Designing & Imagery of Facilities Located in an Emergency Service Under FUZZY Environ

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ABSTRACT

A manufacturing unit is the place where all inputs such as raw material, equipment, skilled labors, etc. come together and manufacture products for customers. One of the most critical factors determining the success of the manufacturing unit is the location. The facility location problem on general graphs is NP-hard to solve optimally, by reduction from (for example) the set cover problem. A number of approximation algorithms have been developed for the facility location problem and many of its variants. Due to the co-being of the randomness and fuzziness in real word, we investigate the facility place – allocation moot point in an accidental fuzzy surroundings. This paper contributed to FLA analysis in the following four aspects. A numerical example was provided to show the pattern of accidental fuzzy capacitated FLA quandary and the performance of the hybrid intelligent algorithm. The computational outcomes of the scalar experiments imply that it is effective to solve it.

INTRODUCTION

The facility location problem, also known as location analysis or k-center problem, is a branch of operations research and computational geometry concerned with the optimal placement of facilities to minimize transportation costs while considering factors like avoiding placing hazardous materials near housing, and competitors' facilities. The techniques also apply to cluster analysis (B. Liu, 1998). The problem of facility location is faced by both new and existing businesses, and its solution is critical to a company’s eventual success. An important element in designing a company’s supply chain is the location of its facilities. Facility Location is the right location for the manufacturing facility, it will have sufficient access to the customers, workers, transportation, etc. For commercial success, and competitive advantage following are the critical factors:

Fig. 1: facilities location.

Overall objective of an organization is to satisfy and delight customers with its product and services. Therefore, for an organization it becomes important to have strategy formulated around its manufacturing unit. A manufacturing unit is the place where all inputs such as raw material, equipment, skilled labors, etc. come together and manufacture products for customers. One of the most critical factors determining the success of the manufacturing unit is the location (Jain, K. and Vazirani, V.V., 2001; L. Hurwicz,).
Fig. 2: Facilities location problems.

For a company which operates in a global environment; cost, available infrastructure, labor skill, government policies and environment are very important factors. A right location provides adequate access to customers, skilled labors, transportation, etc. A right location ensures success of the organization in current global competitive environment. Simple facility location problem is the Weber problem, in which a single facility is to be placed, with the only optimization criterion being the minimization of the weighted sum of distances from a given set of point sites (Samaria, F. & Harter, A., 1994). More complex problems considered in this discipline include the placement of multiple facilities, constraints on the locations of facilities, and more complex optimization criteria. In a basic formulation, the facility location problem consists of a set of potential facility sites $L$ where a facility can be opened, and a set of demand points $D$ that must be serviced. The goal is to pick a subset $F$ of facilities to open, to minimize the sum of distances from each demand point to its nearest facility, plus the sum of opening costs of the facilities.

The facility location problem on general graphs is NP-hard to solve optimally, by reduction from (for example) the set cover problem. A number of approximation algorithms have been developed for the facility location problem and many of its variants. Without assumptions on the set of distances between clients and sites (in particular, without assuming that the distances satisfy the triangle inequality), the problem is known as non-metric facility location and can be approximated to within a factor $O(\log n)$. This factor is tight, via an approximation-preserving reduction from the set cover problem (Swamy, C. and Kumar, A., 2004). If we assume distances between clients and sites are undirected and satisfy the triangle inequality, we are talking about a metric facility location (MFL) problem. The MFL is still NP-hard and hard to approximate within factor better than 1.463. The currently best known approximation algorithm achieves approximation ratio of 1.488. The minimax facility location problem seeks a location which minimizes the maximum distance to the sites, where the distance from one point to the sites is the distance from the point to its nearest facility (Zhang, J., 2004).

Research Background:

A formal definition is as follows: Given a point set $P \subset \mathbb{R}^d$, find a point set $S \subset \mathbb{R}^d$, $|S| = k$, so that $\max_{p \in P} \min_{q \in S} d(p, q)$ is minimized. In the case of the Euclidean metric for $k = 1$, it is known as the smallest enclosing sphere problem or 1-center problem. Its study traced at least to the year of 1860. The classical UFLP and CFLP models have been extended in a number of ways by relaxing one or more of their underlying assumptions mentioned in Sect. 2.1. Here we provide an overview of the major works that extend the classical formulations by increasing the number of products, the number of facility echelons, and the number of time periods included in the model, as well as by the realistic representation of problem parameters through incorporation of possible scale and scope economies and uncertainties (Kolliopoulos, S.G. and Rao, S., 1999).

