) (3) (4) (5) (6) (7) (8) (9) (10)	5424.8	(1) (2) (3 10) (4) (5) (6) (7) (8) (9)	5906.5
(1 3) (2) (4) (5) (6) (7) (8) (9) (10)	5488.2	(1) (2) (3) (4 5) (6) (7) (8) (9) (10)	5954.8
(1 4) (2) (3) (5) (6) (7) (8) (9) (10)	5972.9	(1) (2) (3) (4 6) (5) (7) (8) (9) (10)	5669.4
(1 5) (2) (3) (4) (6) (7) (8) (9) (10)	5416.5	(1) (2) (3) (4 7) (5) (6) (8) (9) (10)	5803.0
(1 6) (2) (3) (4) (5) (7) (8) (9) (10)	5731.3	(1) (2) (3) (4 8) (5) (6) (7) (9) (10)	5769.4
(1 7) (2) (3) (4) (5) (6) (8) (9) (10)	5562.9	(1) (2) (3) (4 9) (5) (6) (7) (8) (10)	5720.1
(1 8) (2) (3) (4) (5) (6) (7) (9) (10)	5619.4	(1) (2) (3) (4 10) (5) (6) (7) (8) (9)	5602.7
(1 9) (2) (3) (4) (5) (6) (7) (8) (10)	5673.7	(1) (2) (3) (4) (5 6) (7) (8) (9) (10)	5688.0
(1 10) (2) (3) (4) (5) (6) (7) (8) (9)	5800.3	(1) (2) (3) (4) (5 7) (6) (8) (9) (10)	5530.7
(1) (2 3) (4) (5) (6) (7) (8) (9) (10)	5406.4	(1) (2) (3) (4) (5 8) (6) (7) (9) (10)	5569.4
(1) (2 4) (3) (5) (6) (7) (8) (9) (10)	6013.5	(1) (2) (3) (4) (5 9) (6) (7) (8) (10)	5627.1
(1) (2 5) (3) (4) (6) (7) (8) (9) (10)	5415.6	(1) (2) (3) (4) (5 10) (6) (7) (8) (9)	5762.2
(1) (2 6) (3) (4) (5) (7) (8) (9) (10)	5779.0	(1) (2) (3) (4) (5) (6 7) (8) (9) (10)	5479.8
(1) (2 7) (3) (4) (5) (6) (8) (9) (10)	5632.2	(1) (2) (3) (4) (5) (6 8) (7) (9) (10)	5431.1
(1) (2 8) (3) (4) (5) (6) (7) (9) (10)	5671.2	(1) (2) (3) (4) (5) (6 9) (7) (8) (10)	5390.3
(1) (2 9) (3) (4) (5) (6) (7) (8) (10)	5725.1	(1) (2) (3) (4) (5) (6 10) (7) (8) (9)	5404.4
(1) (2 10) (3) (4) (5) (6) (7) (8) (9)	5842.8	(1) (2) (3) (4) (5) (6) (7 8) (9) (10)	5393.7
(1) (2) (3 4) (5) (6) (7) (8) (9) (10)	6060.6	(1) (2) (3) (4) (5) (6) (7 9) (8) (10)	5427.1
(1) (2) (3 5) (4) (6) (7) (8) (9) (10)	5496.3	(1) (2) (3) (4) (5) (6) (7 10) (8) (9)	5562.9
(1) (2) (3 6) (4) (5) (7) (8) (9) (10)	5848.4	(1) (2) (3) (4) (5) (6) (7) (8 9) (10)	5387.6*
(1) (2) (3 7) (4) (5) (6) (8) (9) (10)	5716.6	(1) (2) (3) (4) (5) (6) (7) (8 10) (9)	5509.3
(1) (2) (3 8) (4) (5) (6) (7) (9) (10)	5753.4	(1) (2) (3) (4) (5) (6) (7) (8) (9 10)	5458.4
(1) (2) (3 9) (4) (5) (6) (7) (8) (10)	5800.4		

* The minimum value of ICOMP(I-FIM)

Table A-1 (continued)

