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A comparison of *p*-median and maximal coverage location models with *Q*-coverage requirement

Mumtaz Karatas[a(*)], Nasuh Razi[b], Hakan Tozan[c]

[a]*mkaratas@dho.edu.tr, Department of Industrial Engineering, Turkish Naval Academy, Istanbul, 34942, TURKEY*
[b]*nasuhrazi@gmail.com, Institute of Naval Science and Engineering, Turkish Naval Academy, Istanbul, 34942, TURKEY*
[c]*htozan@dho.edu.tr, Department of Industrial Engineering, Turkish Naval Academy, Istanbul, 34942, TURKEY*

Abstract

A facility location problem considers locating a certain number of facilities with the objective of finding their best locations. For most real life situations, it is more realistic to consider the requirement of satisfying a demand with multiple facilities in order to ensure a backup supply. The back-up supply is necessary especially for public or emergency service location problems where a covered demand may not be serviced if its designated facility is engaged serving other demands. Moreover, this issue is more likely to occur when the number of demand locations is much higher. In this study we consider two classic location models, the *p*-median and maximal coverage location, and compare their performances with respect to five decision criteria under *Q*-coverage requirement. For this purpose we generate random problem instances and solve each instance with both models for different *Q*-coverage values. Our comparisons reveal the tradeoffs in selecting the location model for a given problem when the decision maker assesses the performance with multiple criteria.

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Keywords: Location Problem; Facility Problem; *p*-Median; Maximal Coverage

1. Introduction

Location problems seek the best locations for facilities such as warehouses, emergency stations, ports, fire stations or military installations. In most real life situations, the requirement of satisfying a demand with multiple facilities is essential in order to provide a backup supply. This is especially common in large scale emergency location problems where a covered (satisfied) demand may not be serviced immediately if its designated nearest facility is engaged serving other demands. In such cases one alternative would be to create a queue for the demands and serve them when their nearest facility is available. However in emergencies, the difference between life and death can sometimes be measured in minutes. Thus a better alternative is to serve the demand with another facility with appropriate resources. This brings the necessity of developing *Q*-coverage location models which allow the demand to be covered by multiple facilities so that it can be served by another available facility at the time of the emergency incident. A similar concept was first introduced in [1] as backup coverage location problem. The authors define backup coverage as a situation where an extra facility can cover a demand so that the backup coverage of the node will satisfy the demand [2]. In [3], authors discuss a multiple coverage problem where each demand node must be satisfied by a number of facilities. The concept of *Q*-coverage is also common in wireless sensor networks (WSNs). In WSNs, the main purpose of providing multiple coverage is to monitor an area of interest as frequently as possible. It is also used to increase the energy efficiency of a network [4].

* Corresponding author. Tel.: +90-507-337-6135 ; fax: +90-216-395-2658.
E-mail address: mkaratas@dho.edu.tr

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There exist a number of location problems and solution techniques in the literature. Research on location problems mainly focus on two models, i.e. the *p*-median problems (*p*-MP) [5,6,7,8] and covering problems. Covering problems can be categorized as the set coverage problems (SCP) [9,10,11] and the maximal covering location problems (MCLP) [12,13,14]. The *p*-MP aims to find the locations of *p* facilities among *n* candidate locations such that the total weighted distance between all demands and their nearest facilities is minimized [15]. It arises naturally in both public and private sector for locating plants, factories, warehouses or emergency stations to serve/satisfy demand at other plants, warehouses or incident locations.

In his work [16], Haghani states that the facility location problem mainly interests in two factors: operating cost and timeliness of response to demand. However, in some cases, decision-makers make an effort to meet maximum demand in pre-determined coverage level with limited resources. The maximal covering location problem (MCLP) seeks to maximize the total number of demands supplied with a given number of facilities and designated budget [14].

