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Optimization of Static and Mobile Facility Location Selection: Method and Case Study

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by

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Abstract

The Facility Location Problem is an important research topic in spatial analysis that has been the focus of study for over forty years. This thesis focuses on the Static and Mobile Facility Location Problem (SMFLP), which aims to identify those static and mobile facility locations that serve a target area most efficiently and equally. This thesis formalizes the SMFLP as a bi-objective model and then solves the model by using a new heuristic algorithm, named Static and Mobile Facility Location Searching (SMFLS). The algorithm consists of two steps: static facility location searching and mobile facility location searching. In order to solve the model for large datasets efficiently, a clustering-based heuristic method is proposed for the static facility location searching while the mobile facility location searching is implemented using a greedy heuristic method. Experiments on synthetic and real datasets demonstrate the efficiency and practicality of the SMFLS algorithm.

This thesis also presents a customized method for applying the SMFLP to the preventive health care services context. In order to capture the characteristics of preventive health care services, a new accessibility measurement is defined for measuring the utilization of preventive health care facilities. Due to the requirements for high accuracy in the location of static preventive health care facilities, the static facility location searching step in the SMFLS for preventive health care services is implemented using the Interchange algorithm together with two new data structures, ‘population groups’ and ‘candidate string’. A detailed case study of the Alberta breast cancer screening program shows that the method can optimize the location of screening clinics

and mobile screening units so as to maximize the accessibility of the breast cancer screening service in Alberta, Canada.

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Table of Contents

List of Tables

List of Figures and Illustrations

List of Symbols, Abbreviations and Nomenclature

Symbol	Definition
2SFCA	Two-steps Floating Catchment Area
ABCSP	Alberta Breast Cancer Screening Program
API	Application Programming Interface
CSD	Census Subdivision
CT	Census Tract
DA	Dissemination Area
EMS	Emergency Medical Service
FCA	Floating Catchment Area
GIS	Geographical Information System
PCCF	Postal Code Conversion File
PHSMFLP	Preventive Health Care Static and Mobile Facility Location problem
SMFLP	Static and Mobile Facility Location Problem
SMFLS	Static and Mobile Facility Location Searching
VNS	Variable Neighborhood Search

CHAPTER ONE: INTRODUCTION

1.1 General Introduction

The facility location problem is an important research topic in spatial analysis. The aim of the problem is to determine a set of locations for supply facilities so as to minimize the total supply and assignment costs (Owen and Daskin, 1998). Given the importance of effective facility locations, the facility location problem has been widely applied to real world situations that include a broad spectrum of private firms (e.g., industrial plants, banks, retail facilities, etc.), and public firms (e.g., hospitals, bus garages, etc.) (Owen and Daskin, 1998).

According to Cooper (1964), and Brandeau and Chiu (1989), the facility location problem is comprised of the following issues. First, the locations of facilities depend on the locations of clients and their behaviour with respect to how they obtain the service from facilities. Second, the facility location problem includes two questions: *where* to locate facilities and *how* to allocate clients to facilities. Third, the problem can be solved by being formalized in terms of an objective model. Typical objectives include: minimizing the average travelling distance between clients and facilities, minimizing the maximum travelling distance or maximizing the minimum travelling distance between clients and facilities. Different facility location problems are presented with various objectives and have different constraints (ReVelle et al., 1981; Sahina and Sralb, 2007).

1.2 Problem Statement and Research Objectives

This thesis focuses on one type of facility location problems, i.e., the Static and Mobile Facility Location Problem (SMFLP). The problem is to identify locations for both static facilities and mobile facilities in order to serve a given target area efficiently and equally (Gu and Wang, 2010). The static facility is located with the aim of improving the *efficiency* of facility locations, i.e., minimizes the average travelling distance between static facilities and clients. The mobile facility is located with the aim of improving the *equity* of facility locations, i.e., minimizes the maximum travelling distance for clients to get service either from static facilities or mobile facilities. In reality, many services have to be delivered by using a combination of both static and mobile facilities. For example, for emergency medical services, hospitals should be located to achieve full coverage of the people in a target region while ensuring the minimum average travelling distance. This usually results in hospitals being located near to, or within, dense communities. However, patients in sparse and remote areas may live far away from a hospital since the total number of the hospitals is limited. In order to offer fast response service for patients in an entire region, ambulances must be located in a way that shortens the maximum travelling distance for patients to access medical services. Compared with the facility location problems dealing with single facility type (Brandeau and Chiu, 1989; Owen and Daskin, 1998), the SMFLP is more complicated in that it requires two different searching strategies for static facilities and mobile facilities while taking into account the inter-relations between these two types of facilities. However, none of existing methods can be applied to the SMFLP directly.

This thesis formalizes the SMFLP as a bi-objective facility location model and then solves the model by using a new heuristic algorithm named Static and Mobile Facility Location Searching (SMFLS). The algorithm splits the location decision into two steps: static facility location searching and mobile facility location searching. In order to solve the model for large datasets efficiently, a clustering-based heuristic method is proposed for the static facility location searching while the mobile facility location searching is implemented using a greedy heuristic method.

Preventive health care programs can save lives and contribute to a better quality of life by diagnosing serious medical conditions early. The SMFLP of preventive health programs is to identify locations for static preventive health care facilities (e.g., screening clinics) and mobile preventive health care facilities (e.g., mobile screening units) so as to maximize the participation rate. Since preventive services are provided to people with no clear symptoms of illness, people who seek these services have more flexibility as to when and where to receive them and they might not seek these services from the closest preventive health care facility (Verter and Lapierre, 2002; Zhang et al., 2009; Gu et al., 2010). Under this context, it is not suitable for the efficiency and equity of preventive health care facility locations to be defined based only on the travelling distance between facilities and clients.

This thesis presents a customized method for solving the SMFLP for preventive health care services. In order to capture the characteristics of preventive health care services, a new accessibility measurement for quantifying the utilization of preventive health care facilities is defined in the method. Based on the new definition of accessibility, the preventive health care static and mobile facility location model is proposed, whereby the SMFLS algorithm is applied to solving the model. Due to the requirements for high accuracy in the location of static preventive health care facilities, the static facility location searching of the SMFLS algorithm is implemented using the Interchange algorithm (Teitz and Bart, 1968) instead of the clustering-based heuristic method. In addition, two new data structures, 'population groups' and 'candidate string,' are built for accelerating the static facility location searching by pre-storing the accessibility information. The customized method is evaluated for a real application: optimizing the facility location configuration for the breast cancer screening program in Alberta, Canada. Experimental results show that the method can optimize the location of screening clinics and mobile screening units so as to maximize the accessibility of the breast cancer screening service within the province.

1.3 Thesis Outline

Chapter Two gives a literature review of facility location modeling and solution approaches, the methods for assigning facility capacity and the methods for measuring facility workload and regional availability. Chapter Three formalizes and solves the SMFLP. It starts by formalizing the problem as a bi-objective model in terms of efficiency and equality. After that, the SMFLS algorithm is proposed for solving the model. Finally, the SMFLS algorithm is evaluated by applying it to synthetic and real datasets. Chapter Four presents a customized method for solving the SMFLP for preventive health care services. It starts by introducing the characteristics of the preventive health care facility location problem and then defining a new accessibility measurement for capturing the characteristics. After that, the problem is formalized as a bi-objective model based on the new accessibility measurement and the SMFLS algorithm is customized to solve the model. Finally the method is evaluated through applying it to a real application. The final conclusions and recommendations for future work are discussed in Chapter Five.

CHAPTER TWO: LITERATURE REVIEW

This chapter reviews previous studies on the facility location research. First, three basic facility location models and two static and mobile facility location models are presented. Second, the review of the methods of considering facility capacity constraint is given. Third, the measurement of regional availability is introduced. Finally, the review of heuristic solution approaches to facility location models is presented.

2.1 Facility Location Models

Given the importance of the facility location research, a vast number of facility location models has been developed to represent a wide range of facility location problems.

2.1.1 Basic Facility Location Models

Three basic facility location models are: *the P-median model*, *the covering model* and *the center model* (Owen and Daskin, 1998).

The *P*-median model seeks, for a given number of facilities, to identify locations that minimize the average travelling distance from all clients to their closest serving facilities. According to Church and ReVelle (1976), one important way to measure the effectiveness of a facility location is by determining the average travelling distance travelled by those who visit it. With increasing average travelling distance, facility accessibility decreases, and thus, the location's effectiveness decreases. This relationship holds for facilities such as libraries and schools, to which proximity is desirable.

However, this model does not consider the “worst case” situation and so it may result in inequities, forcing a few remote clients to travel far.

The covering model finds locations of a given number of facilities that maximize the total clients covered by these facilities within a maximum acceptable travelling distance. The critical nature of demands for service will dictate a maximum “acceptable” travelling distance or time. The covering model is useful to locate some facilities when minimizing the average travelling distance may not be appropriate. For example, emergency service facilities such as fire stations or ambulances need to be located within 15 minutes travelling time of every client. The covering problem model is widely used to determining the deployment of Emergency Medical Service (EMS) vehicles in various settings (Daskin, 1982; Jia et al., 2007).

The center model, for a given number of facilities, identifies a location arrangement that minimizes the maximum distance between clients and facilities while requiring coverage of all clients. Unlike the covering model, which takes an input coverage distance, this model determines the minimal coverage distance associated with locating a given number of facilities. This model is useful when there are not enough facilities in reality while the service has to cover all the clients within a target region.

2.1.2 Static and Mobile Facility Location Models

The static and mobile facility location problem is a specific type of facility location problem (Sahina and Sralb, 2007). In the problem, the services would be delivered to clients by the cooperation of static and mobile facilities. Several models have been developed for locating static and mobile facilities.

Sanchez (2002) proposes a model to find locations of static and mobile facilities within the industry context. In the model, both static facilities and mobile facilities are located to maximize profits with the constraint that both static facilities and mobile facilities can only serve a given number of clients (called capacity). The static facility cannot be revoked or relocated while the mobile facility can be revoked or relocated in a period for thriving in face of continuous and unpredictable change of clients' demands. The model is useful when only static facilities are no longer the best or the unique solution to satisfy clients' demands in a target area. Since the model is developed for maximizing profits, the equity of facility locations is not discussed.

Lapierre et al. (1997) claim the need of using static and mobile facilities in preventive health care services. In their model, the static facility is hospital, clinic or other medical center where most health care services are delivered. The mobile facility is the one which can give a specific medical service and can be relocated during a period. For example, in mammography screening service, each screening vehicle is a mobile facility which is located in a parking lot or community. The model has two steps. The first step is to find locations of a given number of static facilities that maximize the total clients covered by these facilities within a maximum acceptable distance, which equals to the covering model. The second step is to find locations of mobile facilities that minimize the number of mobile facilities to serve the clients uncovered by the static facilities. Although the equity of facility locations is satisfied in the model (i.e., covering all the clients within an acceptable distance), the efficiency of facility locations is not discussed (i.e., the average travelling from clients and their closest facilities). In addition, the solution approach to the model is not discussed in their work.

2.2 Facility Capacity Constraint

According to the discussion above, some facility location models consider the facility capacity constraint, i.e., each facility can serve a limited number of clients. Previous research adopts two ways for adding the facility capacity constraint, which are facility capacity assignment and facility workload measurement.

2.2.1 Facility Capacity Assignment

Several facility capacity assignment methods have been developed to handle the facility capacity constraint. They assign every client to its closest unfulfilled facility. The difference among various facility capacity assignment methods is the order of assignment, i.e., which client should be assigned first.

To identify the assignment with the optimal overall quality, Ghoseiri and Ghannadpour (2007) propose an urgency facility capacity assignment method. In the method, clients are assigned in a descending order of *urgency*. The urgency is a priority value is calculated for each client as the absolute difference in the distances to its first and second closest facilities.

The urgency assignment method achieves the facility capacity constraint by optimizing the assignment between clients and facilities. Compared with the classical assignment method (Wong et al., 2007) which does the assignment from the closest pair of clients and facilities, the urgency assignment method avoids the case that a client is assigned to a further facility when the facility nearby has no capacity. For example, in Figure 2.1, O_1 and O_2 represent two client sites, each of which has only one client. *a* and *b* represent facilities, each of which can only serve one client. The line between two nodes represents the Euclidean distance between them. Because the closest pair of clients and facilities is the client O_2 and the facility *a*, the classical assignment method will assign the client O_2 to the facility *a* in the first place. After that, the facility *a* has no capacity to serve any other clients. Therefore, the client O_1 has to be assigned to the facility *b*, a further facility to the client O_1. The average travelling distance from clients to their assigned facility under the classical assignment is (2+10)/2 = 6. For the urgency assignment method, the client O_1 and O_2's urgency values are calculated first, which are 4 and 2, respectively. Based on their urgency values, the urgency assignment method will assign the client O_1 to the facility *a* first because of higher urgency value, and then assign the client O_2 to the facility *b*. The average travelling distance from clients to their assigned facility under this assignment is (6+4)/2 = 5.

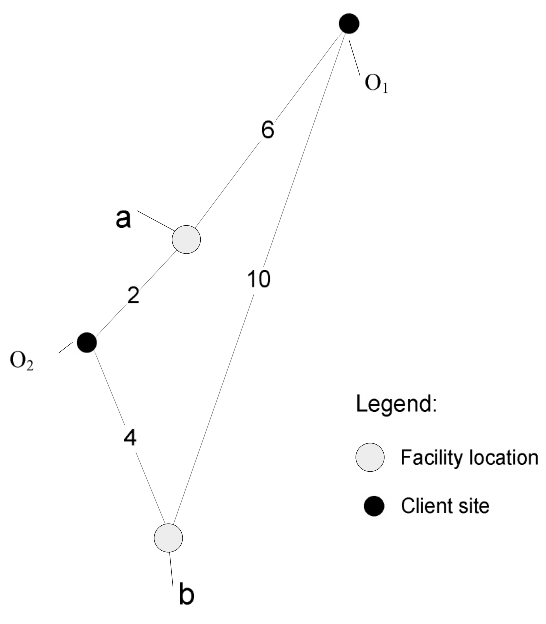


Figure 2.1: An example of capacity assignment

Although the urgency assignment method optimizes the assignment between clients and facilities (i.e., minimize the average travelling distance between clients and facilities), it asks for clients to follow the assignment decision while ignores the clients' choice. Thus, the more control of clients' behaviour a planner has, the more usefulness the urgency assignment method is.

2.2.2 Facility Workload Measurement

For a set of facility locations, facility workload measurement estimates the workload of each facility when the clients' choice needs to be considered for the capacity constraint. The set of facility locations satisfies the facility capacity constraint only if the estimated workload of every facility is lower than its capacity.

One of the most widely used facility workload measurement is the Huff-based competitive location model (Huff, 1964). The model assumes that a client may get service from any facility within the acceptable travelling distance instead of the closest one. The probability of a client getting service from a facility within the acceptable travelling distance is estimated using equation (2.1).

$$P_{ij} = \frac{\dfrac{S_j}{T_{ij}^{\lambda}}}{\sum_{j=1}^{n} \dfrac{S_j}{T_{ij}^{\lambda}}} \tag{2.1}$$

where P_{ij} is the probability of a client at site *i* getting service from a facility *j*;

S_j is the size of a facility *j*;

T_{ij} is the travelling time/distance between site *i* and facility j;

λ is a parameter to reflect the effect of travelling time/distance.

The expected number of clients in each site getting service from a facility can be estimated by multiplying the number of clients on the site with the probability that the clients at the site getting service from that facility. Finally, the workload of each facility is estimated by summing up the number of clients from all sites getting services from the facility.

The Huff-based competitive location model is applied into the example in Figure 2.1. The size of each facility is assumed the same and then S_j is set to one. λ is set to one. The acceptable travelling distance is set to 10. So,

$$P_{O_1a} = \frac{1}{6}/(\frac{1}{6}+\frac{1}{10}) = \frac{5}{8};$$

$$P_{O_1b} = \frac{1}{10}/(\frac{1}{6}+\frac{1}{10}) = \frac{3}{8};$$

$$P_{O_2a} = \frac{1}{2}/(\frac{1}{2}+\frac{1}{4}) = \frac{2}{3};$$

$$P_{O_2b} = \frac{1}{4}/(\frac{1}{2}+\frac{1}{4}) = \frac{1}{3}.$$

The workload of *a* is calculated as $P_{O_1a}*1+P_{O_2a}*1=\frac{5}{8}+\frac{2}{3}=\frac{31}{24}$; the workload of *b* is calculated as $P_{O_1b}+P_{O_2b}=\frac{3}{8}+\frac{1}{3}=\frac{17}{24}$. Since each facility allows serving one client at maximum, according to the Huff-based competitive location model, the distribution of facility locations in Figure 2.1 will violate the facility capacity constraint.

2.3 Measurement of Regional Availability

When the clients' choice is considered, the average travelling distance from clients to their assigned facilities is not the best way to measure the efficiency of facility locations. Regional availability (Joseph and Phillips, 1984) which describes the ratio between clients and facilities within a region has been used to measure the efficiency of facility locations. The regional availability generally assumes that given a specific range for the service being offered at a facility, every resident within that range is a potential client of the service. People living in a higher facility-to-clients ratio region can more conveniently access the service. Thus, more people in higher facility-to-clients ratio regions, more effectiveness of facility locations is.

Many methods have been proposed for measuring the regional availability, the difference of which is how to define the region. Peng (1997) proposes a Floating Catchment Area (FCA) method for measuring the regional availability. The area within a threshold travelling distance of a client is the catchment area of that client. The catchment area 'floats' from one client to another, and the facility-to-client ratio within each catchment area defines the regional availability there. Take Figure 2.2 as an example to illustrate the method. A 15-mile circle around the client O_1 defines its catchment area. There are one facility (i.e., the facility a) and one client (i.e., the client O_1) within the catchment area, and thus the regional availability for the client O_1 is the ratio 1/1. The catchment area floats from client O_1 to client O_5. There are two facilities (i.e., the facility b and c) and four clients (i.e., the client O_3, O_4, O_5, and O_6) within the 15-mile catchment area of client O_5, and thus the regional availability for the client O_5 is the ratio 2/4. The underlying assumption of the FCA method is that facilities that fall within a catchment area are fully available to any clients within that catchment area. However, not all facilities within a catchment area are reachable by every client in the catchment area, and facilities in the catchment area may also serve nearby clients outside the catchment area and thus, not be fully available to clients within the catchment. For example, in Figure 2.2, the facility *c* and the client O_6 are within the same catchment but the distance between them exceed the threshold travel distance (i.e., 15 miles). Furthermore, the facility *c* is within the catchment of the client O_5, but it may not be fully available to serve clients within the catchment because it will also serve a nearby (but outside-the-catchment) client O_7.

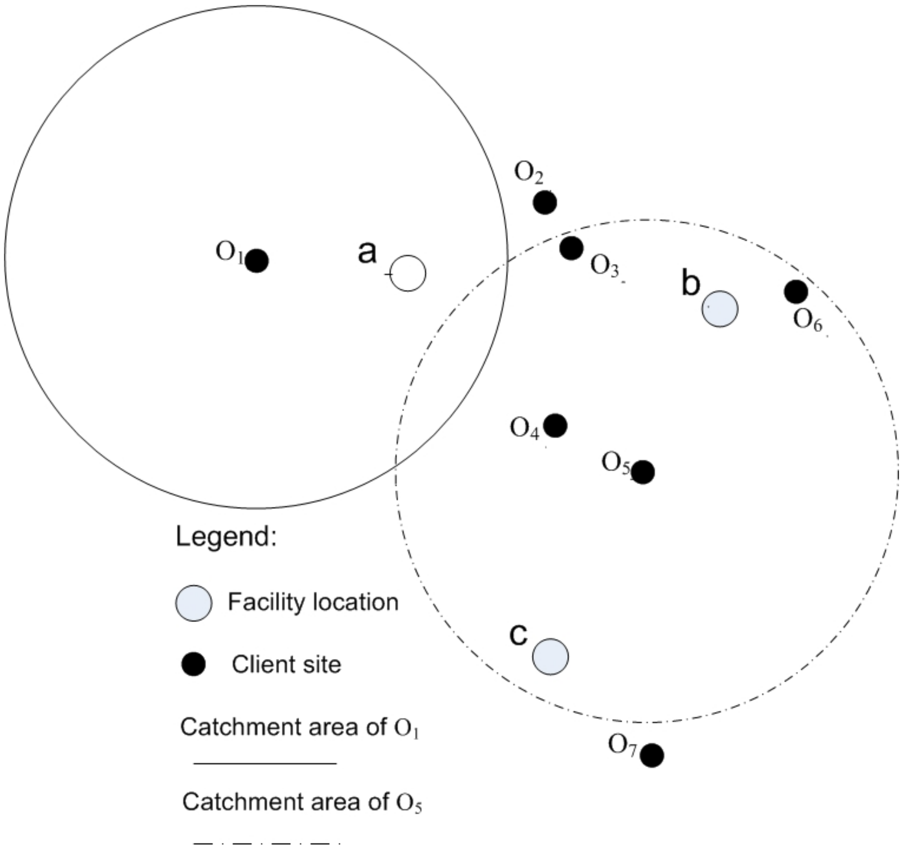


Figure 2.2: Floating catchment area method

The Two-steps FCA (2SFCA) method developed by Radke and Mu (2000) overcomes the above fallacies. It builds “floating catchment area” both for facilities and for clients. First, it computes a catchment area of each facility and calculates a facility-to-client ratio R_j of each facility by counting the number of the clients covered by the facility’s catchment area. Second, it computes a catchment area of each client and calculates the regional availability of each client by summing up all R_j values of the facilities within the client’s catchment area. Figure 2.3 takes an example to illustrate the Two-step FCA method, using the same distributions of clients and facilities as in Figure 2.2 and the threshold traveling distance is 15 miles as well. There are four clients (i.e., the client O_1, O_2, O_3, and O_4) in the catchment area of the facility *a*, and thus a facility-to-client ratio of the facility *a* is 1/4. Similarly, the facility-to-client ratio of the facility *b* is 1/5 and the facility-to-client ratio of the facility *c* is 1/3. Since the catchment area of the client O_1 has one facility (i.e., the facility *a*), the regional availability of the client O_1 is 1/4. For the client O_4, its catchment area has three facilities (i.e., the facility *a*, *b* and *c*) in that its regional availability is 47/60 (the sum of the ratios 1/4, 1/5 and 1/3).