An immediate generalization of UFLP is the multi-commodity facility location problem that relaxes the single product assumption. Although Neebe and Khumawala (1981) and Karkazis and Boffey (1981) offered alternative formulations for this problem, both papers assumed that each facility deals with a single product. Klincewicz and Luss (1987) was the first paper that studied a multi-commodity facility location model without any restrictions on the number of products at each facility. A number of researchers focused on relaxing the single period assumption of the UFLP and CFLP, and developed models and solutions for the dynamic facility
location problem (Rautenbach, D., 2004). The objective was to determine the spatial distribution of the facilities at each time period so as to minimize the total discounted costs for meeting the customer demand over time.

The earliest work on this problem is by Van Roy and Erlenkotter (1982), who extended the dual-based algorithm of Erlenkotter to handle multiple time periods. Lim and Kim (1999) and Canel et al. (2001) proposed alternative methods for solving the problem with capacity restrictions at the facilities. Recently, Melo et al. (2005) presented a dynamic and multi-commodity formulation as an extension of the CFLP and investigated the possible use of the model as a framework for strategic supply chain planning. Another stream of research to extend the classical UFLP and CFLP formulations focuses on improving the realism of the cost representations in these models (Jain, K. and Vazirani, V.V., 2001). These efforts are motivated by the possible economies of scale and scope in the fixed and variable costs, as well as the potential cost implications of the interactions between a plant’s location and the other structural decisions including capacity acquisition and technology selection. Soland (1974) is one of the earliest attempts to develop an extension of the UFLP that incorporates scale economies by representing the fixed facility costs as a concave function of facility size. Holmberg (1994) and Holmberg and Ling (1997) extended the CFLP by formulating the capacity acquisition costs as arbitrary piecewise linear functions.

Verter and Dincer (1995) proposed a model where the capacity costs are assumed to be general concave functions of the capacity acquired at each facility. Erlenkotter’s dual based algorithm is utilized as a subroutine during the progressive piecewise linear under-estimation technique developed in this paper. Dasci and Verter (2001) and Verter and Dasci (2002) provide extensions to a multi-product setting, where the firm is enabled to select among product-dedicated and flexible technology alternatives. At each alternative facility location, the technology options present different forms of scale and scope economies. More recently, a number of authors studied the integration of inventory control and logistics decisions with facility location. Shen (2005) used concave functions to represent economies of scale in the costs pertaining to the firm’s inventories, whereas Snyder et al. (2007) and Sourirajan et al. (2007) presented facility location models that also considered the logistics costs.

**MPLP UFLP Algorithm:**

In comparison to existing approximation algorithms, the MPLP-based approach we describe bears the most similarities to primal-dual methods, as it also performs co-ordinate ascent in a dual LP. Similarly to other methods, at convergence we construct a solution support graph and run a greedy variable assignment algorithm to obtain a 3-approximation solution guarantee. The approximation ratio is comparatively high as the greedy algorithm is fairly simple; however, the primary contribution lies in showing how the MPLP fixed point can be used to construct the support graph and provide a bound on the integral solution. The approximation ratio could likely be decreased by applying the more elaborate techniques described in literature.

**Fig. 3:** Factor Graph Representation.

In practice, it suffices to only keep track of the difference between the two values, which we will denote as \( m = m(1) - m(0) \). Furthermore, we require only the factor-to-variable messages to compute beliefs and make variable assignments.

**Fig. 4:** Message Naming Convention.
In regularity to pattern the capacitated FLA difficulty, the following punctuation are offered:

\((x_i, y_i)\) is the resolve variable which demonstrate the place of easiness \(i\), \(1 \leq i \leq n\);

\(Z_{ij}\) give the meaning the quantity supplied by easiness into client \(j\), \(1 \leq i \leq n, 1 \leq j \leq m\).