Although there is abundant research on these two basic location models, there is no study in the literature that clearly evaluates and compares the performances of these models with respect to a given set of criteria for a given problem instance when *Q*-coverage requirement is considered. In this paper we aim to make a comparison of both *p*-MP and MCLP models by using criteria that are designed to reveal the strong and weak sides of the models when multiple coverage is required by the decision maker. For this purpose, we first generate a number of random problem instances by generating demand and candidate facility locations. Then we solve each instance by both location models for different coverage requirement and range. Finally, using five assessment criteria, we analyze the quality of their solutions and discuss the effectiveness of each technique for different types of problem scenarios.

The paper is organized as follows: a literature research of *p*-MP and MCLP models is presented in Section 2. We explain the *Q*-coverage optimization models and their structure in Section 3. Section 4 includes the numerical results for our test cases. We illustrate our proposed approach and results with respect to the Aegean Sea sub-area in Section 4. Finally, in Section 5, we present a summary and conclusion of our work.

2. Literature Review

There are a number of *p*-MP model applications in literature considering interesting location problems. In their study [17], authors utilize *p*-MP MIP model to determine sensor locations in municipal water networks with the aim of minimizing impact of contamination in municipal water. They use the analytic model to react rapidly in case of emergencies such as accidental contamination or chemical terrorist attacks on municipal water networks, which are threatening cases on the public health. In [18], Antunes formulates a combined optimization model of *p*-MP and capacitated-facility-location models to deal with the problem of determining solid-waste facility locations in Central Portugal. The problems associated with allocating large-scale emergency response systems is also a common application field of *p*-MP models. For example, in their study [19], Serra and Marianov develop a *p*-MP model to allocate fire stations in Barcelona. In another study [20], authors evaluate the efficiency of *p*-MP approach with others, such as covering and center models, on Large-scale Emergency Medical Service (LEMS) in the Los Angeles area. In [21] and [22], an optimization model with *p*-MP is prepared to allocate SAR resources with the aim of intercepting maritime incidents rapidly.

First defined in [12], researchers applied the MCLP to various facility location sectors such as allocation of security-military firms, warehouses, emergency systems and healthcare facilities. In their study [23], authors formulate a MCLP model for determining the locations of video sensors to control the security of an urban area. As another military application, [24] study the problem of enhancing maintenance schedules of Intercontinental Ballistic Missiles (ICBM) for a given security requirement level. They formulate a two-stage MCLP model with the objective of maximizing the satisfaction level of demands at missile alert facilities while confronting US Air Force regulations. In emergency response systems and healthcare facilities, it is important to develop a location plan which allows serving maximum number of people with limited resources on hand. In [25], researchers study the problem of determining the locations for delivering medicines in a large city under a possible bio-terror attack. They develop a special case of the MCLP which considers the distance-dependent coverage and demand uncertainty and apply the model to a possible anthrax attack scenario in city of Los Angeles. In a similar study [26], a Capacitated MCLP model is utilized to allocate the healthcare facilities in Selangor, Malaysia. As a solution approach, they propose a genetic algorithm which analyzes the ratio of coverage of the emergency facilities within the allowable distance specified.

In a number of facility location problems, decision makers require covering each demand point more than one facility at any time. Thus, the problem becomes a *Q*-coverage (also known as *K*-coverage) problem in which the objective is to cover each demand point in the area of interest with at least *Q* facilities. WSN problems constitute a large amount of *Q*-coverage applications in literature. Chaudhary and Pujari study the problem with the objective of maximizing sensor network lifetime while satisfying the desired *Q*-coverage level and propose a heuristic algorithm which provides approximate solutions to optimal [27]. In their study [28], authors consider three kinds of sensor deployment patterns, such as square unit grids deployment, random uniform deployment and Poisson deployment of n sensors while retaining Q-coverage level of protected area at all times. In addition, they consider the sleep schedule of sensors in order to extend the lifetime of the WSN. In another study [29], Hefeeda and Bagheri aim to deploy a WSN for early detection of forest fires in British Columbia, Canada and formulate the problem as a node Q-coverage problem. In [30] Curtin, Hayslett-McCall, and Qiu develop a methodology to integrate Geographic Information System (GIS) with linear programming optimization for generating alternative optimal solutions. They also study the problem of locating police patrol and account for the backup coverage.