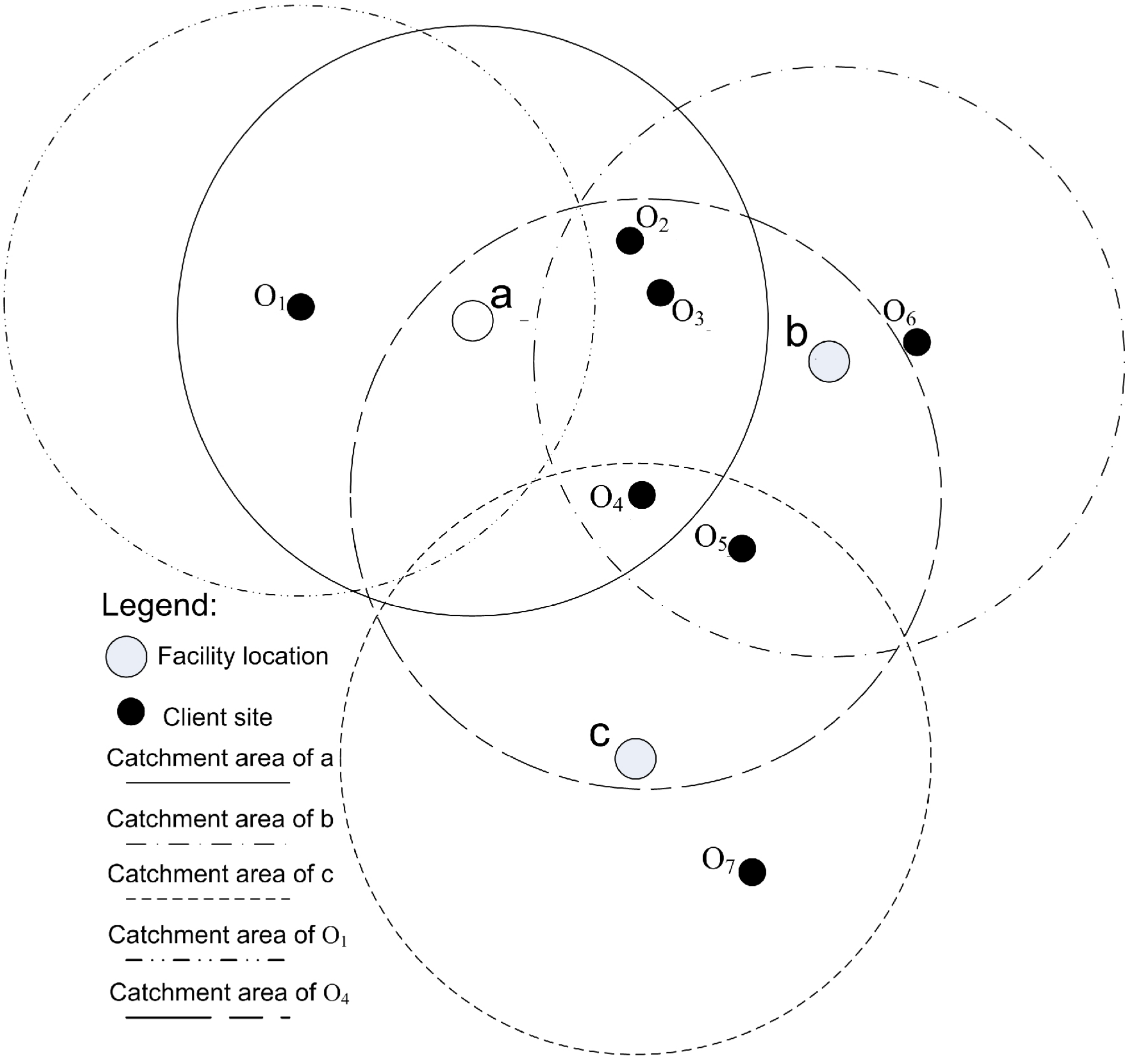


Figure 2.3 Two-steps FCA method

2.4 Heuristic Solution Approaches to Facility Location Models

The facility location problem is NP-hard (Garey and Johnson, 1979) in that attempting a facility location solution consumes a large amount of computational resources. During the past forty years, a large among of algorithms has been developed for solving the facility location models, which can be categorized as two types: *Exact Solution Approach* (Brandeau and Chiu, 1989) and *Heuristic Solution Approach* (Current et al., 2002). The exact solution approach can produce the best solution but cannot handle models with large amounts of constraints and variables since this consumes unacceptable amounts of computational resources. In order to solve a model with large amounts of constraints and variables, the heuristic approach is developed. This can produce acceptable solutions with fewer computational resources but will not guarantee finding the best solution. In the remainder of this section, several of the most common heuristic algorithms are introduced.

2.4.1 Greedy Heuristics

Greedy heuristic algorithms, first proposed by Kuehn and Hamburger (1963), use "rules-of-thumb" to find acceptable solutions of facility location models. The strategy which greedy heuristic algorithms follow is: within each iteration it puts a new facility at the location whichever reduces the total cost most. It starts by an empty configuration and stops if the configuration reaches the desired number of facilities. Once a facility is established in the configuration, it is never moved. The greedy heuristic algorithms always terminate and the computation time is known and small. However, the greedy heuristic algorithms are very likely to get caught in a local optimal solution. Consider a linear network of five points in Figure 2.4 with a demand of one for each point and a distance of one between every two neighbour points. The problem is to find the best locations for two facilities to minimize the average distance from demand points to their closest facilities. The candidate sites for facilities are those five points. The first point greedy algorithms choose is *C* because it has the minimal average distance of 6. The second point can be any of *A*, *B*, *D*, *E* since a new facility at any of these points results in an average distance of 4. However, the global optimal solution of a two-facility configuration is *B* and *D* which has an average distance of only 3.

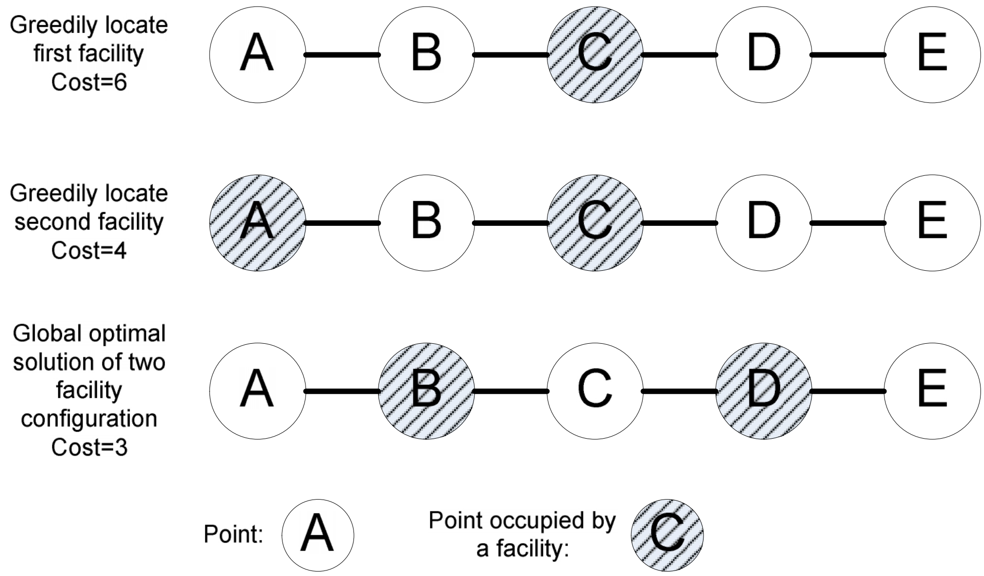


Figure 2.4 Local optimal solution produced by greedy heuristic algorithms and global optimal solution[1]

[1] The example in Figure 2.4 is taken from Figure 2 in (Kaiser, 2000)

2.4.2 Interchange Heuristics

While greedy heuristic algorithms are effective at finding feasible solutions of facility location models with modest computational effort, neither can be relied on to consistently produce good solutions. Therefore, several advanced heuristics approaches have been developed that can produce stable feasible solutions. Among them, the most well-known algorithm is the Interchange algorithm (Teitz and Bart, 1968). The basic idea of the Interchange algorithm is to relocate a facility from its site in the current solution to an unused site. If the relocation produces a better value for a facility location model, then the change is accepted and a new solution is generated. Otherwise, the relocation is cancelled. The search process is repeated until no better solution can be found after relocating every facility.

The following two advantages make the Interchange algorithm popular. First, the Interchange algorithm frequently performs very well to find optimal solutions, compared with other heuristics (Rosing et al., 1979). Second, the Interchange algorithm is not tied to any particular data structure in that it can solve many problems (Hillsman, 1984). The Interchange algorithm can be accelerated to solve a particular facility location model if the spatial structure of that model is considered. A large number of approaches have been proposed to accelerate the Interchange algorithm for solving different facility location models, such as the approach for the location allocation model (Densham and Rushton, 1992), the approaches for the p-median model (Whitaker, 1983; Hansen and Mladenovic, 1997; Resende and Werneck, 2007), and the approach for the p-center model (Mladenovic et al., 2003).

To include the capacity constraint, Liao and Guo (2008) propose a clustering based approach to implement the Interchange algorithm. The workflow of the approach is: First, initialize a set of facility locations from a set of candidate sites. Second, assign the clients to their closest unfulfilled facilities and group each facility together with the clients assigned to it as a cluster. Third, change each facility from its current location to the centroid of the cluster which covers the facility. When a change produces a better value of the facility location model, then that change is accepted and an improved solution is obtained. Repeat the second and third steps until no better solution can be found. However, since a facility is swapped to the centroid of the cluster, the facility locations in the final solution are not limited to be among the candidate sites for the facilities which may not reach the requirement in reality (e.g., the selected location is in a lake).

2.4.3 Metaheuristics

Although solutions produced by the Interchange algorithm are consistently good, it is still a possibility that the Interchange algorithm gets caught in a local optimal solution. To escape local optima, several metaheuristic algorithms have been developed recently. Metaheuristic algorithms can obtain close-to-optimal solutions by exploring a large portion of the search space in an organized fashion.

One of the earliest metaheuristic algorithms is *Tabu search* (Glover and Laguna, 1997). It's based on intelligent problem-solving methods, implementing the "memory" in a strategic and direct way. The tabu search uses a neighborhood search procedure to iteratively move from a solution x to a solution x' in the neighborhood of x, until some stopping criterion has been satisfied. To explore the search space efficiently, the tabu search defines the Tabu list to inhibit moving to some solutions. The Tabu list is a short-term memory structure which contains the solutions that have been visited in the recent past.

The varieties of local optimal solutions identified by conventional heuristic algorithms (e.g., the Interchange algorithm) often have an interesting characteristic. That is the solutions which are quite similar in the set of locations chosen for facilities. Rosing and ReVelle (1997) develop the *Heuristic Concentration* approach by using this characteristic. In the approach, they first apply a conventional heuristic algorithm repeatedly to get a set of local optimal solutions. Second, the selected locations from the set of local optimal solutions are used as a reduced set of potential facility sites. Finally, this reduced set produces a smaller model that can then be solved using an exact solution approach.

Hansen and Mladenovic (1997) present a Variable Neighborhood Search (VNS) algorithm for solving facility location models. In their approach, the notion of a neighborhood is extended. That is, the k-level neighborhood from a facility location solution is the set of solutions that can be obtained by moving k facilities in the original solution. The VNS algorithm first performs a 1-level neighborhood search (e.g., using the Interchange algorithm) on the current solution until it settles in an optima. It then diversifies the search by randomly selecting a solution from a k-level neighborhood from the current best solution. If the new selected solution is better, then the algorithm restarts the search from the new selected solution. The process continues, incrementing k, until some specified maximum value of k is attained. The algorithm compares very well with conventional heuristics as well as the tabu search.

CHAPTER THREE: STATIC AND MOBILE FACILITY LOCATION OPTIMIZATION

This chapter presents a new method for solving the Static and Mobile Facility Location Problem (SMFLP). It starts by formalizing the SMFLP as a bi-objective model. Second, a new heuristic algorithm, named Static Mobile Facility Location Searching (SMFLS) algorithm (Gu et al. 2009a; Gu et al. 2009b; Gu and Wang, 2010), is developed for solving the model. Finally, the SMFLS algorithm is tested on synthetic datasets and a real dataset.

3.1 The Static and Mobile Facility Location Model

Given a set of population centers and a set of candidate sites for facilities, the *Static and Mobile Facility Location Problem* (SMFLP) is to identify locations for the predefined number of static facilities and mobile facilities that maximize the efficiency and equity of facility locations. Unlike the research related with the static and mobile facility before, the SMFLP asks for different strategies to locate the static facility and the mobile facility. The static facility is located with the aim of improving the efficiency of facility locations by minimizing the average travelling distance between static facilities and population centers. Mobile facility is located with the aim of improving the equity of facility locations by minimizing the maximum travelling distance for people in population centers to get service either from the static facility or the mobile facility. In the following, the formalization of the efficiency and equity of facility locations is introduced first. Then, the bi-objective model based on the efficiency and equity for the SMFLP is given for the location optimization.

Definition 1 (**Efficiency**) Given a set of population centers *P* and a set of static facilities *S*, the efficiency of facility locations is the population weighted average travelling distance from population centers to their assigned static facilities, as shown in equation (3.1).

$$\frac{\sum_{p \in P} dist(p,s) * p.w}{\sum_{p \in P} p.w}, \tag{3.1}$$

where, $s \in S$, $p \in P$ and clients in population center p is assigned to get the service from static facility s ; $p.w$ is a positive number representing the number of clients in population center p . With the increase of the value of equation (3.1), the efficiency of facility locations decreases, vice versa.

Definition 2 (**Equity**) Given a set of population centers *P*, a set of static facilities *S* and a set of mobile facilities *M*, the equity of facility locations is the maximum travelling distance for people in population centers to get service either from a static facility or a mobile facility, as shown in equation (3.2).

$$Max \ \{ dist(p, s \,||\, m) \,, p \in P \}, \tag{3.2}$$

where $s \in S$, $m \in M$ and $dist(p, s \,||\, m)$ is the travelling distance from a population center p to its assigned static facility s or to the closest mobile facility m , whichever is shorter. With the increase of the value of equation (3.2), the equity of facility locations decreases, vice versa.

In addition, this thesis considers the static facility capacity constraint, i.e., each static facility can serve a limited number of clients. People in each population center can only be assigned to their closest unfulfilled facilities.

Definition 3 (**A static and mobile facility location model**) Given a set of candidate sites for static facilities and mobile facilities, the predefined number of static facilities and mobile facilities, the locations of static facilities are first chosen by satisfying:

$$Max\, efficiency = Min \frac{\sum_{p \in P} dist(p,s) * p.w}{\sum_{p \in P} p.w} \tag{3.3}$$

Then the locations of mobile facilities are chosen by satisfying:

$$Max\, equity = Min\ Max\ \{\, dist(p, s \,||\, m)\ ,\ p \in P\,\} \tag{3.4}$$

The SMFLP defines the optimization objective only based the cost related with the travelling distance. The other costs, such as capital cost, land price, are not considered in the thesis.

3.2 SMFLS: Static and Mobile Facility Location Searching Algorithm

Since the SMFLP is a NP-hard problem, in this section, a heuristic algorithm called Static Mobile Facility Location Searching (SMFLS) is proposed for solving the model above. The algorithm splits the location decision into two steps: *static facility location searching* and *mobile facility location searching*. The static facility location searching is to find locations for static facilities by satisfying equation (3.3) and also considering the facility capacity constraint. The mobile facility location searching is to find locations for mobile facilities by satisfying equation (3.4) and the search depends on the location of static facilities and population centers. In order to solve the model for large datasets efficiently, in this chapter, the static facility location searching is implemented by a clustering-based heuristic method and the mobile facility location searching is implemented by a greedy heuristic method (as shown in Figure 3.1). But the SMFLS is extendible, in which the static facility location searching and the mobile facility location searching can be implemented by other heuristic methods according to different requirements.

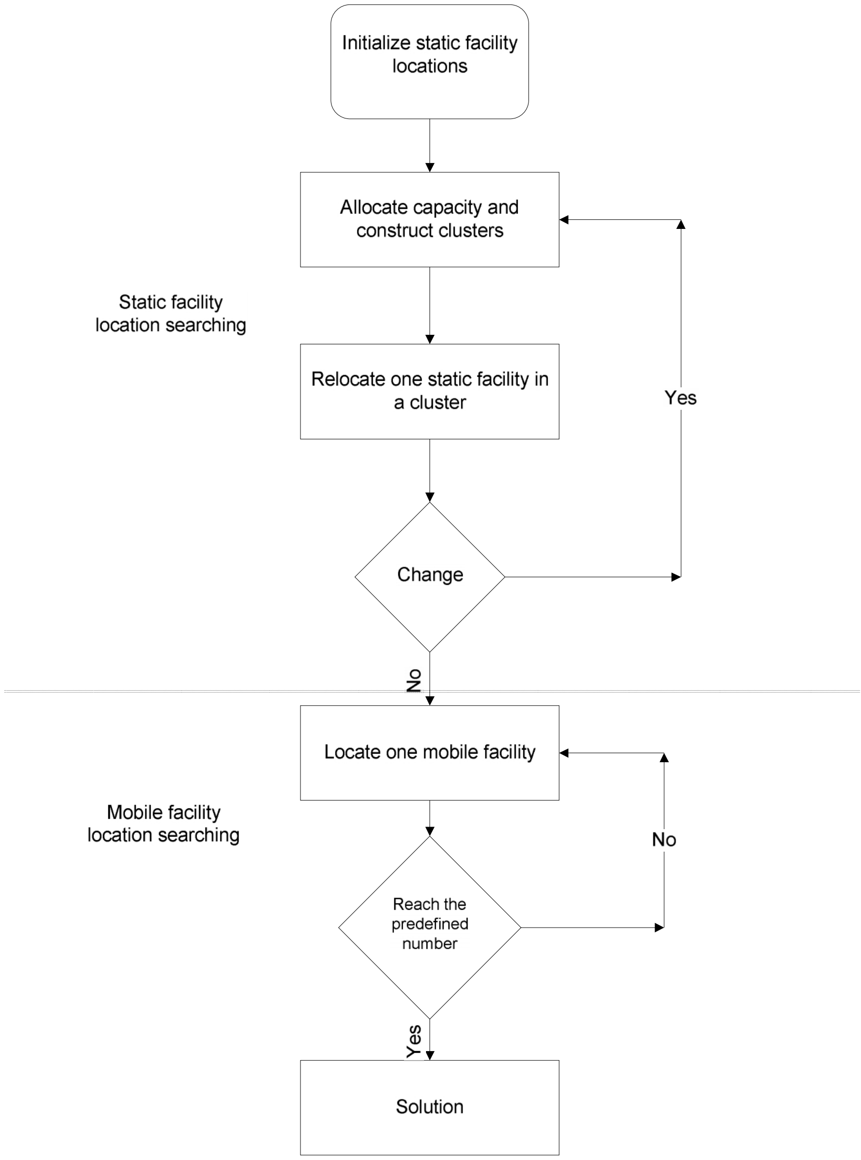


Figure 3.1 Procedure of the SMFLS algorithm implemented by the clustering-based heuristic method and the greedy heuristic method

3.2.1 Static Facility Location Searching

In this chapter, a clustering-based heuristic method is proposed for the static facility location searching step. Clustering is the process of grouping a set of objects into classes so that the objects within a cluster have high similarity to one another, but are dissimilar to the objects in other clusters (Han et al., 2001). The clustering process is used to reduce the searching space for each facility. The procedure involves three steps (the pseudo code is shown in Figure 3.2):

Step 1: initialize. The locations of static facilities are selected randomly among the candidate sites (Line 1).