(2) The Clustering Structures of 8 Groups

Clustering Alternatives	ICOMP (I-FIM)	Clustering Alternatives	ICOMP (I-FIM)
(1 2) (3) (4) (5) (6) (7) (8 9) (10)	5493.3	(1) (2) (3 7) (4) (5) (6) (8 9) (10)	5773.0
(1 3) (2) (4) (5) (6) (7) (8 9) (10)	5553.2	(1) (2) (3 8 9) (4) (5) (6) (7) (10)	5888.9
(1 4) (2) (3) (5) (6) (7) (8 9) (10)	6024.4	(1) (2) (3 10) (4) (5) (6) (7) (8 9)	5960.0
(1 5) (2) (3) (4) (6) (7) (8 9) (10)	5486.6	(1) (2) (3) (4 5) (6) (7) (8 9) (10)	6006.6
(1 6) (2) (3) (4) (5) (7) (8 9) (10)	5788.6	(1) (2) (3) (4 6) (5) (7) (8 9) (10)	5727.3
(1 7) (2) (3) (4) (5) (6) (8 9) (10)	5623.9	(1) (2) (3) (4 7) (5) (6) (8 9) (10)	5857.0
(1 8 9) (2) (3) (4) (5) (6) (7) (10)	5753.9	(1) (2) (3) (4 8 9) (5) (6) (7) (10)	5855.4
(1 10) (2) (3) (4) (5) (6) (7) (8 9)	5856.9	(1) (2) (3) (4 10) (5) (6) (7) (8 9)	5662.9
(1) (2 3) (4) (5) (6) (7) (8 9) (10)	5473.7	(1) (2) (3) (4) (5 6) (7) (8 9) (10)	5744.7
(1) (2 4) (3) (5) (6) (7) (8 9) (10)	6064.2	(1) (2) (3) (4) (5 7) (6) (8 9) (10)	5592.9
(1) (2 5) (3) (4) (6) (7) (8 9) (10)	5481.6	(1) (2) (3) (4) (5 8 9) (6) (7) (10)	5700.2
(1) (2 6) (3) (4) (5) (7) (8 9) (10)	5833.3	(1) (2) (3) (4) (5 10) (6) (7) (8 9)	5818.4
(1) (2 7) (3) (4) (5) (6) (8 9) (10)	5690.2	(1) (2) (3) (4) (5) (6 7) (8 9) (10)	5544.1
(1) (2 8 9) (3) (4) (5) (6) (7) (10)	5806.4	(1) (2) (3) (4) (5) (6 8 9) (7) (10)	5484.2
(1) (2 10) (3) (4) (5) (6) (7) (8 9)	5896.9	(1) (2) (3) (4) (5) (6 10) (7) (8 9)	5472.3*
(1) (2) (3 4) (5) (6) (7) (8 9) (10)	6111.0	(1) (2) (3) (4) (5) (6) (7 8 9) (10)	5484.9
(1) (2) (3 5) (4) (6) (7) (8 9) (10)	5558.9	(1) (2) (3) (4) (5) (6) (7 10) (8 9)	5625.2
(1) (2) (3 6) (4) (5) (7) (8 9) (10)	5902.0	(1) (2) (3) (4) (5) (6) (7) (8 9 10)	5573.2

* The minimum value of ICOMP(I-FIM)

Table A-1 (continued)

(3) The Clustering Structures of 7 Groups

Clustering Alternatives	ICOMP (I-FIM)	Clustering Alternatives	ICOMP (I-FIM)
(1 2) (3) (4) (5) (6 10) (7) (8 9)	5577.6	(1) (2) (3 5) (4) (6 10) (7) (8 9)	5632.9
(1 3) (2) (4) (5) (6 10) (7) (8 9)	5631.6	(1) (2) (3 6 10) (4) (5) (7) (8 9)	6049.1
(1 4) (2) (3) (5) (6 10) (7) (8 9)	6082.4	(1) (2) (3 7) (4) (5) (6 10) (8 9)	5836.1
(1 5) (2) (3) (4) (6 10) (7) (8 9)	5572.0	(1) (2) (3 8 9) (4) (5) (6 10) (7)	5948.3
(1 6 10) (2) (3) (4) (5) (7) (8 9)	5940.2	(1) (2) (3) (4 5) (6 10) (7) (8 9)	6065.5
(1 7) (2) (3) (4) (5) (6 10) (8 9)	5693.8	(1) (2) (3) (4 6 10) (5) (7) (8 9)	5811.8
(1 8 9) (2) (3) (4) (5) (6 10) (7)	5819.7	(1) (2) (3) (4 7) (5) (6 10) (8 9)	5920.2
(1) (2 3) (4) (5) (6 10) (7) (8 9)	5554.3*	(1) (2) (3) (4 8 9) (5) (6 10) (7)	5919.2
(1) (2 4) (3) (5) (6 10) (7) (8 9)	6122.4	(1) (2) (3) (4) (5 6 10) (7) (8 9)	5895.9
(1) (2 5) (3) (4) (6 10) (7) (8 9)	5563.0	(1) (2) (3) (4) (5 7) (6 10) (8 9)	5665.4
(1) (2 6 10) (3) (4) (5) (7) (8 9)	5982.9	(1) (2) (3) (4) (5 8 9) (6 10) (7)	5765.9
(1) (2 7) (3) (4) (5) (6 10) (8 9)	5757.9	(1) (2) (3) (4) (5) (6 10 7) (8 9)	5687.3
(1) (2 8 9) (3) (4) (5) (6 10) (7)	5869.2	(1) (2) (3) (4) (5) (6 10 8 9) (7)	5630.4
(1) (2) (3 4) (5) (6 10) (7) (8 9)	6167.7	(1) (2) (3) (4) (5) (6 10) (7 8 9)	5567.5