Classic facility location problems have been modified to interest in multiple facility types and multiple coverage. In [31], Daskin and Stern formulate Hierarchical Objective Set Covering (HOSC) to determine minimum number of emergency medical service (EMS) vehicles for covering all demand locations while maximizing the extent of multi-covered zones. In [32], authors formulate a model to deploy ambulances in Santa Domingo, Dominican Republic. They aim to maximize the multiple coverage of demands within a pre-determined critical response time with limited number of vehicles. In [33], McLay develops the maximum expected coverage location problem with two types of servers (MEXCLP2) to consider multiple server/facility and demand types and improves survival rates achieved in previous EMS models. In addition to these approaches and applications, a number of surveys provide an excellent vision to covering problems in facility location. For example, [34] displays a view of three classical models, such as median, center and covering models in facility location problems. A distinguished review [2] categorizes covering problems and presents all aspects of each sub-categorize neatly. In [35], authors survey classical facility locations problems and develop a general facility location model which can be shaped as median, center and covering model. They apply the model as covering, center and median models for allocating medical supply storage to distribute antibiotics, vaccines and drugs rapidly under a possible chemical, biological, radiological and nuclear (CBRN) terrorist attack in city of Los Angeles and compare those models.

3. Optimization model

Different from the classical facility location problems, in this study we consider the Q-coverage problem with primary and backup facility assignments. In specific, for each demand, we name its nearest facility as the *primary* facility. In cases when multiple coverage (Q > 1) is required, the remaining facilities that cover (or assigned) a demand are named as the *backup* facilities. For the p-MP model we assume that a demand is Q covered by assigning primary and Q-1 backup facilities to it. We now begin formulating the p-MP and MCLP models with the Q-coverage requirement.

3.1. Q-coverage p-MP problem formulation

- <u>*Sets and Indices:*</u>

$i \in I$: set of candidate locations
$j \in J$: set of demand locations

- <u>*Parameters:*</u>

m = number of candidate sites ($m = |I|$)
p = number of candidate facilities
n = number of demand locations ($n = |J|$)
h_j = weight of demand j
d_{ij} = distance between locations i and j
Q = minimum number of coverage (assignment) required

- <u>*Decision Variables:*</u>

$$y_i = \begin{cases} 1, & \text{a facility is sited at location } i \\ 0, & \text{otherwise} \end{cases}$$

$$z_{ij} = \begin{cases} 1, & \text{demand } j \text{ is assigned to a facility at location } i \\ 0, & \text{otherwise} \end{cases}$$

- <u>*Objective function:*</u>

$$\min \sum_{i \in I} \sum_{j \in J} h_j d_{ij} z_{ij} \qquad (1)$$

- *Constraints:*

$$\sum_{i \in I} y_i = p \tag{2}$$

$$\sum_{i \in I} z_{ij} = Q, \qquad \forall j \in J \tag{3}$$

$$z_{ij} \le y_i, \ \forall i \in I, j \in J \tag{4}$$

$$y_i, z_{ij} \in \{0,1\}, \qquad \forall i \in I, j \in J \tag{5}$$

The objective function (1) seeks to minimize the total weighted distance between demands and their nearest facilities. Constraint (2) restricts the number of sited facilities to p. Constraint (3) ensures that all demand locations are covered by Q facilities. Constraint (4) ensures that the facilities that are nor activated cannot cover any demand. Constraint (5) declares the variable types.