Step 2: allocate capacity and construct clusters. Each population center is assigned to its closest unfulfilled static facility. Each unused candidate site is assigned to its closest static facility and the average population weighted travelling distance from all the population centers to their assigned facilities is saved (i.e., the value of equation 3.1) (Line 3). After the assignment, each static facility together with the population centers and the candidate sites assigned to it is considered as a cluster. Population centers are assigned in a descending order of a priority value. The priority value proposed by Ghoseiri and Ghannadpour (2007) is calculated for each population center as the absolute difference in the distances to its first and second closest static facilities. Because the objects in a cluster are closer to each other than the objects from other clusters, for every static facility in a cluster, there is a high probability that its optimal location is in the cluster. In this case, for each cluster, the optimal location of a facility is the candidate location within that cluster that minimizes the average travelling distance from population centers in the cluster to the static facility. So, the optimal location of a facility in each cluster is searched out by trying every candidate site in the cluster (Line 5). The corresponding average population weighted travelling distance between all the population centers to their assigned facilities is calculated if moving the facility to its optimal location (Line 6). Finally, the optimal facility location and the corresponding average population weighted travelling distance in each cluster are saved (Lines 7-8). Through separating the whole area into different clusters, the search space for every static facility is reduced from the candidate sites in the whole area to the ones in its cluster.

Step 3: relocate one facility. Among all the clusters, the cluster with the smallest corresponding average population weighted travelling distance is searched out (Line 9). The static facility in that cluster is tried to change from its original site to the optimal location in the cluster (Lines 10-12). The change is accepted only if the corresponding average travelling distance of the cluster is smaller than the average travelling distance of the original static facility configuration. Because each cluster is defined as the locations of a static facility and its assigned population centers and candidate sites, after one static facility's location being changed, the distribution of clusters as well as the optimal location in them is also changed. Thus, only one static facility is changed to the optimal location in its cluster in each iteration.

Step 2 and step 3 are iterated until no change happened in step 3.

```
StaticFacilityLocationSearching (P, C, |S|)
  Input: a set of population centers P, a set of candidate sites C for static facilities, and the
         number of static facility |S|.
  Output: a set of facilities S, and the population weighted average travelling distance avgDist
         (the value of equation 3.1) corresponding to S.
  S ← Initialize(|S|, C)
  Repeat
 /*Allocate capacity, construct clusters and calculate avgDist of the current configuration of
   static facilities.*/
    (Clusters, avgDist) ← AllocateCapacity(P, C, S)
    For each cluster ∈ Clusters
/*Find the optimal location in each cluster */
      newIntraPos=FindIntraCluOptimalLoc(cluster)
/* calculate and save the corresponding average travelling distance (i.e., the value of equation
   3.1) if moving the facility to its optimal location */
      newAvgDist=CalAvgDist(newIntraPos, S, P)
      Insert (newIntraPos, posList)
      Insert (newAvgDist, distList)
 /*Relocate one facility: Find the smallest value in distList and its corresponding location in
   posList. Then record this distance as minDist, the corresponding location as newPos, and the
   original static facility location in the same cluster with newPos as oldPos. */
    (newPos,oldPos,minDist) ← FindOptimalLoc(distList, posList, Clusters)
    If minDist < avgDist
       avgDist = minDist
       Exchange(newPos, oldPos)
 Until no more changes
```

Figure 3.2 Pseudo code of the static facility location searching implemented by the clustering-based heuristic method

3.2.2 Mobile Facility Location Searching

The locations of mobile facilities depend on the locations of population centers and static facilities. To reduce the execution time, a greedy heuristic method (Kuehn and Hamburger, 1963) is adopted in this step.

Based on the distribution of population centers and static facilities, one mobile facility is located at a time, always the candidate site that reduces the value of equation (3.2) at most being selected. The method stops when the predefined number of mobile facilities has been sited. The pseudo of the mobile facility location searching implemented by the greedy method is shown in Figure 3.3.

```
MobileFacilityLocationSearching(P, S, T, |M|)
  Input: a set of population centers P, a set of static facilities S, a set of candidate sites T for
        mobile facilities, and the number of mobile facilities |M|
  Output: a set of mobile facilities M and the maximal travelling distance minMaxDist
        (the value of equation 3.2) corresponding to M and S.
  Initialize M as null
  /* Calculate the value of equation (3.2) before locating mobile facility*/
  minMaxDist ← CalculateMaxDist(S, P)
  Repeat
     For each t ∈ T
        If t is not occupied by any static and mobile facility
  /*Calculate the value of equation (3.2) if locating a mobile facility on t */
           tempDist ← TestLoc(t, P, S, M)
  /*choose the candidate site which can reduces the value of equation (3.2) the most and locate
    the mobile facility m on it*/
        If tempDist < minMaxDist
           tempPos = t
           minMaxDist = tempDist
     LocateMobileFac(tempPos, M)
  Until the size of M equals to |M|
```

Figure 3.3 Pseudo code of the mobile facility location searching implemented by the greedy heuristic method

3.3 Experiments on Synthetic Datasets

In this section, computational experiments are made on synthetic datasets to evaluate the SMFLS algorithm. First, the scalability tests are made on the SMFLS algorithm. Specifically, the execution time of the SMFLS algorithm is evaluated on the impact of the following parameters: the number of candidate sites, the number of static facilities, and the number of mobile facilities. Second, to understand the efficiency and accuracy of the clustering-based method in the SMFLS algorithm, the performance of the clustering-based method is compared with that of the Interchange algorithm (one of the most popular heuristic algorithms) under different numbers of candidate sites.

Synthetic datasets for population centers were created in a 300*300 area. All experiments run on three kinds of datasets, in which 80% of the population centers consist of 4, 6, 8 dense clusters, respectively, and the remaining 20% are uniformly distributed in the area. All values in the following experiments are the average of the results from running the algorithm three times on each of three kinds of datasets. All the population centers are treated as the candidate sites for static and mobile facilities. The number of clients in each population center is set to 30. The Euclidean distance between two locations is used to represent the travelling distance between them. In the following experiments, *Average travelling distance* is the value of equation (3.1) representing the efficiency of facility locations and *Maximum travelling distance* is the value of equation (3.2) representing the equity of facility locations. The experiments are performed on a Core 2 Quad 2.40GHz PC with 3GB memory, running on Windows XP platform.

3.3.1 Scalability Tests on the SMFLS Algorithm

In this subsection, the execution time of the SMFLS algorithm is tested under different parameters, i.e., the number of candidate sites, the number of static facilities, and the number of mobile facilities.

First, the execution time of the SMFLS algorithm under different numbers of candidate sites is shown in Table 3.1. The number of static facilities is set to five and the number of mobile facilities is set to ten. To make sure static facilities are adequate to meet the overall demands, the capacity constraint of each static facility is 600,000. The SMFLS algorithm can successfully produce results under different numbers of candidate sites. The execution time increases from 13.0 seconds to 267,756.5 seconds ($\approx$74.4 hours) when the number of candidate sites increases from 1000 to 100,000.

Table 3.1 Execution time of the SMFLS algorithm under different numbers of candidate sites

Number of candidate sites	Execution time (seconds)
1,000	13.0
5,000	358.5
10,000	2,370.5
20,000	10,869.5 ($\approx$3.0 hours)
40,000	41,656.0 ($\approx$11.6 hours)
60,000	131,960.5 ($\approx$36.7 hours)
80,000	214,495.3 ($\approx$59.6 hours)
100,000	267,756.5 ($\approx$74.4hours)

Second, the execution time of the SMFLS algorithm under different numbers of static facilities is shown in Table 3.2. The number of population centers is set to 10,000 and the number of mobile facilities is set to ten. The capacity constraint of each static facility is 300,000. As expected, the increase of the number of static facilities causes more execution time.

Third, the execution time of the SMFLS algorithm under different numbers of mobile facilities is shown in Table 3.3. For the experiment, the number of population centers is set to 10,000 and the number of static facilities is set to five. The capacity constraint of each static facility is 60,000. As expected, the increase of the number of mobile facilities causes more execution time.

Table 3.2 Execution time of the SMFLS algorithm under different numbers of static facilities

Number of static facilities	Execution time (seconds)
1	1,341.9
3	1,759.3
5	2,420.1
10	3,825.3 ($\approx$ 1.1 hours)
15	5,699.2 ($\approx$ 1.6hours)
20	6,035.3 ($\approx$ 1.7hours)

Table 3.3 Execution time of the SMFLS algorithm under different numbers of mobile facilities

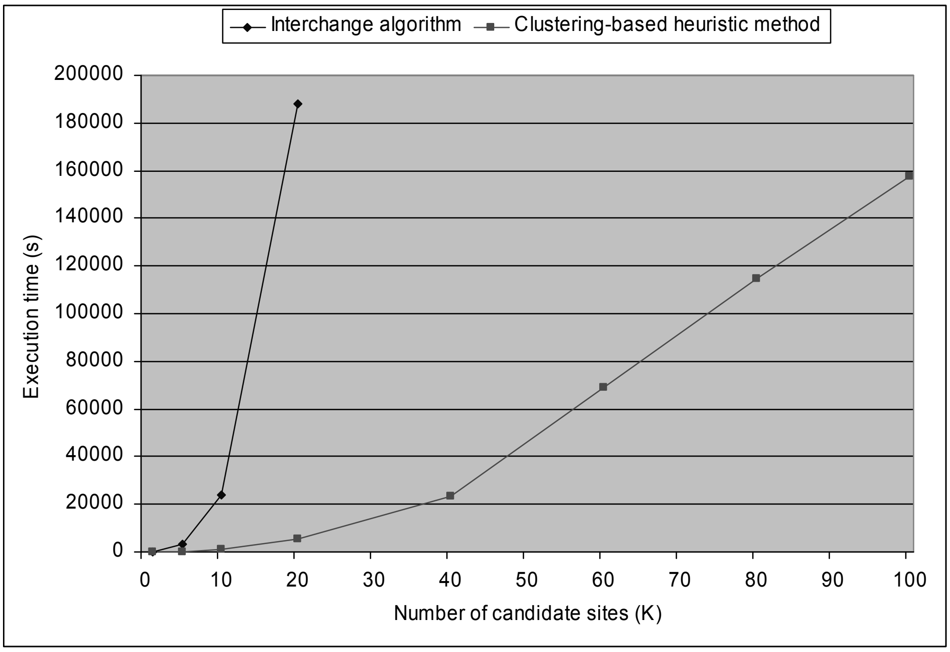
Number of mobile facilities	Execution time (seconds)
1	494.9
3	754.3
5	1,047.1
10	1,718.2
15	2,359.0
20	3,102.9

In summary, the SMFLS algorithm can solve the problem for large number of candidate sites, and different numbers of static facilities and mobile facilities. The number of candidate sites is the key factor influencing the execution time of the algorithm.

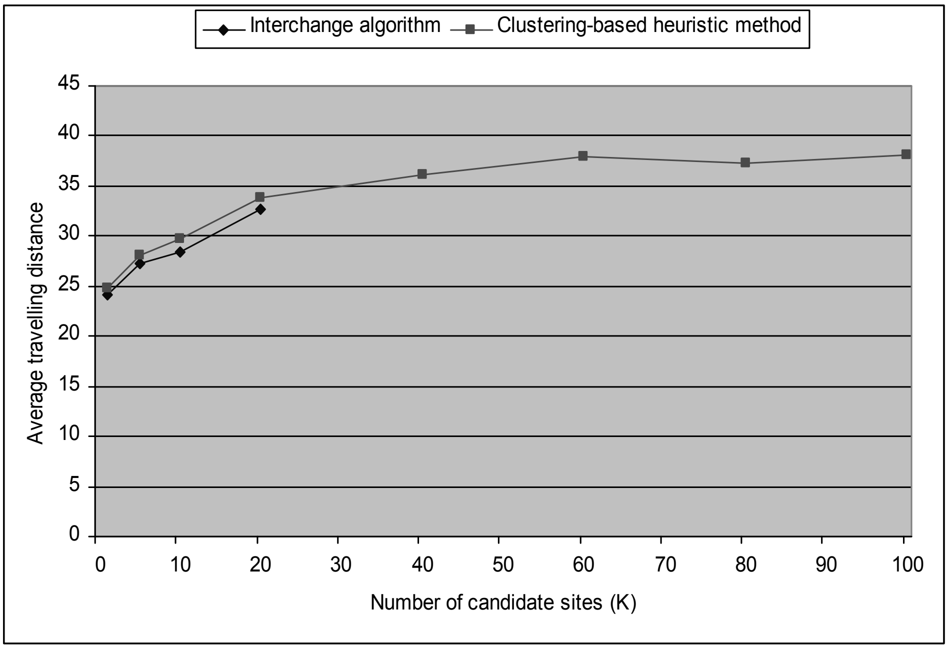
3.3.2 Comparison between the Clustering-based Heuristic Method with the Interchange Algorithm

In this chapter, the clustering-based heuristic method and the greedy heuristic method are used for the static facility location searching and the mobile facility location searching in the SMFLS algorithm, respectively. Since the greedy heuristic method (Kuehn and Hamburger, 1963) has been widely used to solve NP problems, its accuracy and efficiency have been evaluated well (Kaiser, 2000). This subsection will focus on the evaluation of the efficiency and accuracy of the clustering-based method.

To understand the efficiency and accuracy of the clustering-based method in the SMFLS algorithm, the performance of the clustering-based method is compared with that of the Interchange algorithm under different numbers of the candidate sites. The efficiency of an algorithm is measured based on the execution time. The less execution time, the more efficiency the algorithm is. The accuracy of an algorithm is the degree of closeness of the solution given by the algorithm to the optimal solution. In this section, the degree of the closeness is quantified by using the average travelling distance (i.e., equation 3.2). The lower average travelling distance value of an algorithm, the higher accuracy it is. In the following experiments, the number of the static facilities is set to five. To make sure static facilities are adequate to meet the overall demands, the capacity constraint of each static facility is set to 600,000. The comparison results under different numbers of candidate sites are shown in Figure 3.4.



(a). Execution time



(b). Average travelling distance

Figure 3.4 Comparison between the clustering-based heuristic method and the Interchange algorithm

Figure 3.4 (a) shows the execution time of the clustering-based heuristic method increases from 7.9 seconds to 157,756.5 seconds ($\approx$43.8 hours) when the number of candidate sites increases from 1,000 to 100,000. However, when the number of candidate sites increases from 1,000 to 20,000, the execution time of the Interchange algorithm dramatically increases from 46.0 seconds to 188,121.5 seconds ($\approx$52.3 hours), In Figure 3.4, we do not have the execution time for the Interchange algorithm when the number of candidate sites is over 20,000. The reason is that the Interchange algorithm cannot be finished under the available computing resource. Thus, we can conclude that the clustering-based heuristic method is much more efficient than the Interchange algorithm for the static facility searching.

Figure 3.4 (b) shows the average travelling distance of the clustering-based heuristic method increases from 24.7 to 38.1 when the number of candidate sites increases from 1,000 to 100,000. For the Interchange algorithm, its average travelling distance increases from 24.1 to 32.6 when the number of candidate sites increases from 1,000 to 20,000. The relative difference of the average travelling distance can be calculated as:

$$\frac{\text{avg(cluster) ? avg(Interchange)}}{\text{avg(Interchange)}}$$

where avg(cluster) is the average travelling distance of the clustering-based heuristic method and avg(Interchange) is the average travelling distance of the Interchange algorithm. The relative difference is 2.5%, 2.9%, 4.2%, 4.0%, when the number of candidate sites is set to 1,000, 5,000, 10,000, and 20,000 respectively. Thus, we can conclude that the Interchange algorithm produces better results than the clustering-based heuristic method. However, the results produced by the clustering-based heuristic method are acceptable since the relative difference of the average travelling distance between the clustering-based heuristic method and the Interchange algorithm is small.

In summary, compared with the Interchange algorithm, the clustering-based heuristic method can dramatically reduce the execution time and has an acceptable accuracy. The static facility location searching implemented by the clustering-based heuristic method is more useful being applied on real time applications or being applied on large datasets while the Interchange algorithm needs too much computational resource to produce results.

3.4 Experiments on the Real Dataset

This section presents an experiment with a real dataset from South Carolina, USA, on which the proposed method is applied to finding locations for five hospitals (i.e., static facility) and three ambulances (i.e., mobile facility). The data set consists of 867 census tracts (Census2000), with each treated as a population center. The population of each census tract varies from 197 to 16,745. The total population is 4,212,012. Centroids of census tracts are used as the locations of population centers. To make sure hospitals are adequate to meet the overall demands, the capacity constraint of each hospital is set to 900,000. All the locations of census tracts are set as the candidate sites for hospitals and ambulances. The Euclidean distance is adopted to measure the spatial barrier between census tracts and facilities. The projected coordinate system used in the figures of this section is NAD_1927_UTM_Zone_17N. The distribution of population centers in South Carolina is shown in Figure 3.5.

Figure 3.6 presents the result produced by the SMFLS algorithm. The hospitals are located in the high population density areas while the ambulances are located into remote places. The points marked by ▲,⬟and ■ stand for the population centers served by three different ambulances. Two ambulances are located close to each other. One ambulance serves the population centers marked by ■ and another one serves the population centers marked by ▲. In the optimized facility location, the average travelling distance is 56.2 km, and the maximum travelling distance is 130.0 km.

