¢,

www.arpnjournals.com

LINGO BASED PRICING AND REVENUE MANAGEMENT FOR MULTIPLE CUSTOMER SEGMENTS

Anand Jayakumar A. and Krishnaraj C.

Department of Mechanical Engineering, Kalaivani College of Technology, Coimbatore, Tamil Nadu, India E-Mail: jay4upeople@gmail.com

ABSTRACT

Pricing is an important lever to increase supply chain profits by better matching supply and demand. Pricing influences the amount of product demanded and the total revenue generated. Revenue management is the use of pricing to increase the profit generated from a limited supply of supply chain assets. In this paper a numerical problem is solved using the LINGO software.

Keywords: LINGO, pricing, revenue management.

INTRODUCTION

Managing demand and supply can increase supply chain profits. Altering inventories and capacity can change available supply. Advertising and marketing can be used to spur demand. Beyond these levers, pricing is an important lever to increase supply chain profits by better matching supply and demand. Pricing influences the amount of product demanded and the total revenue generated. Revenue management is the use of pricing to increase the profit generated from a limited supply of supply chain assets. Supply chain assets exist in two forms - capacity and inventory. Capacity assets in the supply chain exist for production, transportation and storage. Inventory assets exist throughout the supply chain and are carried to improve product availability.

To increase total margin earned from these assets, managers must use all available levers, including price. This is the primary role of revenue management. Traditionally, firms have often invested in or eliminated assets to reduce the imbalance between supply and demand. Firms build additional capacity during the growth part of a business cycle and shut down some capacity during a downturn. Ideas from revenue management suggest that a firm should first use pricing to achieve some balance between supply and demand and only then invest in or eliminate assets.

Consider a trucking company that owns 10 trucks. One approach that the firm can take is to set a fixed price for its services and use advertising to spur demand in case surplus capacity is available. Using revenue management, however, the firm would seek to do much more. One approach is to charge a lower price to customers willing to commit their orders far in advance and a higher price to customers looking for transportation capacity at the last minute. Another approach is to charge a lower price to customers with long-term contracts and a higher price to customers looking to purchase capacity at the last minute. A third approach is to charge a higher price during the periods of high demand and lower prices during periods of low demand.

LITERATURE SURVEY

Gustavo Vulcano, Garrett van Ryzin and Wassim Chaar have developed a maximum likelihood estimation algorithm that uses a variation of the expectation maximization method to account for unobservable data. The procedure was applied to data for a test market from New York City to a destination in Florida. The outputs are promising in terms of the quality of the computed estimates, although a large number of departure instances may be necessary to achieve highly accurate results.

Tamer Basar and R. Srikant have considered a network where each user is charged a fixed price per unit of bandwidth used, but where there is no congestiondependent pricing. However, the transmission rate of each user is assumed to be a function of network congestion (like TCP), and the price per unit bandwidth.

Ing-ray Chen, Okan Yilmaz and I-ling Yen, have proposed and analyzed call admission control algorithms integrated with pricing for revenue optimization with QoS guarantees to serve multiple service classes in mobile wireless networks.

Tim Pueschel, Dirk Neumann has proposed the use of concepts from revenue management and further enhancements to cloud computing.

Okan Yilmaz, Ing-Ray Chen have utilized admission control algorithms designed for revenue optimization with QoS guarantees to derive optimal pricing of multiple service classes in wireless cellular networks.

Kamaruzzaman Seman, *et al*, have analyze new improved charging scheme with base price, quality premium and QoS networks involved.

Elodie Adida · Georgia Perakis have presented a robust optimization formulation for dealing with demand



uncertainty in a dynamic pricing and inventory control problem for a make-to-stock manufacturing system.

Garrett van Ryzin, Jeff McGill has investigated a simple adaptive approach to optimizing seat protection levels in airline revenue management systems.

Shin-chan Ting, Gwo-hshiung Tzeng have reviewed related research on revenue management for transportation industries.

Dusit Niyato, Ekram Hossain has reviewed the related work on pricing for homogeneous wireless networks in which a single wireless technology is available to the users. Then, they have outlined the major issues in designing resource allocation and pricing in heterogeneous wireless access networks. They have also proposed two oligopolistic models for price competition among service providers in a heterogeneous wireless environment consisting of WiMAX and WiFi access networks.

