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Return-on-investment (ROI) criteria for network design

Mozart B. C. Menezes[a], Seokjin Kim[b,*], Rongbing Huang[c]

[a] Operations Management and Information Systems Department, KEDGE Business School – Bordeaux, 680 cours de la Libération, 33405 Talence Cedex, France
[b] Department of Information Systems and Operations Management, Sawyer Business School, Suffolk University, 8 Ashburton Place, Boston, MA 02108, USA
[c] School of Administrative Studies, York University, Atkinson Building, 4700 Keele Street, Toronto, ON M3J 1P3, Canada

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ABSTRACT

We develop a model for optimal location of retail stores on a network. The objective is to maximize the total profit of the network subject to a minimum ROI (or *ROI threshold*) required at each store. Our model determines the location and number of stores, allocation of demands to the stores, and total investment. We formulate a store's profit as a jointly concave function in demand and investment, and show that the corresponding ROI function is unimodal. We demonstrate an application of our model to location of retail stores operating as an $M/M/1/K$ queue and show the joint concavity of a store's profit. To this end, we prove the joint concavity of the throughput of an $M/M/1/K$ queue. Parametric analysis is performed on an illustrative example for managerial implications. We introduce an upper bound of an optimal value of the problem and develop three heuristic algorithms based on the structural properties of the profit and ROI functions. Computational results are promising.

1. Introduction

One of the widely used objectives for network design is profit maximization. This approach can lead to higher investment (for example, locating more stores) than a return-on-investment (ROI) criterion, where ROI is the profit of an investment divided by the cost of the investment. Starbucks' failure in 2008 invokes the motivation to consider an ROI criterion in addition to profit.

"Starbucks nearly tripled the number of stores worldwide, from 5886 in 2002 to 15,011 in 2007. But in the Great Recession of 2008, it was hurt by rising costs, the cannibalization effects of years of overexpansion, and stiff competition from McDonald's and Dunkin Donuts. By the end of 2008, Starbucks stock, once seemingly invincible, had declined by over 50 percent. 1000 employees were laid off and 600 underperforming locations were closed in the United States." (Excerpted from the New York Times, May 25, 2010) Greer (2010) illustrated the up-and-downs of the number of stores including the plan of adding 500 new stores in 2010. While the stores closed in 2008 were company-owned, the growth in 2010 is based on franchising requiring no upfront investment. Starbucks just collected loyalty streams paid by the stores.

This research was motivated by communications with one of our partners in automobile industry, whose details are omitted per request. The automobile manufacturer considers ROI in location decisions in a sequential manner. Finance first brings a ROI threshold because ROI evaluates the efficiency of an investment from an investor's perspective. While investment decisions are internally made, ROI-incorporated location decisions can be aligned with some metrics interesting to external stakeholders. Examples include financial ratios such as return on equity and return on asset. The ROI threshold is translated into a minimum demand per site, which is then used for an estimate on the number of dealerships to be located. Based on population data, the whole geographical regions are partitioned in a way that the minimum demand requirement would be satisfied in each region. Then, a 1-median problem is solved for a location within each region since customers are sensitive to distance. When the minimum demand requirement is over- or under-achieved in some regions, the whole regions are partitioned with a smaller or larger number of dealerships.

The partner's *sequential* approach to location decisions is a simple heuristic which is not even close to optimal. Thus, we develop an analytical model *simultaneously* determining the decision variables: (i) the number and location of stores, (ii) the allocation of demands to the stores, and (iii) investments at the stores. The objective is to maximize the profit of a retail network subject to a ROI threshold required at each store. The main purpose of this formulation is to deliver useful insights by addressing the impact of a financial requirement such as ROI threshold on the profit.

From a systems perspective, the interface between business functions is critical to a firm's success. However, in the literature, not much attention has been paid to the link between operations and finance via

* Corresponding author. Tel.: +1 617 305 3285; fax: +1 617 994 4228.
E-mail addresses: mozart.menezes@kedgebs.com (M.B.C. Menezes), kim@suffolk.edu, skim.suffolk@gmail.com (S. Kim), rhuang@yorku.ca (R. Huang).

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ROI criteria. Myung, Kim, and Tcha (1997) considered a bi-objective model for uncapacitated facility location where one objective is to maximize the net profit and the other to maximize the profitability (ROI) of the investment. Brimberg and ReVelle (2000) also proposed a bi-criterion model which examines the tradeoff between the total and investment costs. Brimberg, Hansen, Laporte, Mladenovic, and Urosevic (2008) examined the objective of maximizing ROI, but imposed a minimum acceptable level on market share. They showed that an optimal solution without market share constraints is given by a single open facility, but one-facility location is rare in a retail network. These models are intended for the location of manufacturing plants and determine assignment of plants to demand nodes. In a retail environment, however, the traffic to a store is determined rather by customer preference, for example, distance sensitivity. Such customer choices are explicitly incorporated as "closest assignment" constraints in our model.

Our analysis includes an application of our model to location of retail stores operating as an M/M/1/K queue where the stochastic nature of arrival and service processes in retail operations is explicitly treated. Previous research in similar settings can be found in Berman, Krass, and Wang (2006) and Berman, Huang, Kim, and Menezes (2007) from which our model extends using ROI criteria. General problems of finding optimal facility location and resource allocation in a stochastic environment belong to the class of "Location Problems with Stochastic Demands and Congestion" (Berman and Krass, 2002, chap. 11). Snyder (2006) also provided a survey of location models with uncertainty.