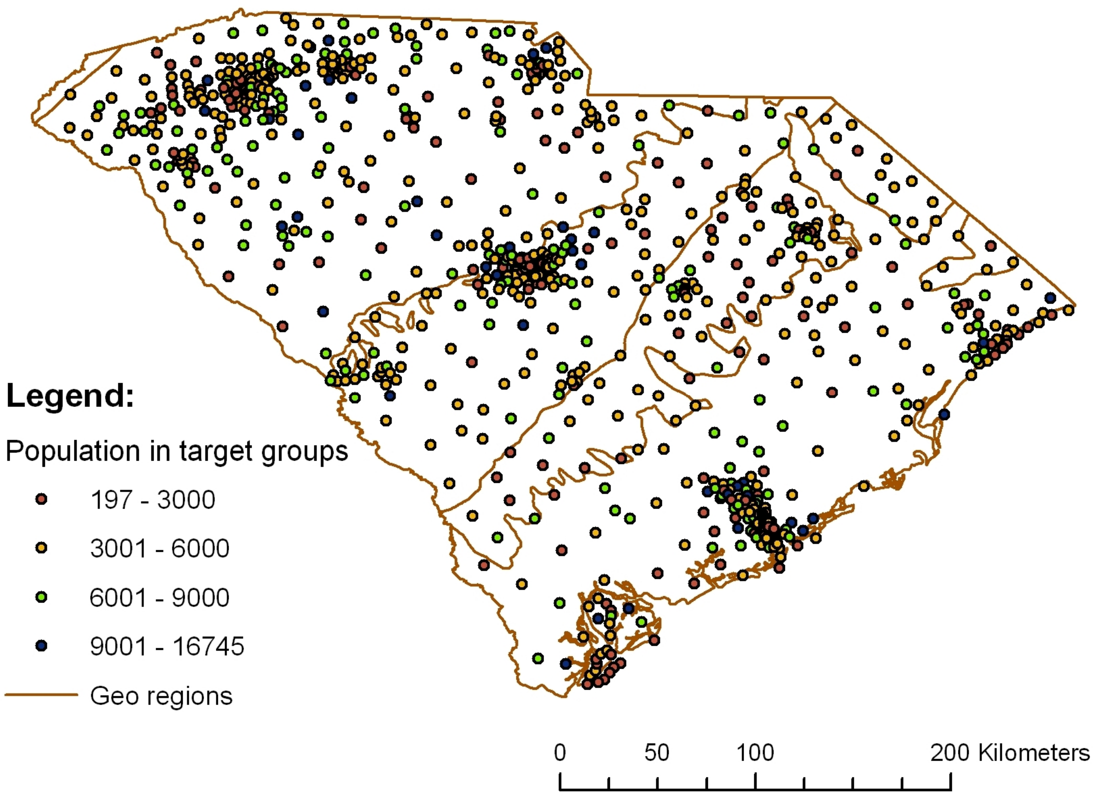


Figure 3.5 Distribution of population centers in South Carolina

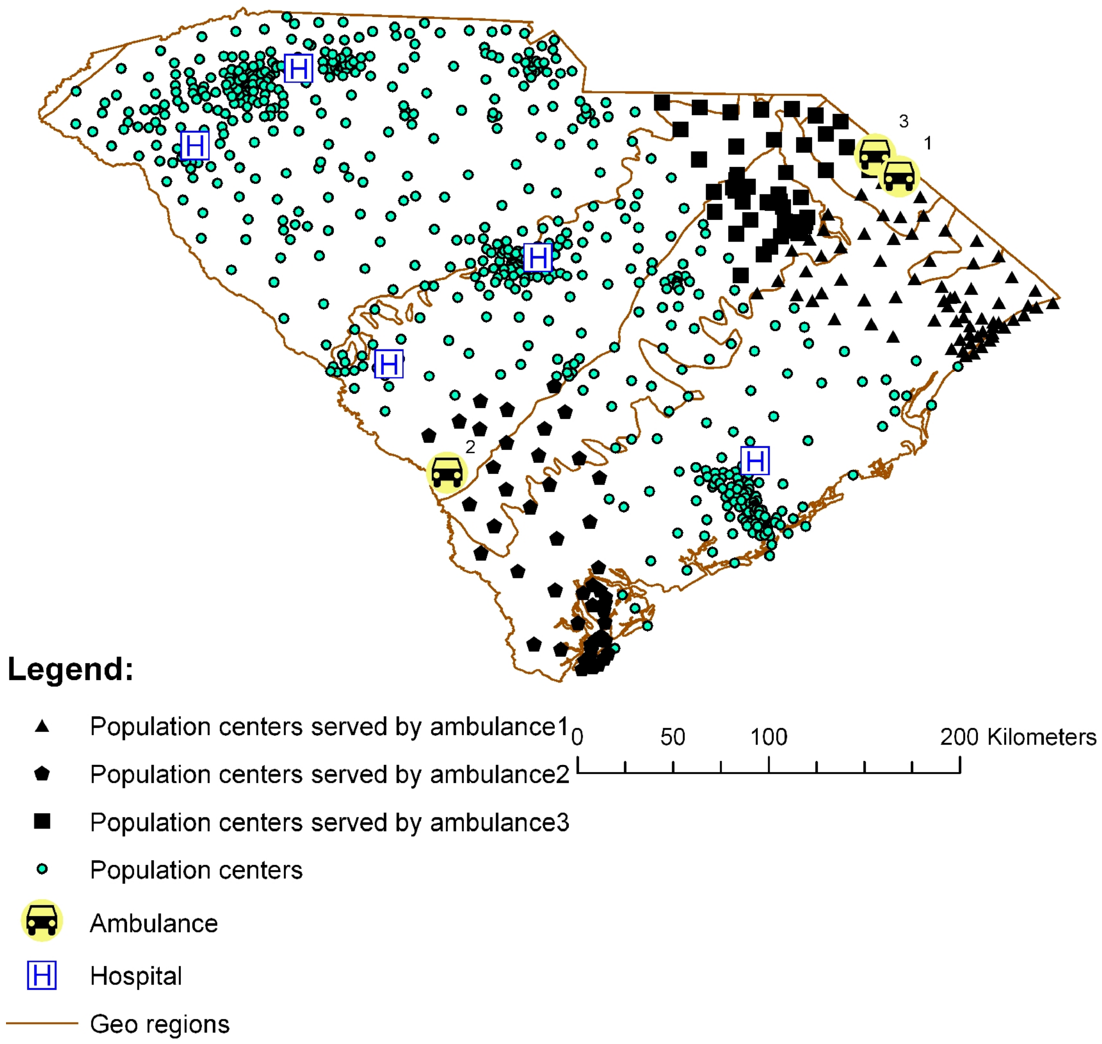


Figure 3.6 The optimized facility location configuration in South Carolina

3.5 Summary

In this chapter, the static and mobile facility location problem is formalized as a bi-objective model and a new heuristic algorithm named SMFLS is developed for solving the model. Section 3.1 starts by formalizing the efficiency and equity of facility locations and then a static and mobile facility location model aiming to optimize both the efficiency and the equity of facility locations is given. In section 3.2, the SMFLS algorithm is proposed for solving the model. The algorithm separates the location decision into two steps. Static facility location searching step is applied first to maximizing the efficiency of facility locations and then mobile facility location searching step is applied to maximizing the equity of facility locations. In order to solve the model for large datasets efficiently, in this chapter, we propose a new clustering-based heuristic method to implement the static facility location searching and implement the mobile facility location searching using a greedy heuristic method. The clustering-based heuristic method separates the candidate sites of static facilities into different clusters and then reduces the searching space for each static facility from the candidate sites in the whole area to the candidate sites in the cluster where the static facility is. The experiments in the section 3.3 show that the SMFLS algorithm can produce the results of the SMFLP under different numbers of candidate sites, static facilities and mobile facilities. In addition, experiments show that the clustering-based heuristic method used in the SMFLS algorithm can dramatically reduce the execution time and has an acceptable accuracy compared with the Interchange algorithm. Finally, in the section 3.4, the experiment on the real dataset proves the practicality of the SMFLS algorithm.

CHAPTER FOUR: STATIC AND MOBILE FACILITY LOCATION OPTIMIZATION FOR PREVENTIVE HEALTH CARE SERVICES

This chapter presents a customized method for solving the SMFLP for preventive health care services. First, the description of the preventive health care facility location problem is presented. Second, the modification of the proposed static and mobile facility location model is introduced which tailors for the characteristics of preventive health care services. Third, the solution approach to the model is presented and tested on synthetic datasets. Finally, the method is evaluated by applying it to a real application: optimizing the facility location configuration for the breast cancer screening program in Alberta, Canada.

4.1 Preventive Health Care Facility Location Problem

Preventive health care programs aim to save lives and contribute to a better quality of life by diagnosing serious medical conditions early and reducing the likelihood of life-threatening disease. Evidence shows that successful treatment of some health problems is more likely if an illness is diagnosed at an early stage. Thus, efficient and effective preventive health care services have been an integral part of many health care reform programs within the past two decades (Goldsmith, 1989; Verter and Lapierre, 2002; Zhang et al., 2009; Gu et al., 2010).

Facility location decisions are a critical element in strategic planning in preventive health care programs (Daskin and Dean, 2004). Previous research proves that facility location plays a key role in the success of preventive health care programs in terms of the participation rate. A survey by Zimmerman (1997) finds that the convenience of access to a facility is a very important factor in a client's decision to have prostate cancer screening. Furthermore, a survey by Facione (1999) reveals that perceptions of lack of access to services are related to a decrease in mammography participation. A recent review by Baron et al. (2008) finds that the efficiency of reducing structural barriers (including distance required to travel to obtain mammograms) increases community access to breast, cervical, and colorectal cancer screening.

Characteristics of preventive health care services are inherently different from other health care services (such as health care for acute diseases), which requires a different location decision method. The first characteristic of preventive health services is that people might not seek services from the closest preventive health care facility. Since preventive services are given to people with no clear symptoms of illness, people who seek preventive services have more flexibility as to when and where to receive preventive health care services (Verter and Lapierre, 2002; Zhang et al., 2009; Gu et al., 2010). For example, for a person living in an area served by two preventive health care clinics within an acceptable travelling distance, the person may choose the closer one because of the proximity. Or he/she may go to the farther clinic, located near a shopping mall, because he/she can go shopping after a medical appointment. The second characteristic of preventive health services is that each facility needs to have a minimum number of clients to retain the accreditation, except when there is a policy decision to provide preventive services to sparsely populated neighbourhoods. For example, the US Food and Drug Administration (2010) requires a radiologist to interpret at least 960 mammograms and a radiology technician to perform at least 200 mammograms in 24 months to retain their FDA accreditation.

According to the report from the World Health Organization (2010), current health care systems do not make optimal use of available resources to support preventive health care programs. One of the reasons is that the location of preventive health care facilities is determined without fully considering the above two characteristics. In the current health care systems most facilities are located based on responding to emergent medical problems, which assumes that people would seek services from the closest facility. Thus, location optimization is performed based on the distance between people and their assigned closest facility (Pacheco et al., 2008).

Since people seek preventive health care services have more flexibility, preventive services require a more decentralized system than primary health care services. In addition, preventive health care services often require less equipment and sophisticated setting than primary health care services, and hence can be delivered outside static facilities (e.g., clinics and hospitals). So, it is possible and attractive to apply both static facilities and mobile facilities into preventive health care services (Lapierre et al., 1997). In preventive health care service systems, the static facility could be a hospital, clinic or other medical center; the mobile facility is the service deliverer which can bring medicine (e.g., flu shot) from static facilities to remote places or get medical samples (e.g., x-ray) from remote places to static facilities. For example, in mammogram screening service, each screening vehicle is a mobile facility which is located in a parking lot or community in a period and then is dispatched to another place. At the end of each period, screening vehicles need to return screening mammograms taken for breast cancer detection to one static facility.

4.2 Problem Formalization

In this section, we will formally define the preventive health care static and mobile facility location problem. Given a set of population centers and a set of candidate sites for facilities, the *Preventive Health Care Static and Mobile Facility Location Problem* (PHSMFLP) is to identify locations for the predefined number of static and mobile preventive health care facilities that maximize the participation rate. Since the major determinant of the participation rate in a preventive program is the accessibility of health care services (Zhang et al., 2009), this thesis solves the PHSMFLP by optimizing the accessibility of preventive health care services to population centers. In the following, how to calculate the accessibility of preventive health care services to each population center is introduced first. Then, a bi-objective model is given for the location optimization.

4.2.1 Accessibility of Preventive Health Care Services

In order to satisfy the characteristics of preventive health care services, the accessibility of preventive health care services is defined as an index to represent the level of convenience for people in each population center receiving the service. The accessibility of preventive health care services is comprised of three factors:

(1) Regional availability of preventive health care services. Regional availability is expressed as a ratio between preventive health care facilities (either static one or mobile one) and clients within a region. A client in a higher ratio region has more convenient access to services. Regional availability considers all of the facilities within an acceptable travelling distance of a client when calculating the accessibility of

preventive health care services to that client. The assumption behind regional availability is that people may go to any facility within the acceptable travelling distance constraint, which satisfies the first characteristic of preventive health care services that people might not seek services from the closest preventive health care facility.

(2) Travelling distance between facilities and clients. The clients within an acceptable travelling distance of a facility do not share this facility equally since usage decreases with distance. The closer client would have higher accessibility to the facility. This factor satisfies the first law of geography (Tobler, 1970), which states that "everything is related to everything else, but near things are more related than distant things" and the well-known fact that distance affects access to health care services (Weiss et al., 1971).

(3) Each static facility should attract a minimum number of clients unless the facility is located in a remote place. This factor satisfies the second characteristic of preventive health care services (Since the mobile facility is the service deliverer, there is no limit of minimum number of clients on it.). The Huff-based competitive location model (Huff, 1964) is used to estimate the workload of static facilities. The assumption behind the model is that the probability of a client getting service from a facility within the acceptable travelling distance constraint is related to two elements. The first element is the attraction of the facility. In the thesis, the attraction of a facility to a client is described by the inverse travelling distance between the facility and the client. The second element is the inverse of the sum of the attractions of all facilities within the acceptable travelling distance constraint, which means the more facilities that are located

within an accessible distance of a client, the lower the chance that a particular facility will be used by the client.

The accessibility of preventive health care services can be calculated using the following two steps.

For the purposes of clarity, the following definitions pertain:

I Set of population centers ($i = 1,\ldots,|I|$);

P_i Number of clients in a population center i;

S Set of candidate sites for the location of static preventive health care facilities ($j = 1,\ldots,|S|$);

n_S The predefined number of static preventive health care facilities;

M Set of candidate sites for the location of mobile preventive health care facilities ($j = 1,\ldots,|M|$);

n_M The predefined number of mobile preventive health care facilities;

y_j If a facility opens at the candidate site j, then $y_j = 1$; Otherwise, $y_j = 0$; $j \in S \,||\, j \in M$

n_j The static facility that is the closest to a candidate site j;

d_{ij} Travelling distance between a population center i and a candidate site j, $j \in S \,||\, j \in M$;

d_0 The travelling distance threshold of a catchment area;

d The travelling distance threshold to define the remote place;

A_i Accessibility of preventive health care services at a population center i;

W_{min} Minimum required workload of a static facility.

Step 1. For each candidate site j ($j \in S \,||\, j \in M$), search all the population locations that are within a travelling distance threshold from the candidate site j (that is, the catchment area of j), and compute the facility-to-client ratio R_j, within the catchment area:

$$R_j = \frac{1}{\sum_{i \in I \bigcap d_{ij} \le d_0} P_i} \tag{4.1}$$

Step 2. For each population center i, search all the facilities whose locations that are within the travelling distance threshold from a population center i (that is, the catchment area of i), and the sum up the inverse distance-weighted facility-to-client ratio R_j.

$$A_i = \sum_{(j \in S \| j \in M) \bigcap d_{ij} \le d_0} \frac{R_j}{d_{ij}} * y_j == \sum_{(j \in S \| j \in M) \bigcap d_{ij} \le d_0} \frac{y_j}{d_{ij} * \sum_{i \in I \bigcap d_{ij} \le d_0} P_i} \tag{4.2}$$

Subject to: $\sum_{j \in S} y_j = n_S$, $\sum_{j \in M} y_j = n_M$ (a)

For $\forall j \in S$, $\sum_{i \in I \bigcap d_{ij} \le d_0} P_i * \frac{d_{ij}^{-1}}{\sum_{j \in J \bigcap d_{ij} \le d_0} d_{ij}^{-1}} \ge W_{min} y_j \,||\, dist(n_j, j) > d * y_j$ (b)

Constraint (a) requires the number of static and mobile facilities to be equal to the predefined number n_S and n_M separately. Constraint (b) ensures that the estimated workload of each static facility is beyond the minimum workload or that facility is open in a remote place. In constraint (b), first the Huff-based competitive model is used to estimate the probability of a client in a population center i getting service from a candidate site j as $d_{ij}^{-1} / \sum_{j \in J \cap d_{ij} \le d_0} d_{ij}^{-1}$. Compared with equation (2.1), S_j is set to one based on the assumption that the size of each preventive health care facility is the same. λ is set to one. Second, from the Huff-based model, the number of clients in a population center i getting service from a candidate site j is estimated by multiplying the number of clients in the population center i with the probability that the clients in the population center i getting service from the candidate site j. Therefore, the workload of the static facility in a candidate site j is estimated by summing up the number of clients from all the population centers within the candidate site j's catchment area. In addition, a predefined travelling distance d is used as a threshold for choosing remote places. For remote areas, the constraint of the minimum workload is not required. A place is treated as remote if the distance from it to the closest facilities is over d (Usually $d \gg d_0$).

In step 1, the facility-to-client ratio R_j describes the regional availability of each facility. A higher ratio indicates that fewer clients share a facility, and vice-versa. Step 2 first adds the distance factor by multiplying the inverse distance with the facility-to-client ratio R_j. This takes into account the fact that all the clients within a facility's catchment area do not share this facility equally, rather that usage decreases with distance from the facility; second, the accessibility to a population center is calculated by summing up the inverse distance-weighted facility-to-population ratios of the facilities within the population center's catchment area. This step satisfies the assumption that people may go to any facility as long as it is within an acceptable travelling distance, which is defined as the travelling distance threshold d_0. In other words, for a given population center, the more facilities are within the acceptable travelling distance and the closer these facilities are to this population center, the higher possibility the clients in the population center access a preventive health care service.

In the thesis, the accessibility of preventive health care services only focuses on structural barriers that are directly related to the number, concentration, and location of preventive health care facilities. The financial barriers (e.g., availability of insurance coverage) and personal barriers (e.g., social and cultural aspects) are not discussed (Institute of Medicine, 1993). Additionally, in the thesis, we only consider the location configuration of preventive health care facilities. The potential interaction between preventive health care facilities with other facilities (i.e., primary health care facility) is not considered.

4.2.2 A Preventive Health Care Static and Mobile Facility Location Model

For the optimal design of preventive health care programs, two important objectives should be considered, efficiency and equity (Mitropoulos et al., 2006). The *efficiency* objective aims to maximize social welfare by achieving an optimal arrangement of health care facilities. The *equity* objective aims to serve more people in a target area. In the above definition, the clients in a population center *i* can access services as long as the value A_i is not zero and a larger value of A_i indicates a better accessibility at a population center *i*. In this sense, the efficiency objective is achieved by locating static facilities to maximize the sum of population weighted accessibility values and the equity objective is achieved by locating mobile facilities to maximize the number of people within the acceptable travelling distance of at least one facility. Therefore, the PHSMFLP can be formalized as follow:

The locations of static facilities are first chosen by satisfying:

$$Max\,efficiency = Max \sum_{i \in I} A_i * P_i \tag{4.3}$$

Then the locations of mobile facilities are chosen by satisfying:

$$Max\,equity = Max \sum_{i \in I \bigcap A_i \neq 0} P_i \tag{4.4}$$

4.3 Solution Approach to the Preventive Health Care Static and Mobile Facility Location Model

The preventive health care static and mobile facility location model is solved by the SMFLS algorithm. Due to the requirements for high accuracy in the location of static preventive health care facilities, in this chapter, the static facility location searching is implemented by the Interchange algorithm. In addition, two new data structures, 'population groups' and 'candidate string,' are proposed to accelerate the static facility location searching by pre-storing the accessibility information.

4.3.1 Data Structures to Accelerate the Static Facility Location Searching

Two new data structures: *population group* and *candidate string* are built to accelerate the static facility location searching. The rationale for building these two data structures is the same as the idea in Densham and Rushton (1992), which is to examine only a subset of population centers to update the sum of population weighted accessibility values whenever a change of static facility locations occurs.

Population group is a data structure that aggregates similar population centers. The population centers in the same group have the same accessibility value since they are covered by the same set of candidate sites. For the example shown in Figure 4.1, Table 4.1 lists the population groups. Each population group records the candidate sites covering it and the potential population weighted accessibility value contributed from those candidate sites. For example, $\{O_4\}$ is covered by the catchment areas of the candidate site *a*, *b* and *c*. According to equation (4.2), the accessibility value A_4 of the population center O_4 is $\frac{R_a}{d_{4a}} * y_a + \frac{R_b}{d_{4b}} * y_b + \frac{R_c}{d_{4c}} * y_c$. So, the potential population weighted accessibility value contributed from the candidate site *a* is $\frac{R_a}{d_{4a}} * P_4$; from the candidate site *b* is $\frac{R_b}{d_{4b}} * P_4$; from the candidate site *c* is $\frac{R_c}{d_{4c}} * P_4$, where P_4 is the number of clients in the population center O_4.

The two new data structures can be built by checking every pair of population centers and candidate sites. Thus, the time complexity of building two data structures is: $O(|I|*|S|)$, where $|I|$ is the size of population centers and $|S|$ is the size of candidate sites for static facilities.