Ioannis Ch. Paschalidis and Yong Liu have considered a communication network with fixed routing that can accommodate multiple service classes, differing in bandwidth requirements, demand pattern, call duration, and routing.

Neil J. Keon, G. Anandalingam has considered pricing for multiple services offered over a single telecommunications network.

Yuri Levin, Jeff McGill, Mikhail Nediak have presented a new model for revenue management of product sales that incorporates both dynamic pricing and a price guarantee.

Yuri Levin, Jeff McGill, Mikhail Nediak have presented a new model for optimal dynamic pricing of perishable services or products that incorporates a simple risk measure permitting control of the probability that total revenues fall below a minimum acceptable level.

Kin-Keung Lai, Wan-Lung Ng have proposed a network optimization model for hotel revenue management under an uncertain environment.

Constantinos Maglaras, Joern Meissner have shown how these wellstudied revenue management problems can be reduced to a common formulation in which the firm controls the aggregate rate at which all products jointly consume resource capacity, highlighting their common structure, and in some cases leading to algorithmic simplifications through the reduction in the control dimension of the associated optimization problems.

Omar Besbes, Costis Maglaras have considered a revenue-maximizing make-to-order manufacturer that serves a market of price- and delay-sensitive customers and operates in an environment in which the market size varies stochastically over time.

The lindo story

Since 1979, LINDO Systems software has been a favorite of business and educational communities alike. LINDO Systems has dedicated itself to providing

powerful, innovative optimization tools that are also flexible and easy to use. LINDO Systems has a long history of pioneering powerful optimization software tools. In 1988, LINGO became LINDO Systems first product to include a full featured modeling language. Users were able to utilize the modeling language to concisely express models using summations and subscripted variables. In 1993, LINGO added a large scale nonlinear solver. It was unique in that the user did not have to specify which solver to use. LINGO would analyze the model and would engage the appropriate linear or nonlinear solver. Also unique to the LINGO's nonlinear solver was the support of general and binary integer restrictions. With the addition of the nonlinear solver. LINGO essentially replaced GINO as LINDO Systems premier product for nonlinear optimization. GINO made its debut in 1984 and was the first ever nonlinear solver available on the PC Platform. In 1994, LINGO became the first modeling language software to be included in a popular management science text. In 1995, the first Windows release of LINGO was shipped. Today, LINDO Systems continues to develop faster, more powerful versions.

What is lingo?

LINGO is a simple tool for utilizing the power of linear and nonlinear optimization to formulate large problems concisely, solve them, and analyze the solution. Optimization helps you find the answer that yields the best result; attains the highest profit, output, or happiness; or achieves the lowest cost, waste, or discomfort. Often these problems involve making the most efficient use of your resources-including money, time, machinery, staff, inventory, and more. Optimization problems are often classified as linear or nonlinear, depending on whether the relationships in the problem are linear with respect to the variables.

LINGO includes a set of built-in solvers to tackle a wide variety of problems. Unlike many modeling packages, all of the LINGO solvers are directly linked to the modeling environment. This seamless integration allows LINGO to pass the problem to the appropriate solver directly in memory rather than through more sluggish intermediate files. This direct link also minimizes compatibility problems between the modeling language component and the solver components.

Local search solvers are generally designed to search only until they have identified a local optimum. If the model is non-convex, other local optima may exist that yield significantly better solutions. Rather than stopping after the first local optimum is found, the Global solver will search until the global optimum is confirmed. The Global solver converts the original non-convex, nonlinear problem into several convex, linear sub problems. Then, it uses the branch-and-bound technique to exhaustively search over these sub problems for the global solution.

The Nonlinear and Global license options are required to utilize the global optimization capabilities.

The modeling framework

In this section, the provided mathematical formulation by Sunil Chopra, Peter Meindl and D V Kalra (18) for logistics network design problems is considered. Our presented model for deterministic SCND problems is largely inspired from this work.