3.2. Q-coverage MCLP problem formulation

In addition to the notation defined above, for formulating the *MCLP* problem we define the additional set N_j and change the z_{ij} variable as z_j as follows:

- *Sets and Indices:*

$i \in I$: set of candidate locations
$j \in J$: set of demand locations
$N_j = \{ i \in I \mid d_{ij} \le r \}$ (r is defined in the parameters group)

- *Parameters:*

m = number of candidate sites ($m = |I|$)
p = number of candidate facilities
n = number of demand locations ($n = |J|$)
h_j = weight of demand j
d_{ij} = distance between locations i and j
Q = minimum number of coverage (assignment) required
r = maximum range of a facility

- *Decision Variables:*

$$y_i = \begin{cases} 1, & \text{a facility is sited at location } i \\ 0, & \text{otherwise} \end{cases}$$

$$z_j = \begin{cases} 1, & \text{demand } j \text{ is assigned to a facility} \\ 0, & \text{otherwise} \end{cases}$$

- *Objective function:*

$$\max \sum_{j \in J} h_j z_j \tag{6}$$

- *Constraints:*

$$\sum_{i \in I} y_i = p \tag{7}$$

$$\sum_{i \in N_j} y_i \ge z_j Q, \qquad \forall j \in J \tag{8}$$

$$y_i, z_j \in \{0,1\}, \qquad \forall i \in I, j \in J \tag{9}$$

The objective function (6) aims to maximize the total weighted number of demands covered. Constraint (7) restricts the number of sited facilities to p. Constraint (8) ensures that all demand locations are covered by at least Q facilities. Constraint (9) declares the variable types.

3.3. Performance Metrics

This section introduces the criteria used to compare the performances of both location model solutions. The criteria considered in this study aim to measure and examine the efficiency of the solutions in terms of distances between demand locations and facilities, and number of demand locations covered. In specific we define five different decision criteria defined as follows:

- C_1 - Mean distance to primary: This criterion evaluates the mean distance between each demand location and its nearest facility. Being a very common criterion, especially in emergency service location analysis studies, this performance metric aims to measure the effectiveness of a given solution in terms of average travel distance. If the problem incorporates mobile demands or facilities with different speeds (such as ambulances or search and rescue vehicles) another alternative to measure of proximity would be the mean response time instead of distance. For the MCLP model we assign each demand with a primary facility without considering the maximum range of a facility. Therefore although a demand does not lie within the maximum range of any facility, it is still assigned with a primary and backup coverage consistent with the definition.

- C_2 - Mean distance to primary and backup: Similar to C_1, this criterion evaluates the mean distance between a demand and its designated Q facilities. In other words, this criteria measures the performance of a solution considering the distances to both primary and backup coverage locations.

- C_3 - Mean distance to backup(s): This criterion evaluates the mean distance between a demand and its designated Q-1 backup facilities. The main purpose of this criterion is to measure the effectiveness of backup supplies when the primary is busy with serving other demands. As mentioned earlier, in emergencies, response time is crucial. Hence, a short mean distance to the backup facilities plays an important role to enhance the performance of an allocation plan especially in cases where the number of demand locations is large.

- C_4 - Ratio of demand with both primary and backup coverage within a range threshold: This criterion measures the ratio of demand locations that are covered by at least Q facilities. When measuring the performance of the p-MP model, we compute this value by assigning the same maximum coverage range r to each facility as defined in the MCLP model. This ratio expresses the ratio of demands that can receive both primary and backup service within a certain time.

- C_5 - Ratio of demand with at least primary coverage within a range threshold: This metric quantifies the ratio of demand locations that are covered by at least one facility. Once again we utilize r parameter for measuring the performance of the p-MP model. By computing this ratio we seek to determine the ratio of demands that receive at least one service within a time or distance threshold.

4. Experimental Results

In our experiments, we generate demand and candidate facility locations uniform randomly inside a 100km x100km square region. We fix the basic parameters as m = 20, n = 200 and p = 10. For all trials we assume that demands are of equal weight and $h_j = 1, \forall j$. Next, we run 30 replications and generate different instances of facility location problems. For each instance, we solve the problem by both location models for three different values of r = 10, 15 and 20 km and three different values of Q = 1, 2 and 3.