* The minimum value of ICOMP(I-FIM)

Table A-1 (continued)

(4) The Clustering Structures of 6 Groups

Clustering Alternatives	ICOMP (I-FIM)	Clustering Alternatives	ICOMP (I-FIM)
(1 2 3) (4) (5) (6 10) (7) (8 9)	5697.2	(1) (2 3) (4 5) (6 10) (7) (8 9)	6118.6
(1 4) (2 3) (5) (6 10) (7) (8 9)	6135.3	(1) (2 3) (4 6 10) (5) (7) (8 9)	5876.2
(1 5) (2 3) (4) (6 10) (7) (8 9)	5654.7	(1) (2 3) (4 7) (5) (6 10) (8 9)	5977.5
(1 6 10) (2 3) (4) (5) (7) (8 9)	5999.4	(1) (2 3) (4 8 9) (5) (6 10) (7)	5977.0
(1 7) (2 3) (4) (5) (6 10) (8 9)	5761.9	(1) (2 3) (4) (5 6 10) (7) (8 9)	5953.1
(1 8 9) (2 3) (4) (5) (6 10) (7)	5883.5	(1) (2 3) (4) (5 7) (6 10) (8 9)	5735.1
(1) (2 3 4) (5) (6 10) (7) (8 9)	6260.3	(1) (2 3) (4) (5 8 9) (6 10) (7)	5828.1
(1) (2 3 5) (4) (6 10) (7) (8 9)	5686.2	(1) (2 3) (4) (5) (6 10 7) (8 9)	5757.1
(1) (2 3 6 10) (4) (5) (7) (8 9)	6155.6	(1) (2 3) (4) (5) (6 10 8 9) (7)	5702.7
(1) (2 3 7) (4) (5) (6 10) (8 9)	5905.6	(1) (2 3) (4) (5) (6 10) (7 8 9)	5647.2*
(1) (2 3 8 9) (4) (5) (6 10) (7)	6044.5		

* The minimum value of ICOMP(I-FIM)

Table A-1 (continued)

(5) The Clustering Structures of 5 Groups

Clustering Alternatives	ICOMP (I-FIM)	Clustering Alternatives	ICOMP (I-FIM)
(1 2 3) (4) (5) (6 10) (7 8 9)	5789.9	(1) (2 3 7 8 9) (4) (5) (6 10)	6131.0
(1 4) (2 3) (5) (6 10) (7 8 9)	6203.4	(1) (2 3) (4 5) (6 10) (7 8 9)	6192.9
(1 5) (2 3) (4) (6 10) (7 8 9)	5743.6*	(1) (2 3) (4 6 10) (5) (7 8 9)	5960.8
(1 6 10) (2 3) (4) (5) (7 8 9)	6066.9	(1) (2 3) (4 7 8 9) (5) (6 10)	6094.0
(1 7 8 9) (2 3) (4) (5) (6 10)	5943.5	(1) (2 3) (4) (5 6 10) (7 8 9)	6028.3
(1) (2 3 4) (5) (6 10) (7 8 9)	6331.4	(1) (2 3) (4) (5 7 8 9) (6 10)	5902.0
(1) (2 3 5) (4) (6 10) (7 8 9)	5772.4	(1) (2 3) (4) (5) (6 10 7 8 9)	5833.4
(1) (2 3 6 10) (4) (5) (7 8 9)	6225.5		

* The minimum value of ICOMP(I-FIM)