The supplier has a cost c of production per unit and must decide on the price pi to charge each segment; di is the resulting demands from segement i. The goal of the supplier is to price so as to maximize its profits. If the available capacity is constrained by Q, the optimal prices are obtained by solving

$$Max \sum_{i=1}^{k} (p_i - c)(A_i - B_i p_i)$$

subject to

$$\begin{split} &\sum_{i=1}^{k} (A_{i} - B_{i}p_{i}) {\leq} Q \\ &A_{i} - B_{i}p_{i} {\geq} 0 \quad for \; i {=} 1, ..., k \end{split}$$

NUMERICAL EXAMPLE

The following example was taken from the book by Sunil Chopra, Peter Meindl and D V Kalra (9).

A contract manufacturer has identified two customer segments for its production capacity - one willing to place an order more than one week in advance and the other willing to pay a higher price as long as it can provide less than one week's notice for production. The customers that are unwilling to commit in advance are less price sensitive and have a demand curve d1 = 5000 - 20p1. Customers willing to commit in advance are more price sensitive and have a demand curve of d2 = 5000 - 40p1. Production cost c = \$10 per unit. If the total production capacity is limited to 4000 units what should the contract manufacturer charge each segment?

The methodology described above has two important assumptions that are unlikely to hold in practice. The first assumption is that nobody from the higher price segment decides to shift to the lower price segment after prices are announced. In other words we have assumed that the attribute such as lead time used to separate the segments works perfectly. In practice this is unlikely to be the case. Our second assumption is that once prices are decided, customer demand is predictable.



Figure-1. A contract manufacturing facility.

LINGO PROGRAM

Model: SETS: PERIOD:A,B,P; ENDSETS DATA: A = 5000, 5000;B = 20, 40;ENDDATA MAX = @SUM(PERIOD(I): (P(I) - C)*(A(I) - C))B(I)*P(I))); @SUM(PERIOD(I):(A(I)- B(I) P(I)))<= 4000; @FOR(PERIOD(I):(A(I) - B(I) * P(I)) >= 0); END

COMPUTATIONAL EFFICIENCY

An intel CORE i5 processor with 4GB RAM was used to process the model. Multistart solver was used.

Numerical problem size

Total variables:	3
Nonlinear variables:	3
Integer variables:	0
Total constraints:	4
Nonlinear constraints:	1
Total nonzeros:	7
#	

Run time

The problem was solved in less than 1 second.



		Total	3
Model Class:	NLP	Nonlinear	3
State:	Local Opt	Integers:	0
Objective:	452083	- Constraints	
Infeasibilitu	4 54747e-013	Total:	4
n nodololiny.	4.04/4/0 010	Nonlinear:	1
Iterations:	42		
Extended Solver Status		l otal:	
Golver Type:	Multistart	Nonlinear:	3
Best Obj:	452083	Generator Memory U:	sed (K) —
Obj Bound:		20	
Steps:	5	Elapsed Runtime (hh:	mm:ss)—
Active:		00:00:0	0



RESULT

Optimal price is shown in the table below

Production capacity =	4000		
Segment	Price	Demand	Profit
1	\$141.7	2166.67	\$285277.8
2	\$79.2	1833.33	\$126805.6
	Total	4000	\$412083.3

Table-1. Result.

CONCLUSIONS

Thus in this paper we have found the optimal price for each segment using LINGO.

REFERENCES

- Gustavo Vulcano, Garrett van Ryzin and Wassim Chaar. 2010. "Choice-Based Revenue Management: An Empirical Study of Estimation and Optimization", Manufacturing and Service Operations Management. Vol. 12, No. 3, pp. 371-392.
- [2] Tamer Basar and R. Srikant. 2002. "Revenue-Maximizing Pricing and Capacity Expansion in a Many-Users Regime", IEEE INFOCOM.