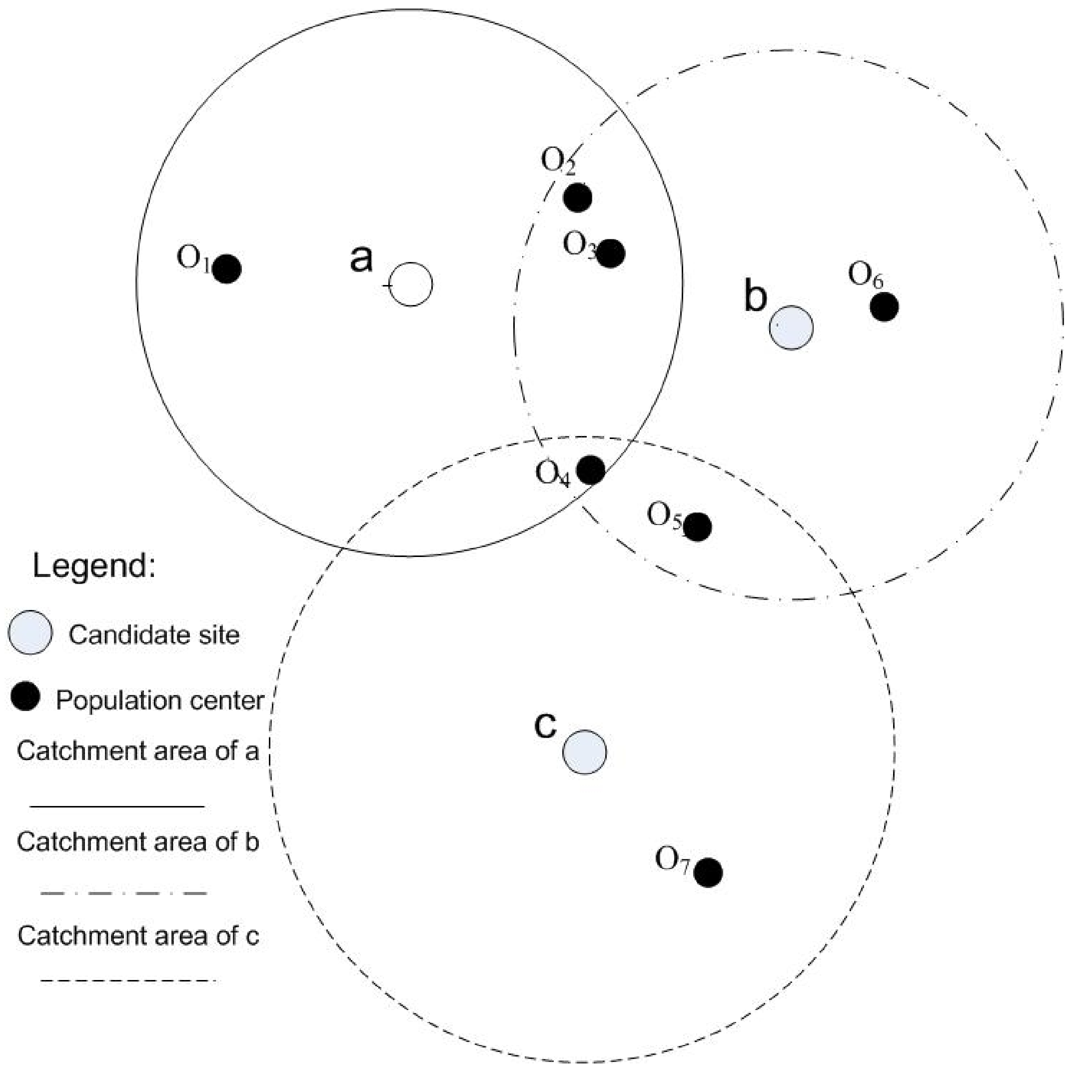


Figure 4.1 Distribution of candidate sites and population centers

Candidate string is a data structure built for every candidate site. A candidate string lists all the population groups that can be covered by the candidate site. It is used to quickly find the population groups affected by the change of facility locations. As shown in Table 4.2, three candidate strings are built for the example in Figure 4.1. In the candidate string of the candidate site *a*, three population groups $\{O_1\}$, $\{O_2, O_3\}$ and $\{O_4\}$ are listed. Population groups $\{O_2, O_3\}$, $\{O_4\}$, $\{O_5\}$ and $\{O_6\}$ are listed in the candidate string of the candidate site *b*. The candidate string of the candidate site *c* has three population groups: $\{O_4\}$, $\{O_5\}$ and $\{O_7\}$.

Table 4.1 Population group for the example in Figure 4.1

Population group	Candidate site	Population weighted accessibility value
$\{O_1\}$	A	$\frac{R_a}{d_{1a}} * P_1$
$\{O_2, O_3\}$	A	$\frac{R_a}{d_{2a}} * P_2 + \frac{R_a}{d_{3a}} * P_3$
	B	$\frac{R_b}{d_{2b}} * P_2 + \frac{R_b}{d_{3b}} * P_3$
$\{O_4\}$	A	$\frac{R_a}{d_{4a}} * P_4$
	B	$\frac{R_b}{d_{4b}} * P_4$
	C	$\frac{R_c}{d_{4c}} * P_4$
$\{O_5\}$	B	$\frac{R_b}{d_{5b}} * P_5$
	C	$\frac{R_c}{d_{5c}} * P_5$
$\{O_6\}$	B	$\frac{R_b}{d_{6b}} * P_6$
$\{O_7\}$	C	$\frac{R_c}{d_{7c}} * P_7$

Table 4.2 Candidate string for the example in Figure 4.1

Candidate string	Population group
A	$\{O_1\}$, $\{O_2, O_3\}$, $\{O_4\}$
B	$\{O_2, O_3\}$, $\{O_4\}$, $\{O_5\}$, $\{O_6\}$
C	$\{O_4\}$, $\{O_5\}$, $\{O_7\}$

When moving a static facility from one candidate site to another, the change of the sum of population weighted accessibility values (i.e., $\sum_{i\in I} A_i * P_i$) can be calculated by only examining the population groups listed under the candidate strings of the two sites. The change of the sum of population weighted accessibility values that results from moving from one site to another can be calculated by subtracting the population weighted accessibility value contributed from one site by that of another. For example, a static facility is changed from the candidate site *a* to *c*. The population groups listed in the candidate string of the candidate site *a* is $\{O_1\}$, $\{O_2, O_3\}$ and $\{O_4\}$. From the population group data structure, it is known that the population weighted accessibility value contributed from the candidate site *a* in population group $\{O_1\}$ is $\frac{R_a}{d_{1a}} * P_1$, population group $\{O_2, O_3\}$ is $\frac{R_a}{d_{2a}} * P_2 + \frac{R_a}{d_{3a}} * P_3$, and population group $\{O_4\}$ is $\frac{R_a}{d_{4a}} * P_4$. Therefore, the population weighted accessibility value contributed by the candidate site *a* is $\frac{R_a}{d_{1a}} * P_1 + \frac{R_a}{d_{2a}} * P_2 + \frac{R_a}{d_{3a}} * P_3 + \frac{R_a}{d_{4a}} * P_4$. The population groups listed in the candidate string of the candidate site *c* is $\{O_4\}$, $\{O_5\}$ and $\{O_7\}$. The population weighted accessibility value contributed from the candidate site *c* in population group $\{O_4\}$,$\{O_5\}$

and $\{O_7\}$ are $\frac{R_c}{d_{4c}} * P_4$, $\frac{R_c}{d_{5c}} * P_5$ and $\frac{R_c}{d_{7c}} * P_7$, respectively. The population weighted accessibility value contributed from the candidate site c is $\frac{R_c}{d_{4c}} * P_4 + \frac{R_c}{d_{5c}} * P_5 + \frac{R_c}{d_{7c}} * P_7$. Thus, the change of the sum of population weighted accessibility values from the candidate site a to c can be calculated by:

$$(\frac{R_c}{d_{4c}} * P_4 + \frac{R_c}{d_{5c}} * P_5 + \frac{R_c}{d_{7c}} * P_7) - (\frac{R_a}{d_{1a}} * P_1 + \frac{R_a}{d_{2a}} * P_2 + \frac{R_a}{d_{3a}} * P_3 + \frac{R_a}{d_{4a}} * P_4);$$

The procedure of the SMFLS algorithm implemented by the Interchange algorithm with two data structures and the greedy heuristic method is shown in Figure 4.2. The two data structures, population group and candidate string, are built at the beginning of the algorithm. Given an acceptable traveling distance threshold, the catchment area of each candidate site and population center are fixed because the number of facilities in a population center's catchment area and the number of population centers in a candidate site's catchment area do not change. Thus, the two data structures do not need to be updated in the algorithm. After initializing the static facility locations, the static facility location searching is to relocate a static facility from its current site to an unused candidate site. If the relocation produces a larger value of the sum of population weighted accessibility values, then the change is accepted. Otherwise, the relocation is cancelled. The change of the sum of population weighted accessibility values can be calculated by only examining the population groups influenced by the relocation, as mentioned above. The search process is repeated until no larger sum of population weighted accessibility values can be generated after relocating every static facility. The mobile facility searching locates one mobile facility at a time, always the candidate site that increases the number of people served (i.e., $\sum_{i \in I \bigcap A_i \neq 0} P_i$) at most being picked.

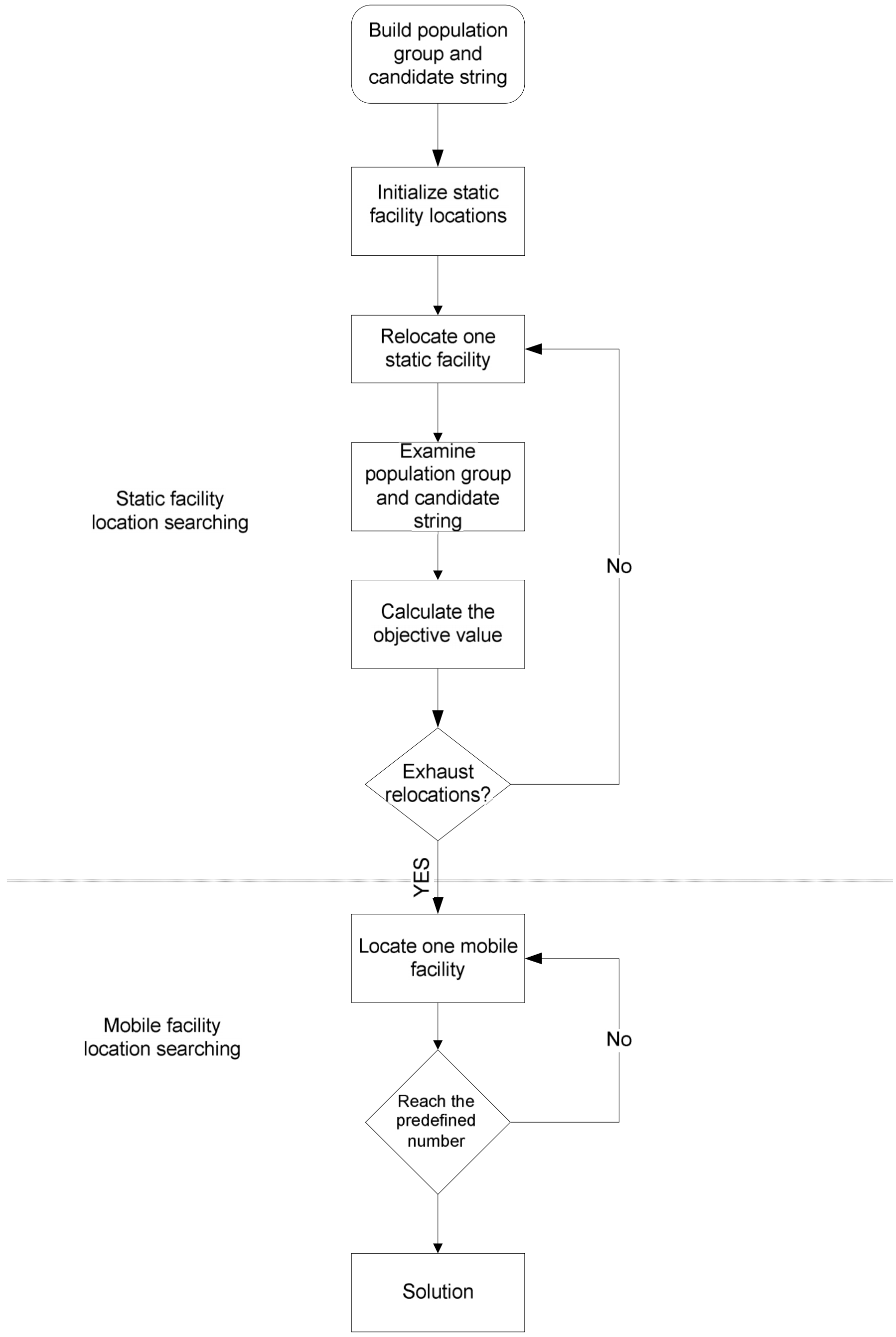


Figure 4.2 Procedure of the SMFLS algorithm implemented by the Interchange algorithm with two data structures and the greedy heuristic method

4.3.2 Experiments on Synthetic Datasets

In this subsection, the performance of the use of two data structures to accelerate the static facility location searching is tested. The comparisons are made between the Interchange algorithm and the Interchange algorithm with the two data structures (named as accelerated Interchange algorithm in the following).

Synthetic datasets for population centers were created in a 300*300 area, in which 80% of the population centers consist of four dense clusters, and the remaining 20% are uniformly distributed in the area. The candidate sites of static facilities are randomly selected from the locations of population centers. Each value in the following experiments is the average value from six runs of the algorithms. In the first group of experiments, the number of candidate sites is set to 50, 100, 500, 1,000 or 5,000 while the number of population centers is fixed at 10,000. In the second group of experiments, the number of population centers is set to 1,000, 5,000, 10,000, 50,000 or 100,000 while the number of candidate sites is fixed at 50. The Euclidean distance between two locations is used to set travelling distance threshold d_0 and *d*. The clients in each population center ranges from 10 to 100. The algorithms were implemented in Java and experiments were performed on a Core 2 Quo 2.40GHz PC with 3GB memory, running on Windows XP platform. The experiments on synthetic datasets focus on comparing the computational performances between the accelerated Interchange algorithm and the Interchange algorithm. The rationale of setting the parameters and the interpretation of the results would be given on the real dataset experiments in the next section.

Problem parameters:

Travelling distance threshold of each facility's service radius d_0 = 30;

Predefined travelling distance for setting remote place d = 60;

Number of facilities n_S = 10;

Minimum workload W_{min} = 1000.

Value measurement:

$$average\ accessibility = \frac{\sum_{i \in I} A_i * P_i}{\sum_{i \in I} P_i} \tag{4.5}$$

The *average accessibility* records the average population weighted accessibility value of all population centers which reflects the efficiency objective. In this section, the accuracy of an algorithm is quantified by using the average accessibility value (i.e., equation 4.5). The larger average accessibility value of an algorithm, the higher accuracy of the algorithm is.

The results produced by using the accelerated Interchange algorithm and the Interchange algorithm are summarized in Tables 4.3 and 4.4. In Table 4.3, when the number of candidate sites increases from 50 to 5,000, the execution time of the Interchange algorithm increases from 16.83 seconds to 3,087.91 seconds. The accelerated Interchange algorithm produces the same values of average accessibility with those of the Interchange algorithm but reduces the execution time which ranges from 0.18 seconds to 16.83 seconds. Table 4.4 shows that when the number of population centers increases from 1,000 to 100,000, the execution time of the Interchange algorithm increases from 1.84 seconds to 208.86 seconds. For the accelerated Interchange algorithm, it produces the same values of average accessibility with those of the Interchange algorithm. However, the execution time of the accelerated Interchange algorithm only reaches 1.57 seconds when the number of population centers equals to 100,000.

The results in Table 4.3 and 4.4 indicate that it is time consuming that using the Interchange algorithm to search the optimal location of static facilities especially when the number of population centers or the number of candidate sites is large. The results also present that the two new data structures could accelerate the static facility location searching without sacrificing accuracy. That is because the two data structures just aggregate the accessibility information and the integration of them and the Interchange algorithm would not influence the accuracy of the algorithm.

Table 4.3 Comparison between the Interchange algorithm and the accelerated Interchange algorithm different numbers of candidate sites

# of candidate sites	# of population centers	average accessibility (10^{-2})	execution time (s)	
		Interchange/ accelerated Interchange	Interchange	accelerated Interchange
50	10,000	1.00	16.83	0.18
100	10,000	1.73	35.08	0.21
500	10,000	1.74	267.77	0.88
1,000	10,000	1.96	570.64	1.42
5,000	10,000	2.86	3,087.91	16.83

Table 4.4 Comparison between the Interchange algorithm and the accelerated Interchange algorithm under different numbers of population centers

# of candidate sites	# of population centers	average accessibility (10^{-2})	execution time (s)	
		Interchange/ accelerated Interchange	Interchange	accelerated Interchange
50	1,000	12.16	1.84	0.06
50	5,000	3.66	2.41	0.09
50	10,000	1.73	19.83	0.18
50	50,000	1.52	126.55	0.61
50	100,000	0.87	208.86	1.57

4.4 The Application of Breast Cancer Screening Program

In this section, the customized method is applied to a real-world application, the breast cancer screening program in Alberta, Canada.

4.4.1 Problem Statement and Data Issues

Breast cancer is the most common cancer among Canadian women. In 2009, an estimated 22,700 Canadian women will be diagnosed with breast cancer and 5,400 would die from the disease; one in 9 women is expected to develop breast cancer during her lifetime and one in 28 will die from it (Canadian Cancer Statistics, 2010). Evidence from randomized controlled trials supports the recommendation that women aged 50 to 69 years be screened with annual or biennial mammography to reduce their risk of dying from breast cancer (Towards Optimized Practice, 2010). A population-based program to increase the number of Alberta women screened regularly for breast cancer was implemented in 1990 and today the Alberta Breast Cancer Screening Program (ABCSP) recommends Alberta women between the ages of 50 and 69 have a screening mammogram at least once every two years (Alberta Breast Cancer Screening Program website, 2010). A key challenge is to determine the optimal number of screening facilities and their locations.

This thesis considers the demand for services as measured by population in target groups (women between the ages of 50 and 69) in various locations. Estimates of the target population (Alberta women aged 50 to 69 years) are derived from census data at the Dissemination Area (DA) level (Data quality index for census geographies, 2010) from the 2006 Canadian census (Statistics Canada). There are 327,830 women within the target age in Alberta. In order to calculate the distance between the DAs and the facilities, the Postal Code Conversion File (Postal Code Conversion File Reference Guide, 2010) is used to estimate the location of the DAs. A total of 5,180 DAs are used. Their values range from 0 to 920.

The existing 53 screening clinics (i.e., static facilities) providing screening mammography in Alberta are extracted from the ABCSP. In addition, 92 unused candidate screening sites for screening clinics in Alberta are extracted from the Alberta Health Services website (2010). The unused candidate screening sites are defined as hospitals and cancer care facilities registered in Alberta but not used for breast cancer screening. The locations of screening clinics and the unused candidate screening sites are geocoded to point locations using the GIS address matching technique (ArcGIS

Extensions, 2010). Figure 4.3 shows the location of the DAs, the location of existing screening clinics, and the unused candidate sites for screening clinics.

Besides the screening clinics, ABCSP also operates mobile screening units (i.e., mobile facilities) that provide outreach services to on-site locations. The mobile screening unit is a vehicle with necessary screening equipments and screening staff. Each mobile screening unit is located a community in a period and then is dispatched to another community. At the end of each period, mobile screening units need to return screening mammograms taken for breast cancer detection to one of the screening clinics. Right now, two mobile units are dispatched based on the appointment from the clients who were inconvenienced to get the service. The precise schedule of the mobile units is lacking in the thesis in that the location of the existing mobile screening units is unknown. Since the mobile screening units can be located in the community where clients live, in the thesis all the locations of the DAs are treated as the candidate sites for mobile screening units. The projected coordinate system used in the figures of this section is GCS_North_American_1983.