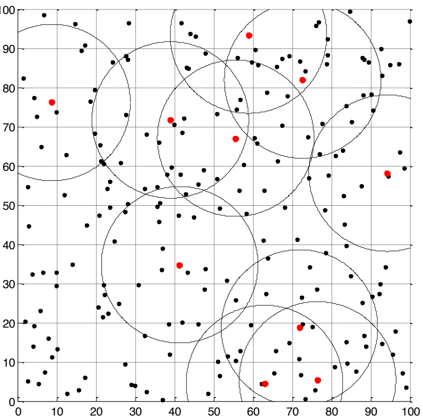

Fig. 1. (a) Exemplary MCLP solution. Each circle represents the coverage region of a facility. A demand location that lies within a circle is assumed to be covered.

Fig. 1 is an exemplary solution for MCLP model with 10 facilities and 200 demand. In the figure a demand location that lies within a circle is assumed to be covered. The model aims to cover as many demand locations as possible with respect to the Q-coverage requirement. Fig. 2 shows the primary and backup facility assignments for the given MCLP solution given in Fig.1. for Q = 1, 2 and 3. In Fig. 2(a) each demand is assigned to its nearest facility (primary only) since the coverage requirement is one. However in Fig. 2(b) and (c) each demand is additionally assigned to one and two backup facilities, respectively.

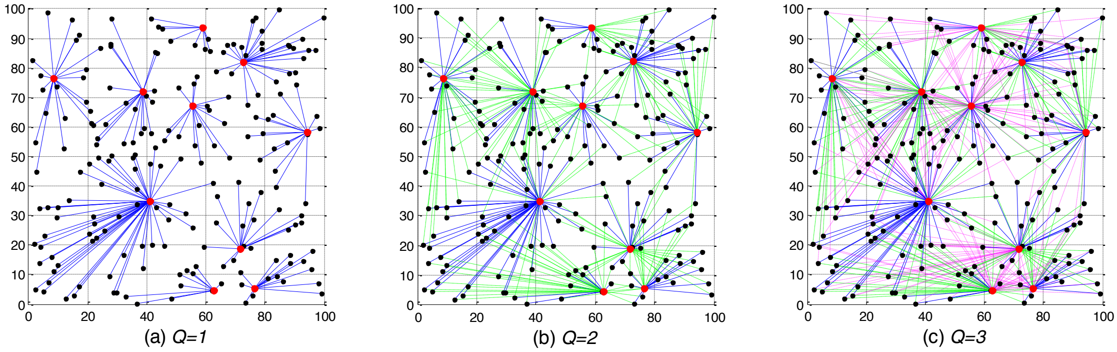

Fig. 2. Example of primary and backup facility assignments for (a) Q = 1; (b) Q = 2; (c) Q = 3. Each line represents the assignment for a demand. For Q = 2 and 3 each demand is assigned with both primary and backup facilities. Blue solid, green dashed and purple dotted lines represent the assigned primary, first backup and second backup facilities, respectively.

We generate problem instances and solve the optimization models in the General Algebraic Modeling System (GAMS©) environment using CPLEX 12.2.0.2. Tables 1, 2 and 3 summarize the performances of models with respect to five decision criteria for r = 10, 15 and 20, respectively. The values in the tables represent the averaged values over all 30 replications. We use those averaged values to compare the models considered in this study.

Table 1. Experimental results and comparison of model solutions for r = 10.

		Q = 1		*Q = 2*		*Q = 3*	
Criteria #	Definition	*p*-MP	MCLP	*p*-MP	MCLP	*p*-MP	MCLP
C_1	Mean distance to primary	13.621	14.743	14.619	21.596	15.466	21.016
C_2	Mean distance to primary and backup	13.621	14.743	18.811	23.838	23.141	28.565
C_3	Mean distance to backup(s)	-	-	23.004	26.08	26.978	32.34
C_4	Ratio of demand with both primary and backup coverage within a range threshold	31,833%	34.883%	4.3%	10.417%	0.45%	2.64%
C_5	Ratio of demand with at least primary coverage within a range threshold	31,833%	34.883%	30.017%	21.867%	26.283%	21.967%

Table 2. Experimental results and comparison of model solutions for r = 15.