- [3] Ing-Ray Chen, Okan Yilmaz And I-Ling Yen. 2006.
 "Admission Control Algorithms for Revenue Optimization with QoS Guarantees in Mobile Wireless Networks", Wireless Personal Communications. 38: 357–376
- [4] C Krishnaraj, KM Mohanasundaram. 2012. "Design and Implementation Study of Knowledge Based Foundry Total Failure Mode Effects Analysis Technique", European Journal of Scientific Research. Vol.71, No.2, pp. 298-311.
- [5] Tim Pueschel, Dirk Neumann. 2009. "Management of Cloud Infrastructures: Policy-Based Revenue Optimization", International Conference on Information Systems (ICIS).
- [6] Okan Yilmaz, Ing-Ray Chen. 2009. "Utilizing call admission control for pricing optimization of multiple service classes in wireless cellular networks", Computer Communications. 32: 317–323.
- [7] Kamaruzzaman Seman, Fitri Maya Puspita, Bachok M.Taib, Zurina Shafii. 2012. "An Improved Optimization Model of Internet Charging Scheme in Multi Service Networks", TELKOMNIKA. Vol. 10, No. 3, September, pp. 592-598.
- [8] Elodie Adida · Georgia Perakis. 2005. "A Robust Optimization Approach to Dynamic Pricing and Inventory Control with no Backorders", Math. Program. Ser. B.
- [9] C Krishnaraj, KM Mohanasundaram, S Navaneethasanthakumar. 2012. "Implementation Study Analysis of FTFMEA Model in Indian Foundry Industry", Journal of Applied Sciences Research. Vol. 8, No. 2, pp. 1009-1017.
- [10] Garrett van Ryzin, Jeff McGill. 2000. "Revenue Management without Forecasting or Optimization: An Adaptive Algorithm for Determining Airline Seat Protection Levels", Management Science. Vol. 46, No. 6, June, pp. 760-775.
- [11] Shin-Chan Ting, Gwo-Hshiung Tzeng, "An optimal containership slot allocation for liner shipping revenue management", MARIT. POL. MGMT. Vol. 31, No. 3, 199-211.
- [12] Dusit Niyato, Ekram Hossain. 2008. "Competitive Pricing in Heterogeneous Wireless Access Networks:



Issues and Approaches", IEEE Network• November/December.

- [13] Ioannis Ch. Paschalidis and Yong Liu. 2002. "Pricing in Multiservice Loss Networks: Static Pricing, Asymptotic Optimality, and Demand Substitution Effects", IEEE/ACM Transactions on Networking. Vol. 10, No. 3, June.
- [14] Neil J. Keon, G. Anandalingam. 2003. "Optimal Pricing for Multiple Services in Telecommunications Networks Offering Quality-of-Service Guarantees", IEEE/ACM Transactions on Networking, Vol. 11, No. 1, February.
- [15] Yuri Levin, Jeff McGill, Mikhail Nediak. 2007. "Price Guarantees in Dynamic Pricing and Revenue Management", Operations Research. Vol. 55, No. 1, January–February, pp. 75-97.
- [16] Mohanasundaram, K. M., N. Godwin Raja Ebenezer, and C. Krishnaraj. 2012. "Forward Kinematics Analysis of SCORBOT ER V Plus using LabVIEW." European Journal of Scientific Research. 72(4): 549-557.
- [17] Yuri Levin, Jeff McGill, Mikhail Nediak. 2008. "Risk in Revenue Management and Dynamic Pricing", Operations Research. Vol. 56, No. 2, March–April, pp. 326-343.
- [18] Kin-Keung Lai, Wan-Lung Ng. 2005. "A stochastic approach to hotel revenue optimization", Computers and Operations Research. 32: 1059-1072.
- [19] Constantinos Maglaras, Joern Meissner. 2006. "Dynamic Pricing Strategies for Multiproduct Revenue Management Problems", Manufacturing and Service Operations Management. Vol. 8, No. 2, pp. 136-148.
- [20] Krishnaraj, C., K. M. Mohanasundram, and S. Navaneethasanthakumar. 2012. "Implementation Study Analysis of Ftfmea Model in Indian Foundry Industry." Journal of Applied Sciences Research. 8(2).
- [21] Omar Besbes, Costis Maglaras. 2009. "Revenue Optimization for a Make-to-Order Queue in an Uncertain Market Environment", Operations Research. Vol. 57, No. 6, November-December. pp. 1438–1450.

- [22] Sunil Chopra, Peter Meindl and D V Kalra, "Supply Chain Management Strategy, Planning and Operation", 5th Edition, Pearson.
- [23] LINDO Systems Inc, "LINGO the Modeling Language and Optimizer".
- [24] LINDO Systems Inc, "Optimization Modeling with LINGO", 6th Edition.