Table A-2

ICOMP(I-FIM) Values for 52 Clustering Alternatives

# of groups	Clustering Alternatives	ICOMP (I-FIM)	# of groups	Clustering Alternatives	ICOMP (I-FIM)
5	(1 5) (2 3) (4) (6 10) (7 8 9)	5743.6*	3	(1 5 7 8 9) (2 3 4) (6 10)	6527.7
4	(1 5 2 3) (4) (6 10) (7 8 9)	5893.0*	3	(1 5 7 8 9) (2 3 6 10) (4)	6418.4
4	(1 5 4) (2 3) (6 10) (7 8 9)	6348.8	3	(1 5 7 8 9) (2 3) (4 6 10)	6290.2
4	(1 5 6 10) (2 3) (4) (7 8 9)	6209.8	3	(1 5) (2 3 4 6 10) (7 8 9)	6562.9
4	(1 5 7 8 9) (2 3) (4) (6 10)	6079.9	3	(1 5) (2 3 4 7 8 9) (6 10)	6490.7
4	(1 5) (2 3 4) (6 10) (7 8 9)	6423.2	3	(1 5) (2 3 4) (6 10 7 8 9)	6504.8
4	(1 5) (2 3 6 10) (4) (7 8 9)	6316.4	3	(1 5) (2 3 6 10 7 8 9) (4)	6389.6
4	(1 5) (2 3 7 8 9) (4) (6 10)	6223.8	3	(1 5) (2 3 6 10) (4 7 8 9)	6497.8
4	(1 5) (2 3) (4 6 10) (7 8 9)	6055.6	3	(1 5) (2 3 7 8 9) (4 6 10)	6384.4
4	(1 5) (2 3) (4 7 8 9) (6 10)	6188.1	3	(1 5) (2 3) (4 7 8 9 6 10)	6277.9
4	(1 5) (2 3) (4) (6 10 7 8 9)	5926.3	2	(1 5 2 3 4 6 10) (7 8 9)	6659.2
3	(1 5 2 3 4) (6 10) (7 8 9)	6487.6	2	(1 5 2 3 4 7 8 9) (6 10)	6576.2
3	(1 5 2 3 6 10) (4) (7 8 9)	6400.8	2	(1 5 2 3 4) (6 10 7 8 9)	6567.7
3	(1 5 2 3 7 8 9) (4) (6 10)	6299.8	2	(1 5 2 3 6 10 7 8 9) (4)	6484.1
3	(1 5 2 3) (4 6 10) (7 8 9)	6147.2	2	(1 5 2 3 6 10) (4 7 8 9)	6582.0
3	(1 5 2 3) (4 7 8 9) (6 10)	6261.9	2	(1 5 2 3 7 8 9) (4 6 10)	6460.8
3	(1 5 2 3) (4) (6 10 7 8 9)	6049.7*	2	(1 5 2 3) (4 6 10 7 8 9)	6352.4*
3	(1 5 4 6 10) (2 3) (7 8 9)	6489.2	2	(1 5 4 6 10 7 8 9) (2 3)	6535.8
3	(1 5 4 7 8 9) (2 3) (6 10)	6420.1	2	(1 5 4 6 10) (2 3 7 8 9)	6626.7
3	(1 5 4) (2 3 6 10) (7 8 9)	6557.3	2	(1 5 4 7 8 9) (2 3 6 10)	6623.8
3	(1 5 4) (2 3 7 8 9) (6 10)	6495.8	2	(1 5 4) (2 3 6 10 7 8 9)	6614.4
3	(1 5 4) (2 3) (6 10 7 8 9)	6431.4	2	(1 5 6 10 7 8 9) (2 3 4)	6644.0
3	(1 5 6 10 7 8 9) (2 3) (4)	6263.9	2	(1 5 6 10) (2 3 4 7 8 9)	6657.4
3	(1 5 6 10) (2 3 4) (7 8 9)	6598.6	2	(1 5 7 8 9) (2 3 4 6 10)	6651.6
3	(1 5 6 10) (2 3 7 8 9) (4)	6428.1	2	(1 5) (2 3 4 7 8 9 6 10)	6605.9
3	(1 5 6 10) (2 3) (4 7 8 9)	6448.5	1	(1 5 2 3 4 6 10 7 8 9)	6706.3*

* The minimum value of ICOMP(I-FIM) at each number of groups.

VITA

Dong Woo Ha was born in Kwangju, the Republic of Korea on August 6, 1952. After graduating from Kwangju Jeil High School in 1970, he entered Seoul National University and received a degree of Bachelor in Business Administration in 1974, and an MBA degree in 1976. In August 1991, he entered the University of Tennessee, Knoxville and in August 1994, received a degree of Doctor of Philosophy in Business Administration. His field of specialization was in Logistics and Transportation with a supporting area in Statistics.

Before coming to the University of Tennessee, he was employed by Korea Maritime Institute, Seoul, Korea for eight years. He was on leave from the Institute and returned upon completion of his degree in the United States. Prior employment was with a Korean shipping company, Sammi Line, as a member of its planning department.