		Q = 1		*Q = 2*		*Q = 3*	
Criteria #	Definition	*p*-MP	MCLP	*p*-MP	MCLP	*p*-MP	MCLP
C_1	Mean distance to primary	13.625	13.912	14.624	20.267	15.152	23.764
C_2	Mean distance to primary and backup	13.625	13.912	18.687	22.72	23.265	29.342
C_3	Mean distance to backup(s)	-	-	22.749	25.174	27.322	32.132
C_4	Ratio of demand with both primary and backup coverage within a range threshold	62.25%	63.7%	16.183%	26.616%	2.15%	10.817%
C_5	Ratio of demand with at least primary coverage within a range threshold	62.25%	63.7%	56.817%	42.533%	54.333%	36.5%

Table 3. Experimental results and comparison of model solutions for $r = 20$.

		$Q = 1$		$Q = 2$		$Q = 3$	
Criteria #	Definition	p-MP	MCLP	p-MP	MCLP	p-MP	MCLP
C_1	Mean distance to primary	13.625	13.849	14.625	17.844	15.152	23.427
C_2	Mean distance to primary and backup	13.625	13.849	18.687	20.657	23.265	28.782
C_3	Mean distance to backup(s)	-	-	22.75	23.471	27.322	31.459
C_4	Ratio of demand with both primary and backup coverage within a range threshold	83.633%	85.35%	37.633%	46.817%	9.223%	24.25%
C_5	Ratio of demand with at least primary coverage within a range threshold	83.633%	85.35%	77.4%	64.717%	74.767%	50.333%

The experimental results reveal the strong and weak sides of both location models in terms of decision criteria. For all values of r, p-MP outperforms MCLP in terms of mean distance to primary, mean distance to primary and backup, and mean distance to backup(s), as expected. In general, the difference increases as the required coverage is increased. On the average p-MP outperforms MCLP in C_1 by 4% for $Q = 1$, 36% for $Q = 2$ and 49% for $Q = 3$. Considering C_2, p-MP outperforms MCLP approximately by 4% for $Q = 1$, 20% for $Q = 2$ and 24% for $Q = 3$. Lastly the difference in C_3 is approximately 10% for $Q = 2$ and 17% for $Q = 3$. MCLP outperforms p-MP only in terms of the ratio of demand with both primary and backup coverage (C_4) within the range threshold (r). This is mainly because the purpose of MCLP is solely to maximize the number of demands with Q-coverage. The p-MP performs significantly bad for $Q = 2$ and 3. As expected the both models perform better for large values of r. For the ratio of demand with at least primary coverage within a range threshold criteria (C_5), p-MP and MCLP have almost equal performances for $Q = 1$. However, for $Q = 2$ and 3 p-MP solutions have higher ratios of demand with at least a primary coverage. For example for $Q = 3$ and $r = 20$ p-MP ends up with 75% of demands with at least a primary coverage whereas MCLP ends up with 50% of demands with at least a primary coverage.

5. Conclusion

In this study we evaluated the performances of two classic facility location problems, i.e. p-MP and MCLP, under Q-coverage requirement with respect to a number of criteria. Our methodology involves generating multiple scenarios and solving each scenario by both location models for different Q and r values. In order to create a fair comparison of models, we evaluated them basically for mean distances to primary and/or backup coverages as well as the ratio of demand with primary and/or backup coverage. The results show that, in general p-MP outperforms MCLP in four criteria out of five. Thus, a decision maker who wants to minimize the mean distance to designated facilities while trying to maximize the ratio of demand locations with at least a primary coverage should prefer p-MP to MCLP. The effectiveness of MCLP increases as Q-coverage level requirement and range r increases.

Future work may consider the sensitivity of our comparison results to changes in other factors, such as the number of demands and facilities, and the size of the area. Future work may also extend the comparison for other extensions of the models, such as capacitated facilities, stochastic demand, etc.

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