For an capacitated FLA difficulty, we requirement to select \(n\) place from a certain area \(R = \{(x, y) \mid g_i(x_i, y_i) \leq 0, i = 1, 2, \ldots, n\}\) and resolve the amount \(Z_{ij}\) from easiness its client \(j\). Also the easiness \(i\) cannot supply things endlessly, which middle they have valence \(S_i\). An allocation \(z\) is said to be pragmatic if the second limitation states that the demand of each client should be satisfied sans wasting. The third limitation implies that the supplied amount of each easiness should not exceed its valence. We denote the practical allocation set by in this department, we shall state some basic concepts and outcomes on random easiness variable. The interested reader may consult Liu, where consequential confidants of random easiness variables are recorded. Let \(\theta\) be a nonempty set, \(P(\theta)\) the authority set of \(\theta\), and \(\text{Pos}\) a possibility size. Then the triplet \((\theta, P(\theta), \text{Pos})\) is called a possibility space. A fuzzy variable \(\theta\) is determined as a function from a possibility space \((\theta, P(\theta), \text{Pos})\) to the set of real numbers.

\[
Z = \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} z_{ij} \leq S_i, i = 1, 2, \ldots, n \right\}
\]

\[
C(x, y) = \max \left\{ \sum_{i=1}^{n} \sum_{j=1}^{m} z_{ij} \sqrt{(x_i - a_j)^2 + (y_j - b_j)^2} \right\}
\]

Possibility and exigency of a fuzzy event \(\{\Omega \leq r\}\) can be represented by a accidental fuzzy variable is a function from a possibility space \((\theta, P(\theta), \text{Pos})\) to a set of accidental variables. Usually there is some relevant information in operation.

\[
\theta_{ij}(x_{ij}) = \begin{cases} 
-c_{ij} x_{ij}, & \text{if } \sum_{i=1}^{n} x_{ij} > 0 \\
0, & \text{otherwise.}
\end{cases}
\]

\[
\theta_{ij}^+(x_{ij}) = \begin{cases} 
-f_j, & \sum_{j=1}^{m} x_{ij} = 1 \\
-\infty, & \text{otherwise.}
\end{cases}
\]

It is thus conceivable to characterize intervals in which the value of \(\mu\) and \(\Omega\) are presumably to lie, or to give the approximate estimation of the values of \(\mu\) and \(\Omega\) quite. If the value of \(\mu\) and \(\Omega\) are provided as fuzzy changing, then \(\theta\) is an accidental fuzzy variable. Let \(\_\) be a accidental fuzzy variable, and \(B\) a Borel set of \(R\). Then the chance of accidental fuzzy event \(\_{\_} \mid B\) is a function from \((0, 1]\) to \([0, 1]\), defined as this section wants to describe the client demands using accidental fuzzy variables offered in Section 3. We use \(\theta j (\theta, \_\) to denote the accidental fuzzy demand of client \(j\), \(j = 1, 2, \ldots, m\). Similar to Section 2, we can give the feasible allocation set by in the Hurwicz yardstick, the parameter \(\theta 2 [0, 1]\), which reflects the degree of the decision maker’s optimism, must be determined by the decision maker.

Generally speaking, it is difficult to determine the appropriate \(\Omega\) for resolve makers, since it varies from person to person. By varying the parameter \(\Omega\), the Hurwicz criterion becomes various criteria, e.g., when \(\theta = 1\), the criterion is the upbeat criterion; when \(\theta = 0\), it degenerate to a pessimistic criterion. This fact means that the Hurwicz criterion is inherently pliable. In the history of possibility place –allocation quandary in hesitant surroundings, many researchers use the concept of limit programming (Charnes and Cooper, Liue), which want to minimize the _-upbeat or _-pessimistic value. In order to overcome the inordinate cases of these two values, we hire the Hurwicz criterion introduced in department 3.1 to pattern the accidental fuzzy FLA problem. The new model named \((\Omega, \theta)\)-cost minimization pattern under the Hurwicz yardstick is as follows: conforming to various cases, the resolve maker can set _ with various values. The model is various from traditional programming models because there is a suboptimal moot point in it, i.e.

\[
Z(\theta, \_\) = \left\{ z_{ij} \geq 0, i = 1, 2, \ldots, n, j = 1, 2, \ldots, m \right\}
\]
It can be resolved completely by resolve makers or by ascertainment and lysis, even by history data. Generally speaking, the parameter $\theta$ is various in various cases with various methods. This fact means that the $(\theta, \Omega)$-cost minimization model under the Hurwiczce is even-handedly pliable by varying the value $\Omega$, e.g. when $\theta = 1$, the model degenerates to the upbeat model. The FLA moot point has two levels: location and allocation. At allocation level which is a linear programming, we adopt the simplex algorithm to dissolve it. The location level is solved by the genetic algorithm. In this part, we complete the simplex algorithm, accidental fuzzy simulations and genetic algorithm to produce a connective sagacious algorithm for solving the $(\theta, \Omega)$-cost minimization model under the Hurwicz yardstick. Here we briefly characterize the algorithm, and the interested reader may consult Liu.