We summarize key contributions. First, a more general modeling structure is introduced. In the previous location models with ROI criteria, profit or cost is formulated as a linear function and ROI as a linear fractional function. We generalize profit as a nonlinear function and ROI as a nonlinear fractional function. The resulting formulation inherits the complexity of classical location problems and the nonlinearity of profit and ROI functions adds more challenges. In particular, the profit function in our model is jointly concave in demand and investment, and can be applied to many practical settings where the marginal benefit of an increasing demand or investment decreases. Given these assumptions, we show the corresponding ROI function is unimodal. Second, in our application to location of retail stores operating as an $M/M/1/K$ queue, we show the "queueing-based" profit function is also joint concave. To this end, we prove the joint concavity of the throughput of an $M/M/1/K$ queue. This result is not available in the queueing literature to the best of our knowledge. Third, we introduce an upper bound of an optimal value of the problem and develop three heuristic algorithms based on the structural properties of the profit and ROI functions. While our framework was motivated by retail networks, these results can be applied in other potential research in network design. The first two contributions have implications for various other areas in operational research.

Our framework does not explicitly incorporate competition between retail chains. Direct applications include monopolistic chains with low competition. When high competition exists, the effect can implicitly be captured by estimating parameters with cautions. For example, market share can be used instead of total demand at any demand point. Also customers' distance sensitivity can be adjusted to a high value (page 1016 in Berman et al., 2007).

The rest of the paper is planned as follows. In Section 2, we present the problem framework and assumptions. We also formulate the profit and ROI functions of a store, and show their structural properties. In Section 3, we formulate the problem and decompose it into stores' subproblems. We also show some structural properties of a subproblem. In Section 4, we apply our model to location of retail stores operating an $M/M/1/K$ queue. An example of the problem is illustrated in Section 5. Section 6 highlights some observations from parametric analysis using the example in Section 5. In Section 7, we introduce an upper bound of an optimal value of the problem and develop three heuristic algorithms. Section 8 includes numerical results from a computational experiment with random graphs. The conclusion with suggested future research follows in Section 9.

2. The framework

A chain has retail stores located within the area represented by a discrete undirected network $G = (N, L)$, where N is the node set with $|N| = n$ and L is the link set. Customers are concentrated at the nodes and demands originate from node i at the rate of w_i per unit time. The shortest distance between nodes i and j is denoted to be d_{ij}. Customers from a node patronize the closest store. Customers' choice based on distance has been used in the location literature (Berman et al., 2006; Gerrard and Church, 1996). As illustrated in our communications with an automobile manufacturer in the previous section, businesses use distance as one of the key contributing factors in customers' preference. While this assumption is still realistic, different or more refined versions are possible. For example, customers rank facilities by travel and waiting times (Marianov, Rios, & Icaza, 2008). Given the distance-based customers' choice, for a given set $X \subset N$ of store locations, a demand node can be "assigned" to the closest node with a located store. The set of nodes assigned to a store at node j (or "store j") is denoted to be N_j. Demands from a node, even though assigned to the closest store, might still be "lost" due to the following two sources (Berman et al., 2006):

1. Inconvenience. Customers from a node (i) are "sensitive" to distance and are lost when the store (j) they patronize is not close enough. The function $\phi(d_{ij})$ detailed below maps the likelihood of customers from node i travelling to store j.
2. Incapacity. Customers from node i are sensitive to congestion at store j (and also to service delays, overall appearance, layout, etc). Even though a customer from node i travels to store j, upon arrival, she might not join it due to congestion. The capacity of a store is determined by the level of investment.

Given that node i is assigned to store j, let the fraction of customers from node i travelling to store j be $\phi(d_{ij}) \geq 0$, where the "coverage decay function" $\phi(d)$ is non-increasing. For numerical examples and computational experiments in this paper, we use a piecewise linear convex function, $\phi(d) = \max\{1 - d/(\theta d_{\max}), 0\}$ (Berman et al., 2007), where $d_{\max}$ is the largest shortest distance of G and $\theta > 0$ is a constant representing customers' distance sensitivity. For example, a larger value of θ can be used under higher competition as noted in the previous section. See Berman, Krass, and Drezner (2003) for more examples of $\phi(d)$. However, a choice of $\phi(d)$ does not affect the results in the remainder of this paper. From the definition of $\phi(d)$, we define below the unit-time demand of store j

$$\lambda_j = \sum_{i \in N_j} w_i \phi(d_{ij})$$

which represents the average number of customers arriving at store j per unit time.

The decision maker determines the set X of store locations and investment (or *variable* investment cost) $I_j \geq 0$ of a store at node j. Note that the number of stores ($m = |X|$) is not pre-specified. There is also a *fixed* setup cost $S \geq 0$ for locating a store. The objective is to maximize the total profit of all stores located on the network subject to a pre-specified ROI threshold α required at each store. The full formulation of this problem is presented in the next section. We first develop the profit and ROI functions of a store, and investigate their structural properties in this section.

Suppose a store is located at some node with some λ and I (dropping the index "j"). We assume that the "throughput" or unit-time sales of the store, $T(\lambda, I)$, is a non-decreasing and jointly concave function of λ and I, with the boundary conditions $T(\lambda, 0) = 0$ and $T(0, I) = 0$. Examples include the Cobb–Douglas function $T(\lambda, I) = A\lambda^{\beta} I^{\gamma}$, where $0 \leq \beta \leq 1, 0 \leq \gamma \leq 1$, and $\beta + \gamma \leq 1$. Let p and c be