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A reliability model for facility location design under imperfect information

Lifen Yun [a,b], Yong Qin [a], Hongqiang Fan [b], Changxu Ji [a], Xiaopeng Li [c,*], Limin Jia [a]

[a] State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, No. 3 Shangyuancun, Haidian District, Beijing 100044, PR China
[b] School of Traffic and Transportation, Beijing Jiaotong University, No. 3 Shangyuancun, Haidian District, Beijing 100044, PR China
[c] Department of Civil and Environmental Engineering, Mississippi State University, 501 Hardy Road, Starkville, MS 39759, USA

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ABSTRACT

This paper aims to propose a modeling framework for reliable facility location design under imperfect information, i.e., when customers do not know the real-time information of facility disruption states. We consider a realistic "trial-and-error" strategy for a customer to visit facilities without knowing their states until arriving at this facility; i.e., a customer keeps trying a number of pre-assigned facilities until she acquires the service or is forced to give up trying. The research problem is to determine the best facility location that minimizes the total system cost, including initial facility investment and expected long-term operational cost from transportation and loss of service, when facilities are subject to probabilistic disruptions and customers use the trial-and-error strategy. This problem is formulated into a compact integer program (IP), and we develop a Lagrangian relaxation algorithm to solve it. A set of case studies are conducted to test the performance of the proposed algorithm, and illustrate the applicability of the proposed model. The results reveal a number of interesting insights into the system design, including the significance of multi-level customer-facility assignments and the existence of a robust system design against variation of the loss-of-service penalty.

1. Introduction

1.1. Motivation

A central decision in planning infrastructure systems in various private (e.g., a logistics network) or public (e.g., emergency response facilities) sectors is to select the best locations for service facilities. This location decision essentially leverages the tradeoff between a system's one-time infrastructure construction investment and its long-term operational performance. Traditional location models aim to design the leanest facility system that has the most economic life-time cost, assuming that all built facilities are always functioning perfectly (see Drezner (1995) and Daskin (1995) for reviews on this topic). However, in observing massive facility disruptions in recent natural and anthropogenic disasters (D'Amico, 2002; Schewe, 2004; Godoy, 2007), people recognized the vulnerability of a traditional lean facility system design to unexpected disruptions, which led to the inception of reliable location design concepts on the balance between a system's efficiency and its resilience. One of such concepts is that a customer is allowed to access multiple facilities, and thus she may still obtain the

* Corresponding author. Tel.: +1 662 325 7196.
E-mail address: xli@cee.msstate.edu (X. Li).

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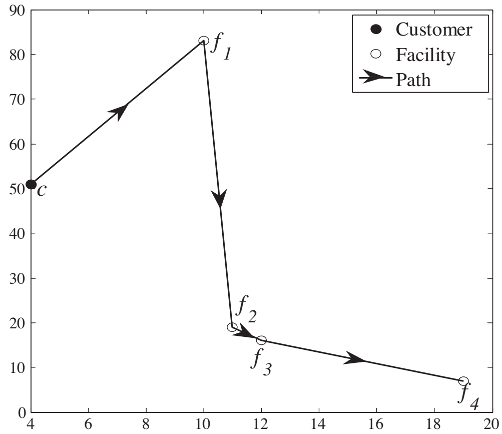
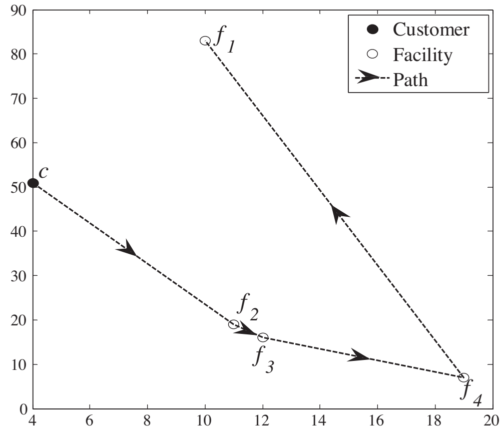
backup service when her primary facility is disrupted (Snyder and Daskin, 2005). Most existing reliable facility location models of this kind assume that a customer is constantly informed with facility functional states in real time and thus can always immediately identify and directly visit the nearest functioning facility in any disruption scenario.