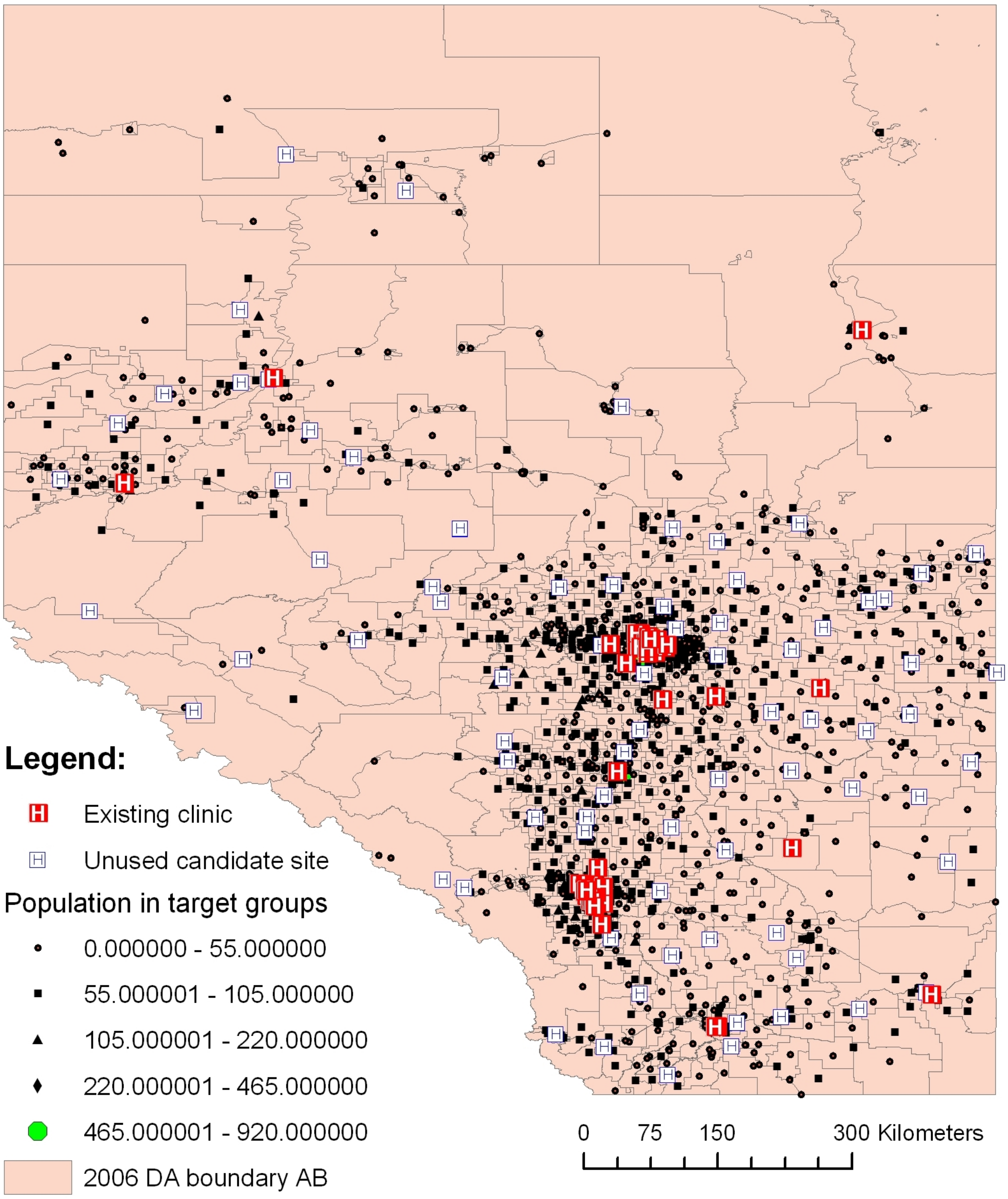


Figure 4.3 Distribution of the DAs, the existing screening clinics and the unused candidate sites for screening clinics in Alberta breast cancer screening program

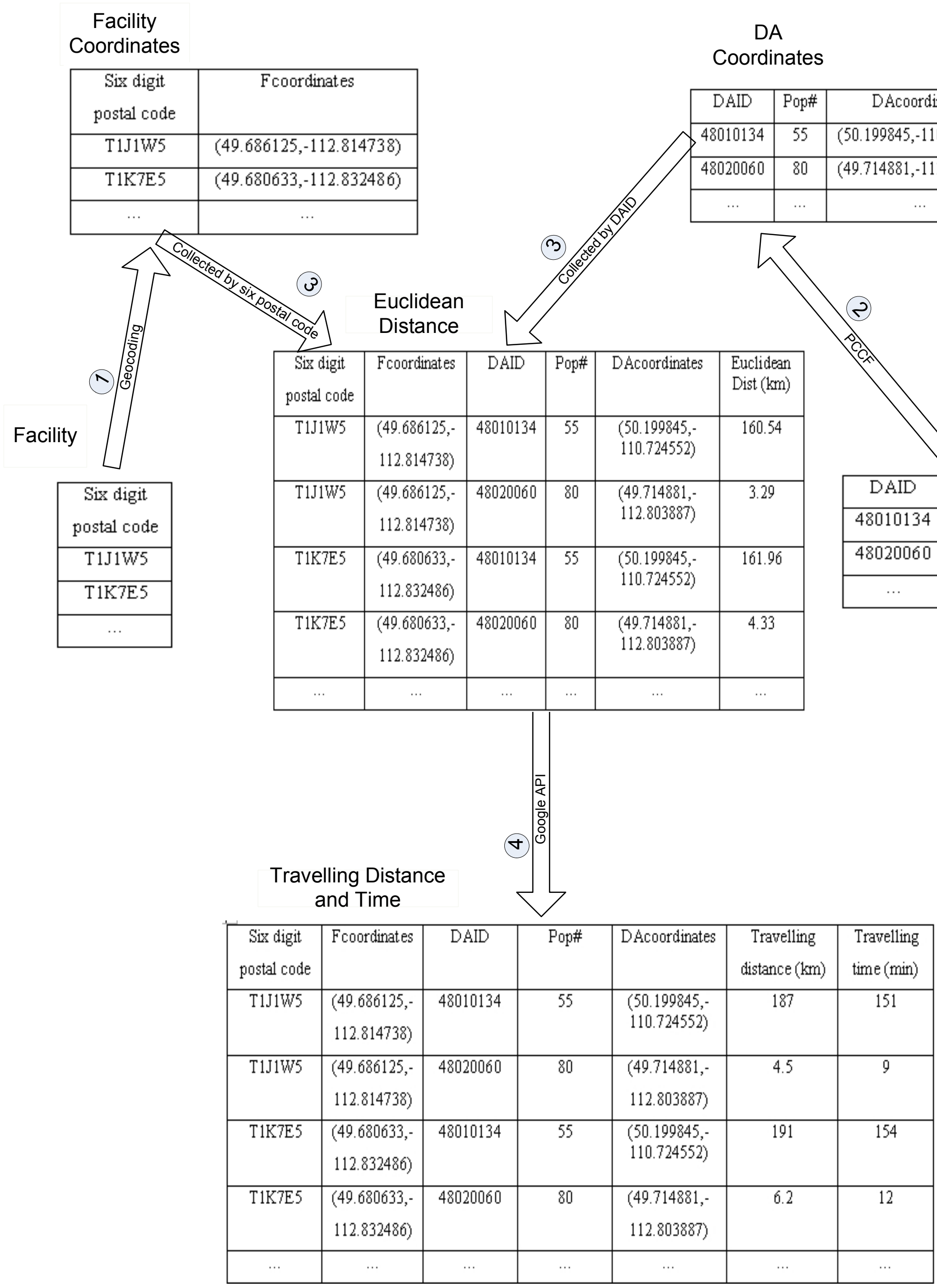
4.4.2 Travelling Distance and Travelling Time Estimation

In this thesis, travelling distance and travelling time are used to measure the spatial barrier between clients and preventive health care facilities. The travelling distance is defined as the distance between two points according to a road network. The travelling time is defined as the estimated driving time between two points according to a road network. The travelling distance and travelling time are estimated by calling the Google Maps Application Programming Interface (API) (Google Maps API, 2010). The Google Maps API is a software program that defines how other software can request services (the same services we can get from the http://maps.google.com web page manually) from the Google. The Google Maps API is easier than the previous travelling time estimation methods (Lovett et al., 2002; Wang and Luo, 2005) in that it does not need users to supply speed limit maps and gather traffic rules. The process of using the Google maps API to estimate the travelling distance and travelling time between any pair of DA and facility is comprised of four steps (as shown in Figure 4.4):

(1) Save the location information of facilities in the Facility Table as a Six digit postal code attribute. Create the Facility Coordinates Table by geocoding each six digit postal code in the Facility Table to the coordinates.

(2) Save the ID number and the population number of each DA in the DA Table. Create the DA Coordinates Table by using the PCCF to estimate the coordinates of each DA record in the DA Table.

(3) Create the Euclidean Distance Table by calculating Euclidean distance between any pair of the DA in the DA Coordinates Table and the facility in the Facility Coordinates Table.



Facility

Six digit postal code
T1J1W5
T1K7E5
…

Facility Coordinates

Six digit postal code	Fcoordinates
T1J1W5	(49.686125,-112.814738)
T1K7E5	(49.680633,-112.832486)
…	…

DA

DAID	Pop#
48010134	55
48020060	80
…	…

DA Coordinates

DAID	Pop#	DAcoordinates
48010134	55	(50.199845,-110.724552)
48020060	80	(49.714881,-112.803887)
…	…	…

Euclidean Distance

Six digit postal code	Fcoordinates	DAID	Pop#	DAcoordinates	Euclidean Dist (km)
T1J1W5	(49.686125,-112.814738)	48010134	55	(50.199845,-110.724552)	160.54
T1J1W5	(49.686125,-112.814738)	48020060	80	(49.714881,-112.803887)	3.29
T1K7E5	(49.680633,-112.832486)	48010134	55	(50.199845,-110.724552)	161.96
T1K7E5	(49.680633,-112.832486)	48020060	80	(49.714881,-112.803887)	4.33
…	…	…	…	…	…

Travelling Distance and Time

Six digit postal code	Fcoordinates	DAID	Pop#	DAcoordinates	Travelling distance (km)	Travelling time (min)
T1J1W5	(49.686125,-112.814738)	48010134	55	(50.199845,-110.724552)	187	151
T1J1W5	(49.686125,-112.814738)	48020060	80	(49.714881,-112.803887)	4.5	9
T1K7E5	(49.680633,-112.832486)	48010134	55	(50.199845,-110.724552)	191	154
T1K7E5	(49.680633,-112.832486)	48020060	80	(49.714881,-112.803887)	6.2	12
…	…	…	…	…	…	…

Figure 4.4 Flow diagram of travelling distance and time estimation using the Google Maps API

(4) Create the Travelling Distance and Time Table by calculating the travelling distance and time between the DA and the facility in each record in the Euclidean Distance Table. The calculation is implemented in JavaScript (JavaScript for the Total Non-Programmer, 2010) by calling the Google maps API. The pseudo code in Figure 4.5 shows how to calculate the travelling distance and time between one DA / Facility pair. First, an object instance called directionObject is created for the class GDirections in Line 1. GDirections is a class defined in the Google Maps API and is used to obtain driving information and display these on a map. Second, the coordinates of the facility and the DA are uploaded as a string query using the function load() in the GDirections class (Lines 2-3). The load function extracts the coordinates from the string and sets the departure and destination location for the next step in the calculation. Finally, the travelling distance and time between the uploaded DA and facility are calculated by using the functions getDistance( ) and getDuration( ) in the GDirections class (Lines 4-5).

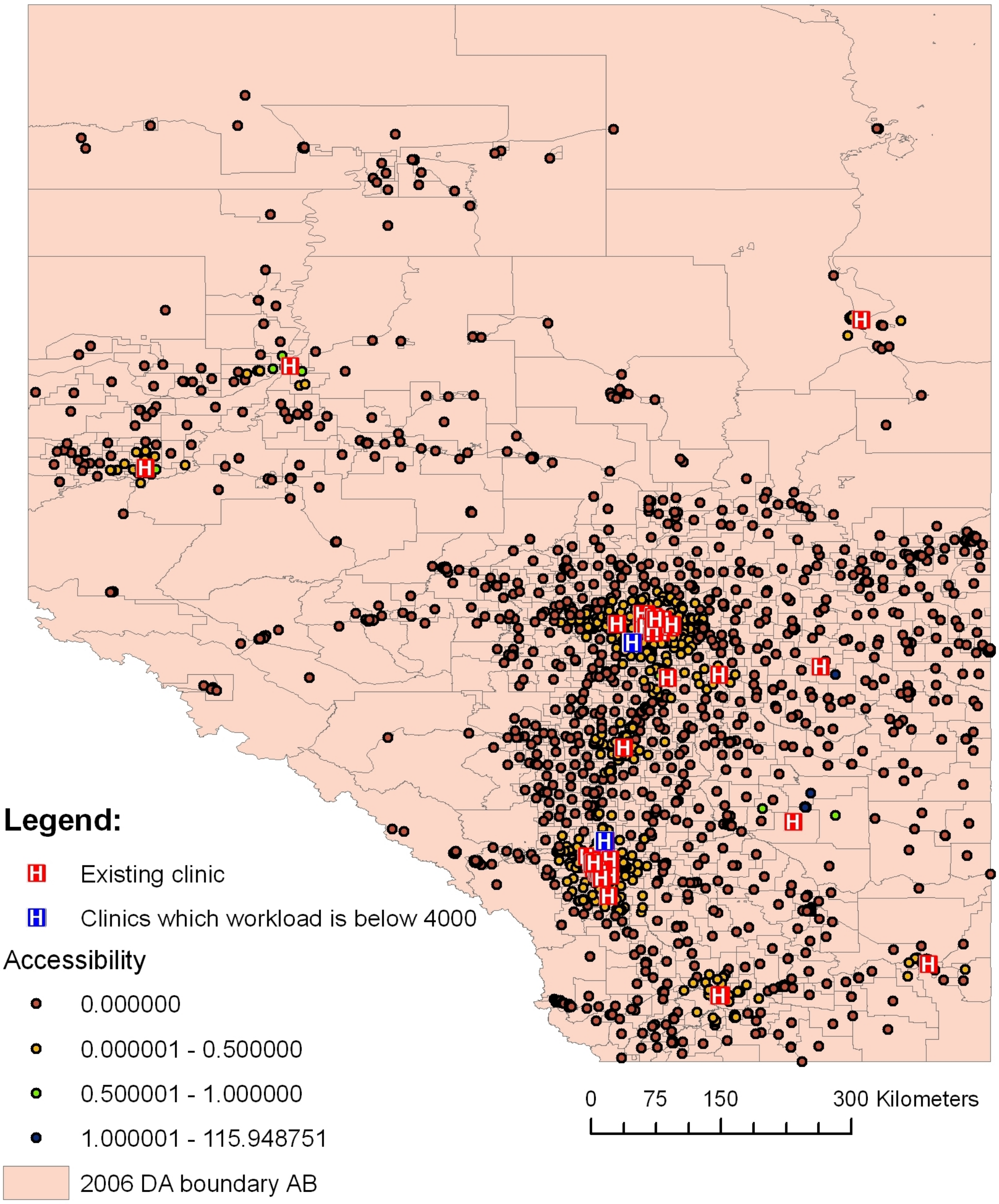
```
Function DistCalculation(Fcoordinate, DAcoordinate)
  Input: a coordinate of a facility Fcoordinate, a coordinate of a DA DAcoordinate.
  Output: the travelling distance TravellingDist and the travelling time TravellingTime between
        the facility and the DA.
1  directionObject = new GDirections();
2  query = "from: "+ Fcoordinate + " to: "+ DAcoordinate;
3  directionObject.load(query);
/*return the travelling time in seconds*/
4  TravellingDist = directionObject.getDuration().seconds;
/*return the travelling distance in meters */
5  TravellingTime = directionObject.getDistance().meters;
```

Figure 4.5 Pseudo code for calculating the travelling distance and time by using the Google API

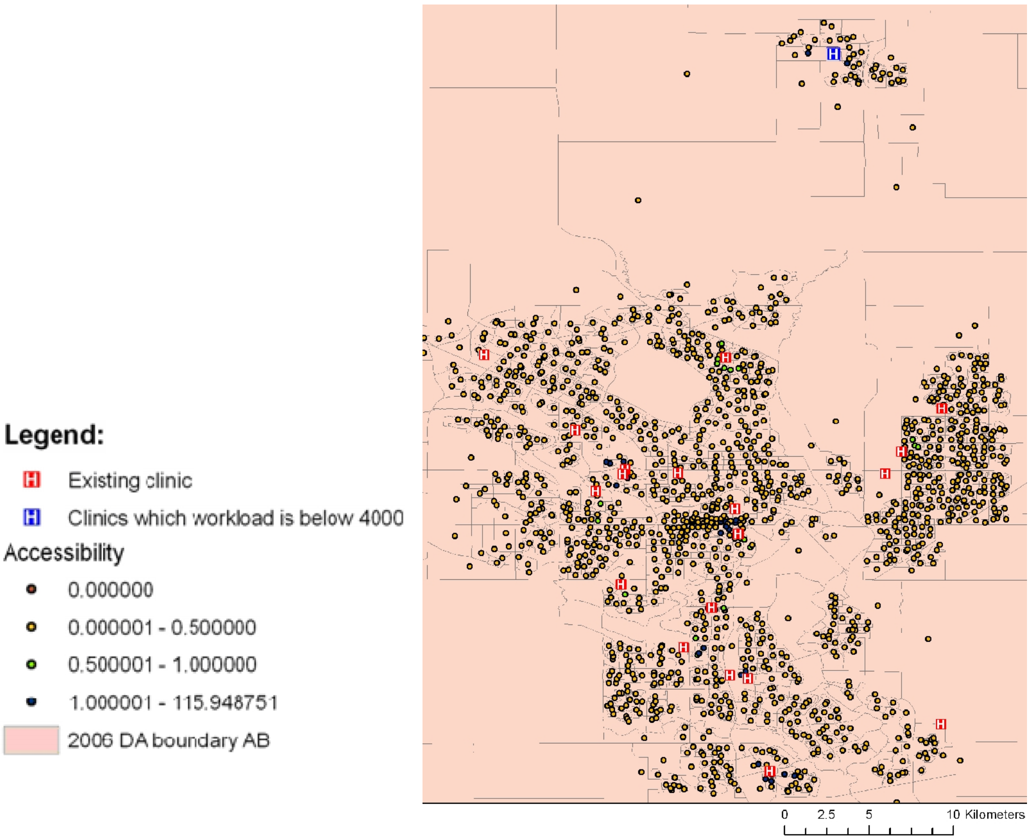
4.4.3 Optimized Facility Configurations

In this subsection, the method is used to optimize the locations of screening clinics and mobile screening units. Since the number of current screening clinics in Alberta is 53, the number of screening clinics n_S is set to 53. Right now the ABCSP operates two mobile screening units. In this thesis, we assume that each mobile screening unit stays in a place for two months and the effect of mobile screening units is the same with screening clinics. Then each year, the two mobile screening units would visit twelve sites. So, the method should find twelve locations for mobile faculties and n_M is set to twelve. We also assume that the geocoded coordinates of population centers and facilities, and the estimated travelling distance and time are accurate. The threshold travelling distance d_0 of each facility is defined as a distance of thirty minutes driving time, a standard used by the U.S. Department of Health and Human Services for defining service areas (Wang et al., 2008). Minimum required workload at each screening clinic W_{min} is set to 4000 according to the policy decision made by the Ministry of Health (Verter and Lapierre, 2002). The predefined travelling distance for remote location d is set to $2*d_0$.

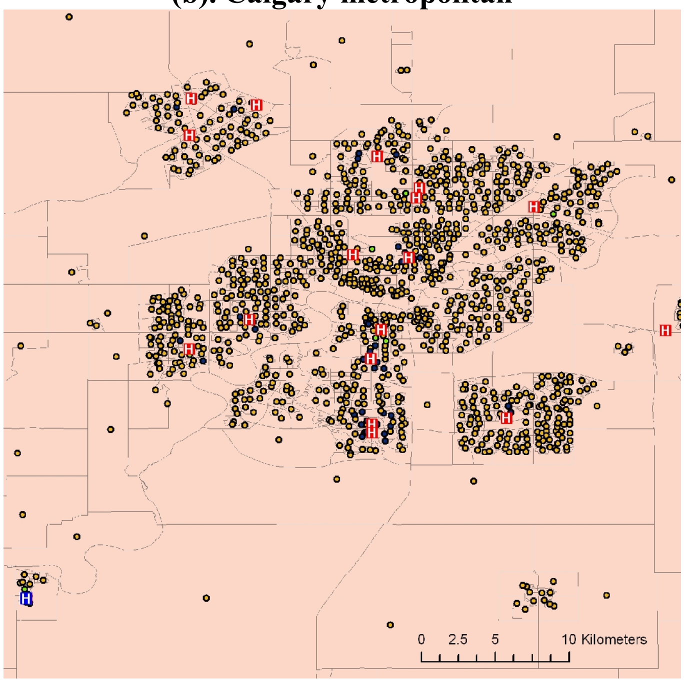
Figure 4.6 shows the influence of the accessibility measurement on the existing screening clinic configuration. The accessibility values of population centers range from 0 to 115.95. In Figure 4.6 (a), it is obvious that most screening clinics are located in two large metropolitan areas, Calgary and Edmonton while remote locations, such as the east border area, are lacking clinics. Figure 4.6 (b) and 4.6 (c) show the locations of screening clinics in Calgary metropolitan and Edmonton metropolitan areas, respectively. Based on the Huff-based competitive location model, one screening clinic in north Calgary and one in southwest Edmonton cannot serve enough clients.