Table 1: Location and random fuzzy demand.

<table>
<thead>
<tr>
<th>Customer / Location</th>
<th>Demand</th>
<th>Customer / Location</th>
<th>Demand</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(28, 42)</td>
<td>1</td>
<td>(60, 50)</td>
</tr>
<tr>
<td>2</td>
<td>(18, 50)</td>
<td>3</td>
<td>(12, 4)</td>
</tr>
<tr>
<td>4</td>
<td>(74, 6)</td>
<td>5</td>
<td>(14, 78)</td>
</tr>
<tr>
<td>5</td>
<td>(70, 18)</td>
<td>6</td>
<td>(90, 36)</td>
</tr>
</tbody>
</table>

Conclusion:

Due to the co-being of the randomness and fuzziness in real world, we investigate the facility place – allocation moot point in an accidental fuzzy surroundings. This paper contributed to FLA analysis in the following four aspects: (a) In order to overcome the inordinate cases of the $\Omega$- upbeat model and $\theta$-pessimistic models, the $(\theta, \Omega)$-cost minimization pattern under the Hurwicz criterion was offered. By varying the value $\theta$, it can balance the upbeat level of the resolve makers; (d) We have proved that the $(\theta, \Omega)$-cost minimization pattern under the Hurwicz criterion can decadent to the accidental and fuzzy cases, which means that the model can deal various FLA problems in accidental, fuzzy and accidental fuzzy surroundings; (c) To dissolve the pattern efficiently, we integrated the simplex algorithm, accidental fuzzy dramaturgy and genetic algorithm to produce a hybrid intelligent algorithm; (d) A numerical example was provided to show the pattern of accidental fuzzy capacitated FLA quandary and the performance of the hybrid intelligent algorithm. The computational outcomes of the scalar experiments imply that it is effective to solve the $(\theta, \Omega)$-cost minimization pattern under the Hurwicz criterion.

REFERENCES


Hurwicz, L., Optimality criteria for decision making under ignorance, Cowles Commission Discussion.


ANNEX

\[ \sum_{i=1}^{n} a_i \leq \sum_{j=1}^{m} b_j \leq \sum_{i=1}^{n} a_i \]

We define \( \alpha \rightarrow \max \{\alpha - d_0\} \). Using this definition and inequalities (2) and (3) of the factor-revealing LP (LPF) we obtain

\[ \forall \in \mathbb{R} \Rightarrow x_i \geq \alpha - d_0 \Rightarrow \max \{\alpha - d_0, 0\} \geq \max \{\alpha - d_0\} \]

We assume \( \alpha \geq 0 \) here because that, if on contrary \( \alpha < 0 \), we can always set \( \alpha \) equal to \( d_0 \) without violating any constraint in the factor-revealing LP (LPF) and increase \( \alpha \).

Inequality (2b) and \( p_i \leq 1 - p_i \) imply

\[ \sum_{i=1}^{n} \left( \frac{1}{1 - p_i} \right) \alpha_i + \sum_{i=1}^{n} \left( \frac{1 - p_i}{k - i + 1} \right) \alpha_i + \sum_{i=1}^{n} \left( \frac{p_i}{k - i + 1} \right) \alpha_i \]

\[ \leq \sum_{i=1}^{n} \left( \frac{1 - p_k}{1 - p_k} \right) \alpha_i + \sum_{i=1}^{n} \left( \frac{1 - p_k}{k - i + 1} \right) \alpha_i + \sum_{i=1}^{n} \left( \frac{p_i}{k - i + 1} \right) \alpha_i \]

Let \( \zeta = \sum_{i=1}^{n} \). Thus,

\[ \zeta \leq \sum_{i=1}^{n} \left( \frac{p_i}{k - i + 1} \right) + \sum_{i=1}^{n} \left( \frac{1 - p_i}{k - i + 1} \right) \]

\[ \leq \sum_{i=1}^{n} \left( \frac{p_i}{k - i + 1} \right) + \sum_{i=1}^{n} \left( \frac{1 - p_i}{k - i + 1} \right) \]

\[ \leq \sum_{i=1}^{n} \left( \frac{p_i}{k - i + 1} \right) + \sum_{i=1}^{n} \left( \frac{1 - p_i}{k - i + 1} \right) \]

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