This assumption, however, may not accurately reflect the reality in certain service systems where customers do not have access to perfect information of real-time facility states. Even in today's data-rich environment, real-time information sharing remains a critical challenge due to sensor technology limitations (Baillieul and Antsaklis, 2007) and various institutional and technological barriers (Birenbaum, 2009). There are many service systems in our everyday life where we usually do not know a facility's operating state until physically visiting it. Examples (Berman et al., 2009) include automated teller machines (an ATM unable to provide service because of network disruptions, maintenance, or simply not servicing a particular customer's card), retail stores (customers looking to buy a product in a store that is however out of stock), hospital emergency rooms (excessive waiting times may cause newly arriving patients to seek service elsewhere). Further, the difficulty in accessing real-time information can be magnified in unexpected emergency scenarios due to communication and facility disruptions (Bakuli and MacGregor Smith, 1996; Pan et al., 2006; Litman, 2006; Cho et al., 2011; KRIHS, 2013). For example, when gas stations around the New York City area were disrupted due to Hurricane Sandy's impacts in 2012, many vehicles were circulating in the streets trying gas stations one by one without being notified which ones remain working (HSRTF, 2013). When the real-time information is not available, a customer usually follows a "trial-and-error" strategy to visit facilities. In any disruption scenario, she tries visiting nearby facilities sequentially by a pre-specified order independent of disruption realizations, and stops at the first functioning facility if available or gives up the service after several unsuccessful tries.

However, there are few suitable reliable facility location models to address such visiting behavior under imperfect information. To our best knowledge, the only reliable location model considering imperfect information is proposed by Berman et al. (2009). They studied a reliable median location problem where a customer does not know facility states and has to try them out one by one. This study assumed that a customer's visiting sequence of the facilities is always ordered by the distances between the customer and the facilities; i.e., in any facility disruption scenario, this customer always visits the closest facility first, then if this facility is not functioning, she will visit the next closest facility from her current location, and so forth. Although this visiting sequence (which we refer as Berman's sequence later) appears to be a good visiting sequence, it may yield a significantly higher cost compared to the true optimal sequence. This is illustrated in the following motivating example in Fig. 1. We consider five randomly generated nodes in a rectangle area $[0,20]\times[0,90]$, including a customer, denoted by c at location (4, 51), and four service facilities, f_1 at (10,83), f_2 at (11,19), f_3 at (12, 16) and f_4 at (19, 7), ordered by their distances from the customer c. We assume each facility disrupt independently with a 20% probability, the transportation cost for this customer to visit a facility is equal to the straight-line travel distance, the customer will receive a penalty of 1000 if she gives up the service, and the expected operational cost is the sum of the expected transportation cost and the expected penalty cost. Fig. 1(a) shows the path of the visits if the customer follows Berman's sequence, which yields a total expected operational cost of 47. Whereas Fig. 1(b) shows the optimal visiting path after enumerating all possible visiting sequences, which yields an operational cost of only 36. We see that the operational cost from Berman's sequence is over 30% higher than that from the optimal visiting sequence. With a closer look into the comparison in Fig. 1, we see that the optimal sequence first visits a slightly more distant facility f_2 that is yet clustered with another facility f_3. Although such a move may slightly increase the distance of the first leg of travel, it can largely reduce the travel distances in the possible following legs once entering the cluster. Therefore, it would be a more rational sequence for a customer to weigh the tradeoff between the current move and the following ones. This example can be easily scaled up to multi-customer cases, and



(a) Berman's visiting sequence



(b) Optimal visiting sequence

Fig. 1. The motivating example.