(a). Alberta province



(b). Calgary metropolitan

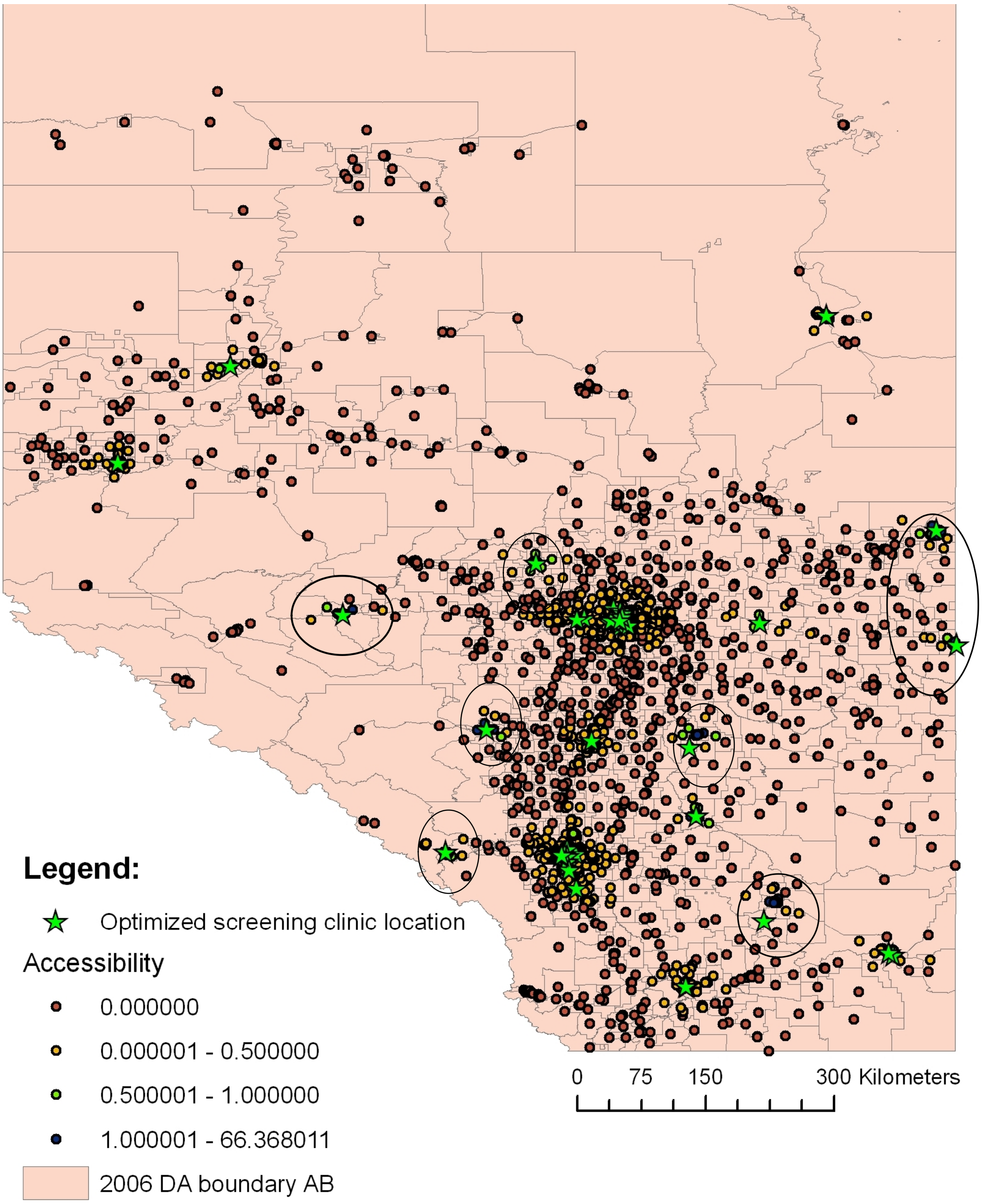


(c). Edmonton metropolitan

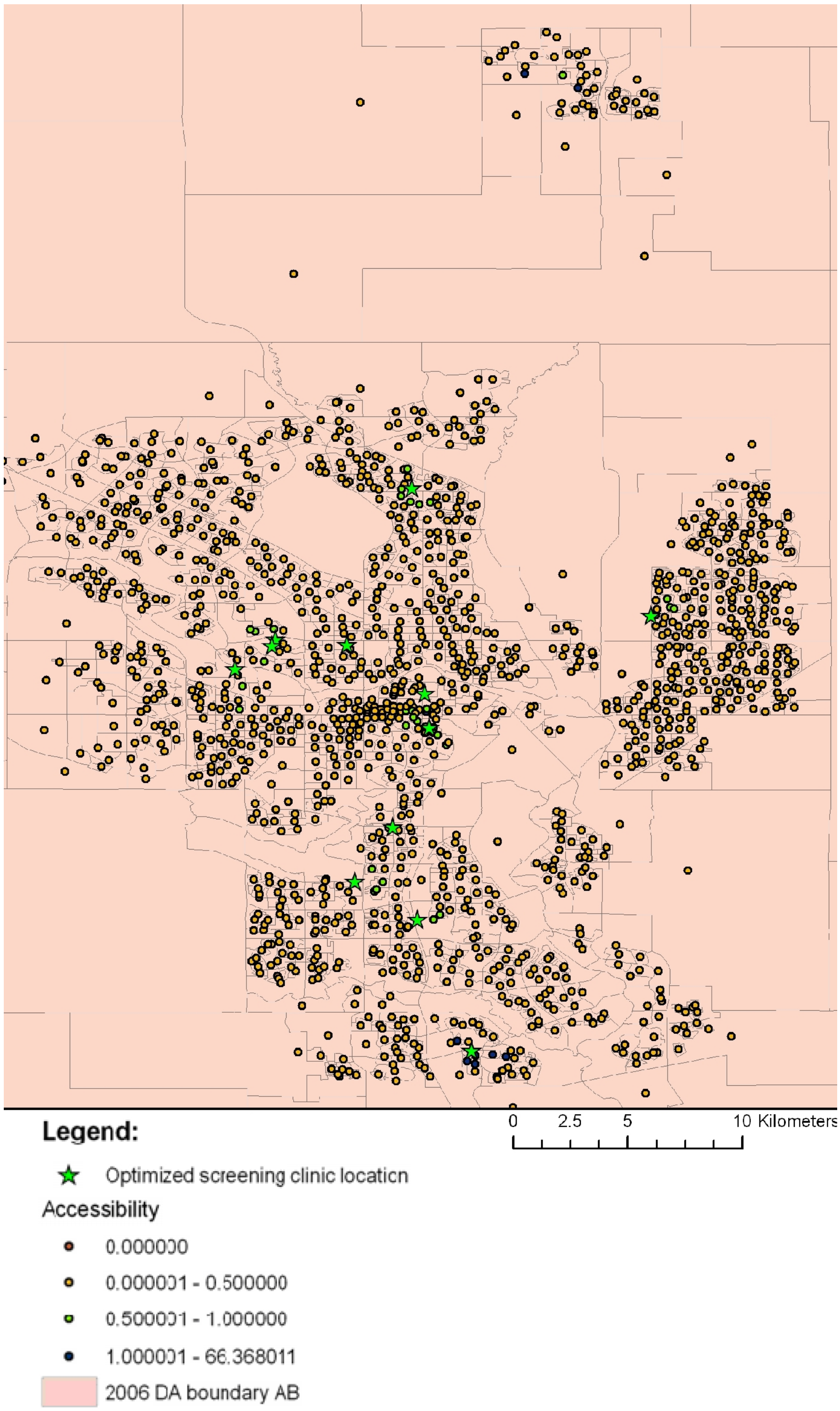
Figure 4.6 Accessibility measurement on the existing screening clinic configuration

The method first finds the locations of screening clinics from the existing screening clinic locations and the unused candidate sites to maximize the sum of population weighted accessibility values (i.e., the equation 4.3). Figure 4.7 shows the accessibility measurement on the optimized screening clinic configuration. The accessibility values of population centers range from 0 to 66.37. Compared with the existing screening clinic configuration, the accessibility values in seven areas under the optimized screening clinic configuration (shown in the circles in Figure 4.7 (a)) are dramatically higher. The screening clinics in Calgary metropolitan and Edmonton metropolitan areas are shown in Figure 4.7 (b) and 4.7 (c) respectively. In addition, all of the screening clinics in the optimized screening clinic configuration have sufficient clients.

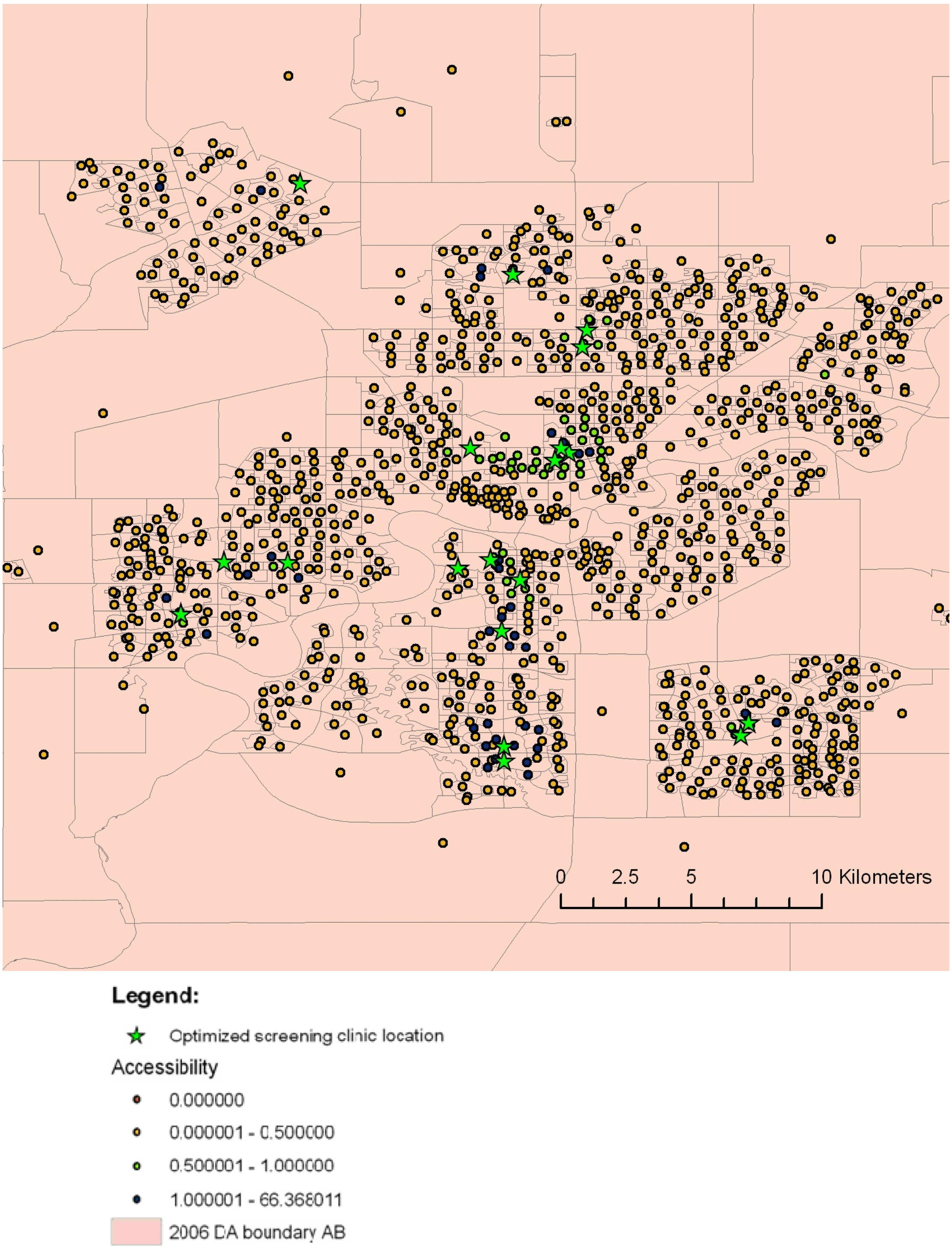
Compared with the existing screening clinic configuration, twenty clinics are moved to new sites in the optimized screening clinic configuration. Although the optimized configuration can dramatically improve the accessibility values in several areas, in reality, only a small number of screening clinics can be moved because of the budget limit. In the thesis, the method allows the decision maker to set the maximal number of screening clinics to be moved. For example, Figure 4.8 (a) shows the optimized location of screening clinics when the number of screening clinics allowed moving is set to one. The only moved clinic is the one in the Edmonton metropolitan which cannot serve enough clients in the existing screening clinic configuration (as shown in Figure 4.8 (b)). The accessibility values of population centers range from 0 to 115.95.



(a). Alberta province

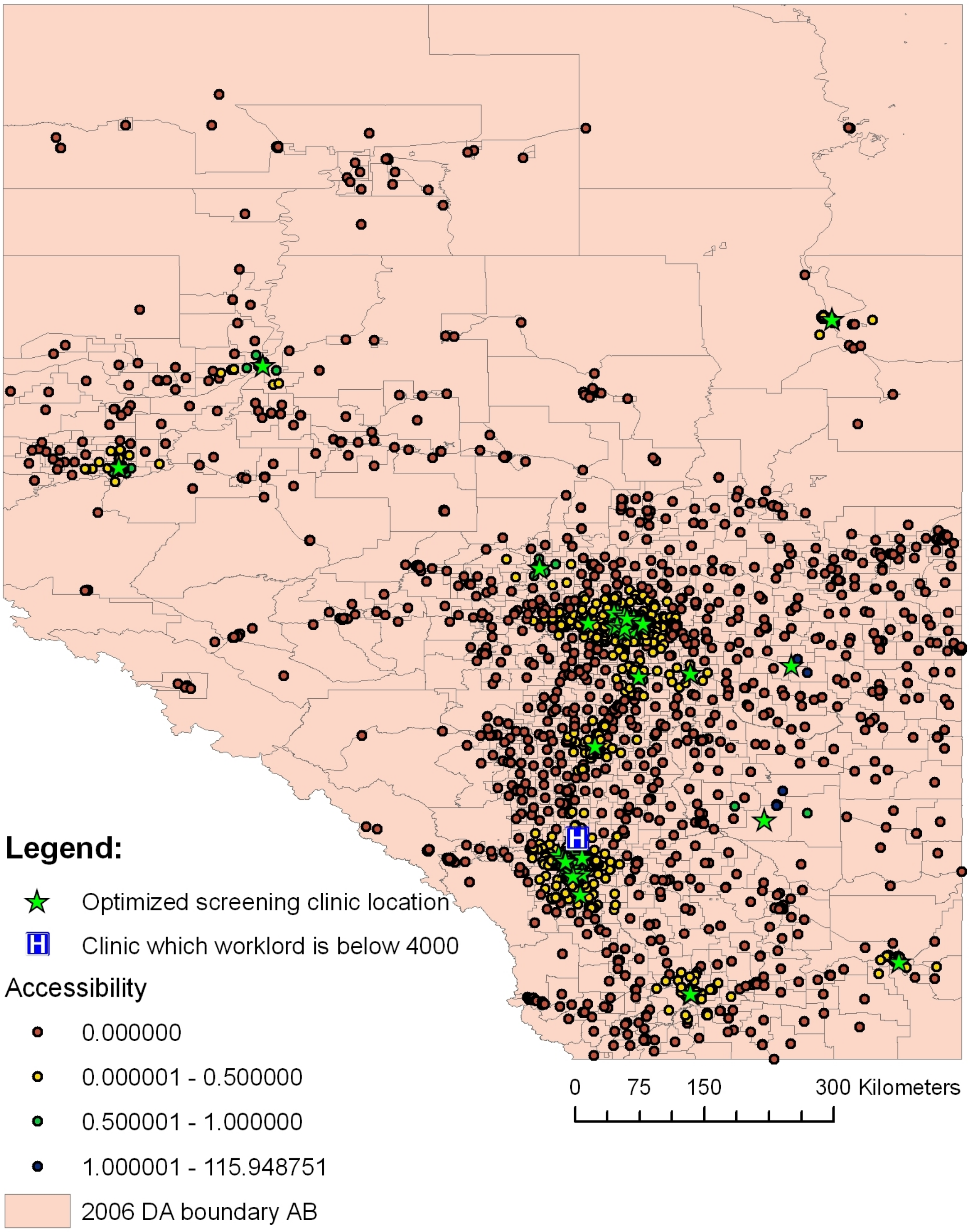


(b). Calgary metropolitan

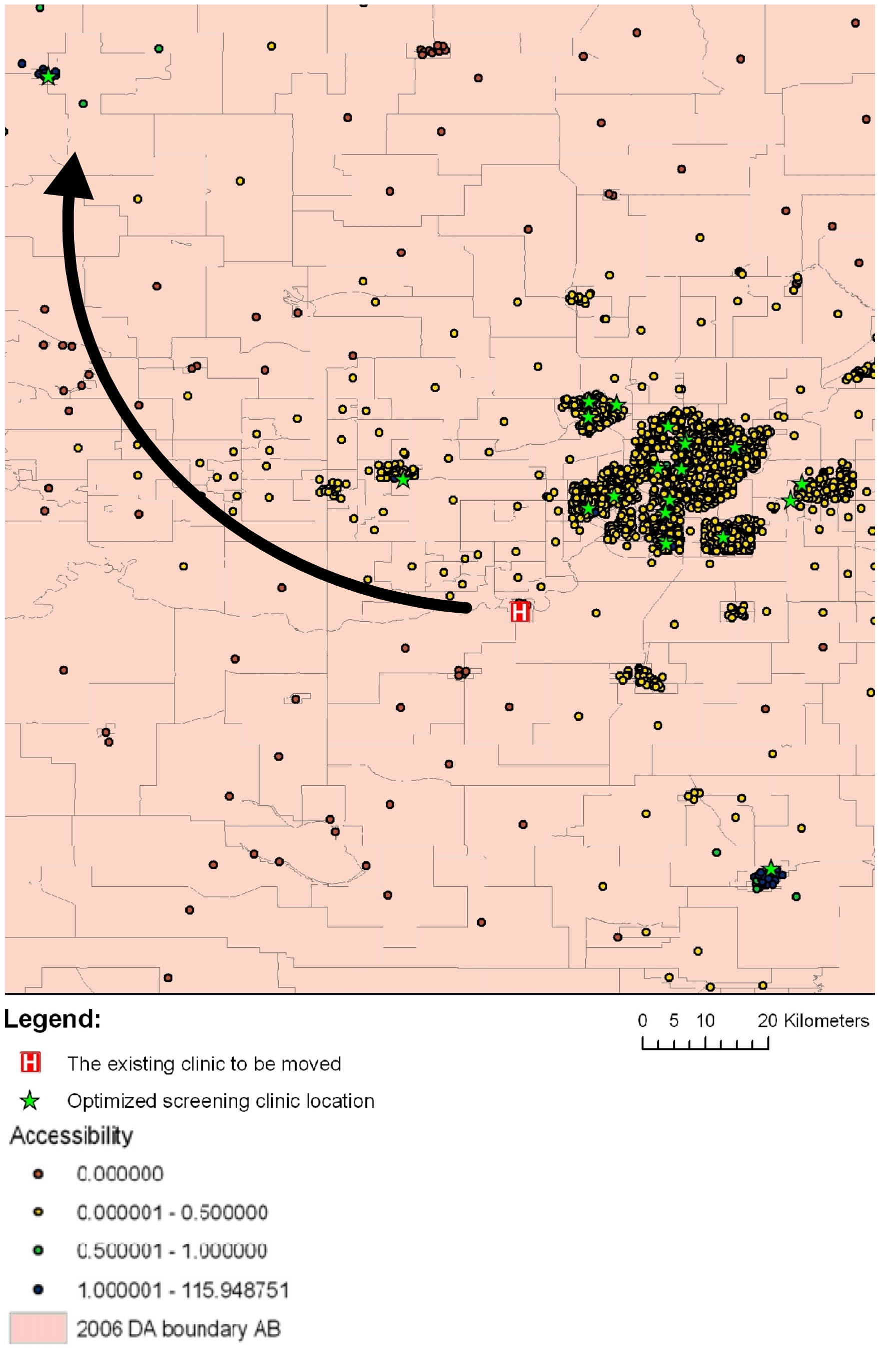


(c). Edmonton metropolitan

Figure 4.7 Accessibility measurement on the optimized screening clinic configuration



(a). Alberta province



(b). The details in the circle area in Figure 4.8 (a). The arrow shows the movement of the clinic from its exiting location to the optimized location.

Figure 4.8 Accessibility measurement on the optimized screening clinic configuration when the number of screening clinics allowed moving is set to one

After locating the screening clinics to the optimized locations, the method finds the twelve locations for the mobile screening units from the candidate sites to maximize the number of people within the acceptable travelling distance of at least one facility (i.e., equation 4.4). Figure 4.9 shows the accessibility measurement on the optimized configuration of screening clinics and mobile screening units. Most mobile screening units are located around two large metropolitan areas, Calgary and Edmonton. The accessibility values of population centers range from 0 to 136.69.

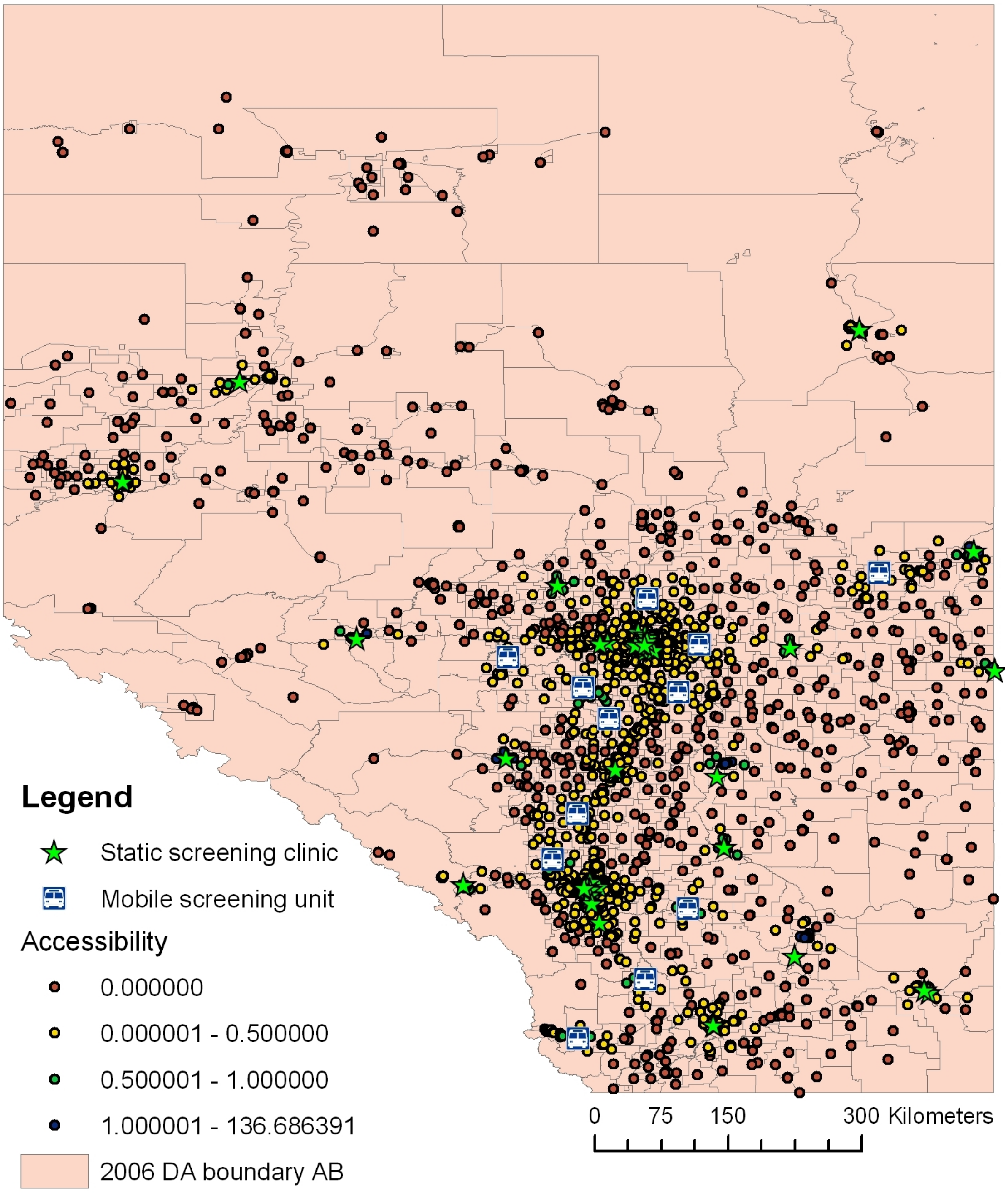


Figure 4.9 Accessibility measurement on the optimized configuration of screening clinics and mobile screening units

Table 4.5 compares the optimized facility configurations with the existing screening clinic configuration based on *average accessibility*, *coverage*, and *maximal accessibility*. The average accessibility is calculated according to equation (4.5). The coverage is defined by dividing the sum of the number of clients on the population centers whose accessibility value is not zero into the total number of clients, which reflects the equity objective. The coverage is calculated by using equation (4.6). The maximal accessibility records the maximal accessibility value of all population centers. In Table 4.5, the existing screening clinic configuration is referred to as *configuration 1*. The optimized screening clinic configuration with setting maximal movement number to one is referred to as *configuration 2*. The optimized screening clinic configuration is referred to as *configuration 3*. The optimized configuration of screening clinics and mobile screening units is referred to as *configuration 4*.

$$coverage = \frac{\sum_{i \in I \cap A_i \neq 0} P_i}{\sum_{i \in I} P_i} \tag{4.6}$$

Compared with the configuration 1, the configuration 2 achieves better results in that it increases the average accessibility from 0.35 to 0.39 and improves the coverage from 78.42% to 78.59%. The maximal accessibility value of the configuration 2 is the same with that of the configuration 1. Since only one screening clinic can be moved, the improvement brought by the configuration 2 is limited. The accessibility value is separated into different value segments and the number of people involved in each segment is counted. People in the zero segment cannot be 'covered' by any facility. People in higher value segments can get more convenient service. Compared with the configuration 1, the configuration 2 is better because it reduces the number of people in the zero segment and brings more people into higher value segments.

Table 4.5 Comparison between the existing screening clinic configuration and the optimized facility configurations

	average accessibility	coverage (%)	maximal accessibility	accessibility value segement			
				0	(0,0.5)	[0.5,1)	[1,max]
Configuration 1	0.35	78.42	115.95	70,745	233,700	7,855	15,530
Configuration 2	0.39	78.59	115.95	70,195	233,690	7,870	16,075
Configuration 3	0.41	79.70	66.37	66,560	228,080	14,240	18,950
Configuration 4	0.77	87.96	136.69	39,455	252,205	16,140	20,030

Note: max means the maximal accessibility value under a facility location configuration.
configuration 1: the existing screening clinic configuration
configuration 2: the optimized screening clinic configuration with setting maximal movement number to one
configuration 3: the optimized screening clinic configuration
configuration 4: the optimized configuration of screening clinics and mobile screening units

Compared with the configuration 2, the configuration 3 is better. It increases the average accessibility to 0.41 and improves the coverage to 79.70%. The maximal accessibility value of the configuration 3 is smaller compared with that of the configuration 1 and the configuration 2 because with the method some facilities in the high accessibility value area in the existing screening clinic configuration are relocated to remote places. The configuration 3 reduces the number of people in the zero segment and brings more people into higher value segments further.

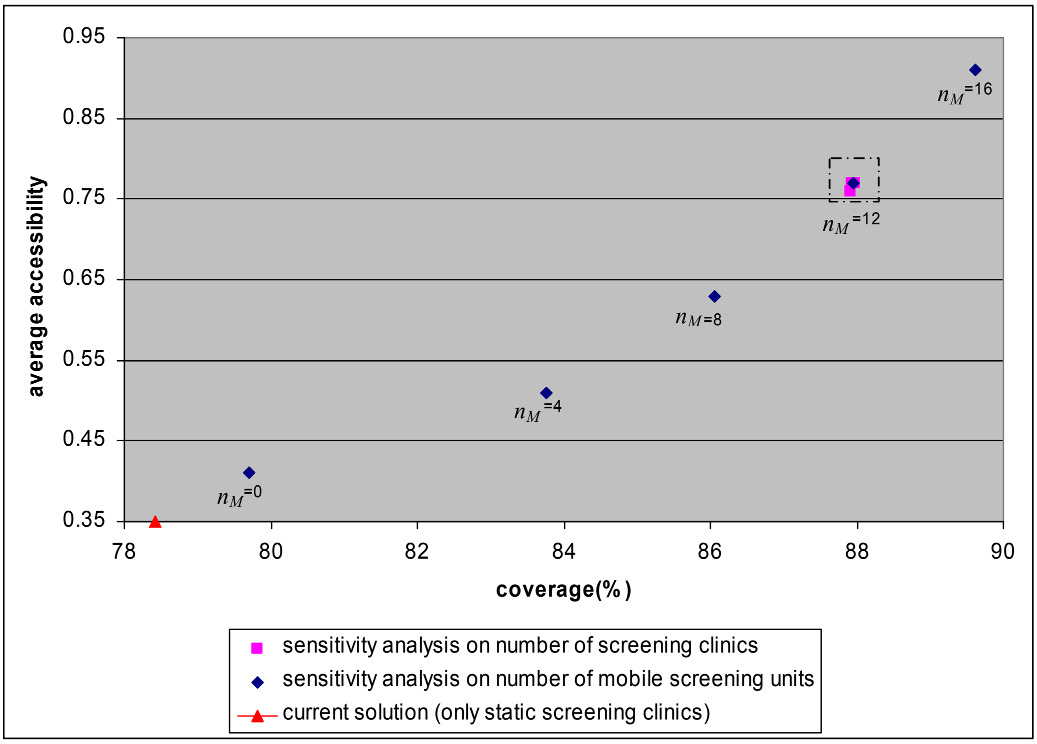
The configuration 4 produces the best results. It increases the average accessibility to 0.77 and improves the coverage to 87.96%. The maximal accessibility value of configuration 4 is larger than that of any other configuration. The configuration 4 minimizes the number of people in the zero segment to 39455 and maximize the number of people in (0, 0.5), [0.5, 1), and [1, max) segments to 252205, 16140 and 20030 respectively.

4.4.4 Parametric Analyses

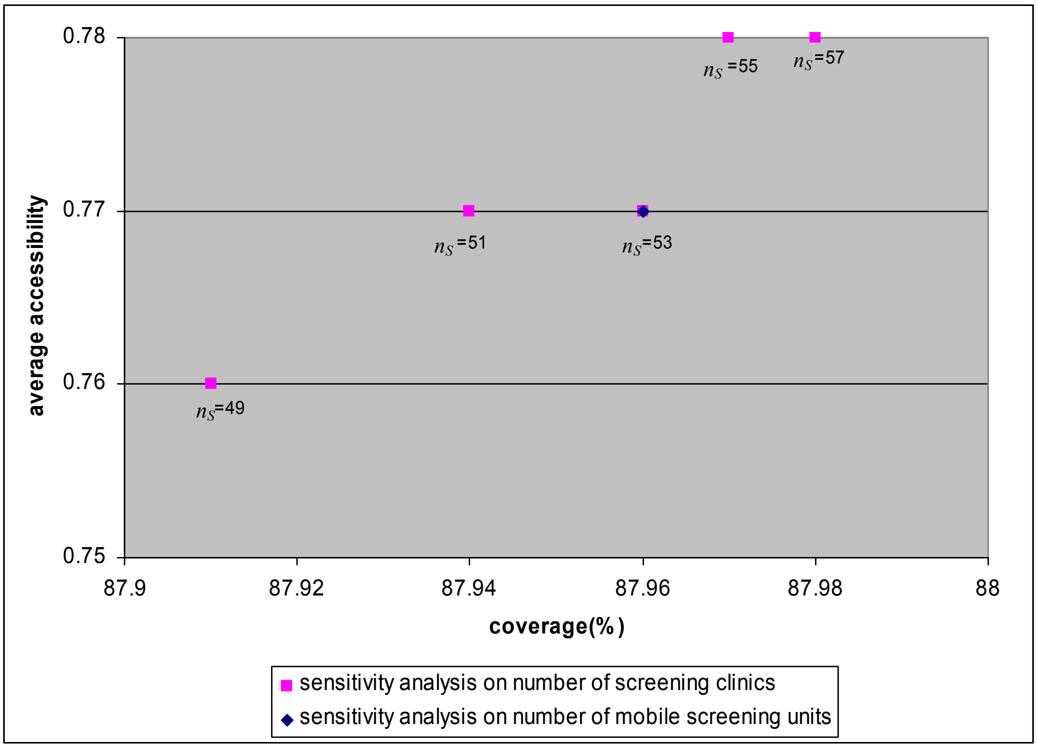
In this subsection, sensitivity analyses are performed on the impact of the following parameters in the real application.

- n_S the number of screening clinics;
- n_M the number of mobile screening units;

In Figure 4.10, the optimized configurations of screening clinics and mobile screening units with different parameters and the existing screening clinic configuration are plotted into a solution space. The solution space have two dimensions: Y axis represents the average accessibility value of a facility configuration and the X axis represents the coverage value of that facility configuration. From Figure 4.10, two conclusions can be made. First, with an increase of the number of mobile screening units in a facility configuration (the number of screening clinics is fixed to 53 at the mean time), both the average accessibility value and the coverage value of that configuration increase (denoted by diamonds). Second, increasing the number of screening clinics (the number of mobile screening units is fixed to 12 at the mean time) could improve the average accessibility value and the coverage value slight (denoted by squares). That is because after screening clinics being located, the mobile screening units would be located to serve the areas uncovered by screening clinics. Thus, with the increase of screening clinics, more people can be served by screening clinics, and hence the people served by each mobile screening unit facility reduce. In total, the average accessibility value and the coverage value do not change very much. This indicates that fewer screening clinics are needed to achieve an acceptable average accessibility value and coverage value when mobile screening units are located properly.



(a). The whole solution space



(b). The details in the rectangle in Figure 4.10 (a)

Figure 4.10 Distribution of solutions

4.5 Summary

In this chapter, the customized method for optimizing the locations of static and mobile facilities for preventive health care services is given. It starts by presenting the description of the preventive health care facility location problem in section 4.1. To capture the characteristics of preventive health care services, a new accessibility measurement is developed that combines the two-step floating catchment area method, the distance factor and the Huff-based model. Based on the new accessibility measurement method, a bi-objective model aiming to optimize both the efficiency and the equity of preventive health care facility locations is given in section 4.2. In section 4.3, the SMFLS algorithm is applied to solving the preventive health care static and mobile facility location model. To solve the model accurately and efficiently, the static facility location searching and the mobile facility location searching of the SMFLS algorithm is implemented by the Interchange algorithm with two new data structures and the greedy heuristic method respectively. The computational experiments show that the integration of the Interchange algorithm with the two data structures can dramatically reduce the execution time without sacrificing accuracy compared with using the Interchange algorithm alone. Finally, the real application in section 4.4 demonstrates that the method can improve the performance of the Alberta breast cancer screening program.

CHAPTER FIVE: CONCLUSIONS AND FUTURE WORK

In this final chapter, the conclusions are made and priorities for further research are discussed.

5.1 Conclusions

In this thesis, the Static and Mobile Facility Location Problem (SMFLP), which has not yet been well studied, is introduced. Compared with other facility location problems in the literature, this new problem has the following distinctive characteristics:

- It considers two objectives for optimizing facility locations: efficiency and equity.
- It includes the use of both static and mobile facilities.
- It integrates capacity constraint and assignment.

The method for solving the SMFLP is successfully developed. First, the problem is formalized as a bi-objective model. Second, a new heuristic algorithm, called Static Mobile Facility Location Searching (SMFLS), is proposed for solving the model. The algorithm consists of two steps: static facility location searching and mobile facility location searching. In order to solve the model for large datasets efficiently, the thesis proposes a clustering-based heuristic method to do the static facility location searching and adopts a greedy heuristic method to do the mobile facility location searching. The clustering-based heuristic method separates the candidate sites of static facilities into different clusters and then reduces the searching space for each static facility from the candidate sites in the whole area to the candidate sites in the cluster where the static facility occurs. Experiments on synthetic datasets show that the clustering-based heuristic method can dramatically reduce execution time and has an acceptable accuracy compared with the Interchange algorithm. Thus, the static facility location searching implemented by the clustering-based heuristic method is recommended to be applied on real time applications or be applied on the large datasets. Experiments on synthetic datasets also show that the SMFLS algorithm can produce the results of the SMFLP under different numbers of candidate sites, static facilities and mobile facilities. Application to the South Carolina population dataset demonstrates the practicality of the SMFLS algorithm.

In addition, a customized method to optimize static and mobile facility locations for preventive health care services is developed. The preventive health care facility location problem is inherently different from other facility location problems because of the two unique characteristics:

- First, people should have more flexibility to select service locations. People might not seek services from the closest preventive health care facility.
- Second, each preventive health care facility needs to have a minimum number of clients in order to retain accreditation.

In order to satisfy the characteristics of preventive health care services, the accessibility of preventive health care services is defined in the customized method that combines the two-step floating catchment area method, the distance factor and the Huff-based model. Based on the new definition of accessibility, a preventive health care static and mobile facility location model is proposed. To solve the model accurately and efficiently, the static facility location searching and the mobile facility location searching of the SMFLS algorithm is implemented using the Interchange algorithm with two new data structures and the greedy heuristic method, respectively. The computational experiments show that the integration of the Interchange algorithm with the two new data structures can dramatically reduce the execution time without sacrificing accuracy compared with using the Interchange algorithm alone.

Finally, the customized method is applied to a real-world application, the breast cancer screening program in Alberta, Canada. The method optimizes 53 locations of screening clinics (i.e., static facility) and 12 locations of mobile screening units (i.e., mobile facility) so as maximize the average population weighted accessibility value and the percentage of the people who can reach the screening facility (either clinic or mobile unit) within a distance of thirty minutes driving time. Compared with the existing screening clinic configuration, the optimized configuration of screening clinics and mobile screening units increases the average population weighted accessibility value from 0.35 to 0.77 and increases the percentage of the people ‘covered’ by any screening facility from 78.42% to 87.96%. In addition, parametric analyses show that fewer screening clinics are needed to achieve an acceptable average accessibility value and ‘covered’ percentage when mobile screening units are located properly.

5.2 Future Work

Several extensions to the research represent priorities for future research and are listed as follows:

- The problem investigated in the thesis only considers the capacity of static facilities, i.e., each static facility can satisfy a limited number of clients. The capacity of mobile facilities is not considered because of the assumption that mobile facilities are always available to meet a demand from population centers. However, in many cases, there is a high probability that some mobile facilities will be busy attending to other demands. Thus, including the probability that each mobile facility is busy and then applying the capacity constraint to the mobile facility would be a significant extension of the research.

- In the thesis, the SMFLS algorithm is developed to solve the problem efficiently. Even though the SMFLS algorithm can dramatically reduce the execution time, when the number of candidate sites is large the time is still unacceptable for some applications (especially for web applications). The extension would be to include a pre-processing method and spatial data index in the algorithm to reduce the execution time further.
- The solution approaches proposed in the thesis are derived from the greedy heuristic algorithm and the Interchange algorithm. While these can dramatically accelerate the solving process, accuracy is not improved. As discussed in the literature review, some meta-heuristic algorithms, such as VNS (Variable Neighborhood Search) (Hansen and Mladenovic, 1997) and Tabu (Glover and Laguna, 1997), have been developed to improve optimization accuracy. Therefore, it would be interesting to incorporate strategies from meta-heuristic algorithms in order to increase accuracy.
- The Modifiable Areal Unit Problem (MAUP) is an issue in the analysis of spatial data aggregated in zones, where the analysis result depends on the particular shape or size of the zones used in the analysis (Openshaw, 1984). It has been shown that the aggregation of spatial data into zones of different shapes and sizes can lead to different conclusions. One important future work is to evaluate the proposed method on different levels of aggregated data and to identify the proper

aggregation level for the specific facility location problem such as the preventive healthcare problem.

The census data used in this thesis is the data systematically recording information about the members of a given population. In Canada, the census data is acquired, recorded and released by the Statistic Canada (Statistic Canada, 2010). Considered the privacy issues, the census data released by the Statistic Canada is not on the individual level but is aggregated on different geographic unit levels (Data quality index for census geographies, 2010), such as the Census Subdivision (CSD) level, the Census Tract (CT) level and the Dissemination Area (DA) level. For the health care service planning, the census data in the CSD level, the CT level and the DA level are widely used to present the location of population centers. In Chapter 4, the DA level of census data is used since it is the finest census dataset with non-spatial attributes (e.g., age and sex).

Figure 4.11 shows the distribution of population centers in the CSD level. The CSD census data is one level above the DA level census data. In the CSD census dataset, the locations of residents in the Edmonton and Calgary metropolitan areas are aggregated as two points (shown as big green points in Figure 4.11). Figure 4.12 shows the optimized screening clinic locations in the Edmonton metropolitan area by running the proposed method on the CSD census dataset. Since the locations of residents in big metropolitan areas are presented by very few points, the locations of population centers under the CSD level do not reflect the geographic location of residents in reality. In the future, we will conduct experiments on lower level census datasets for the application.

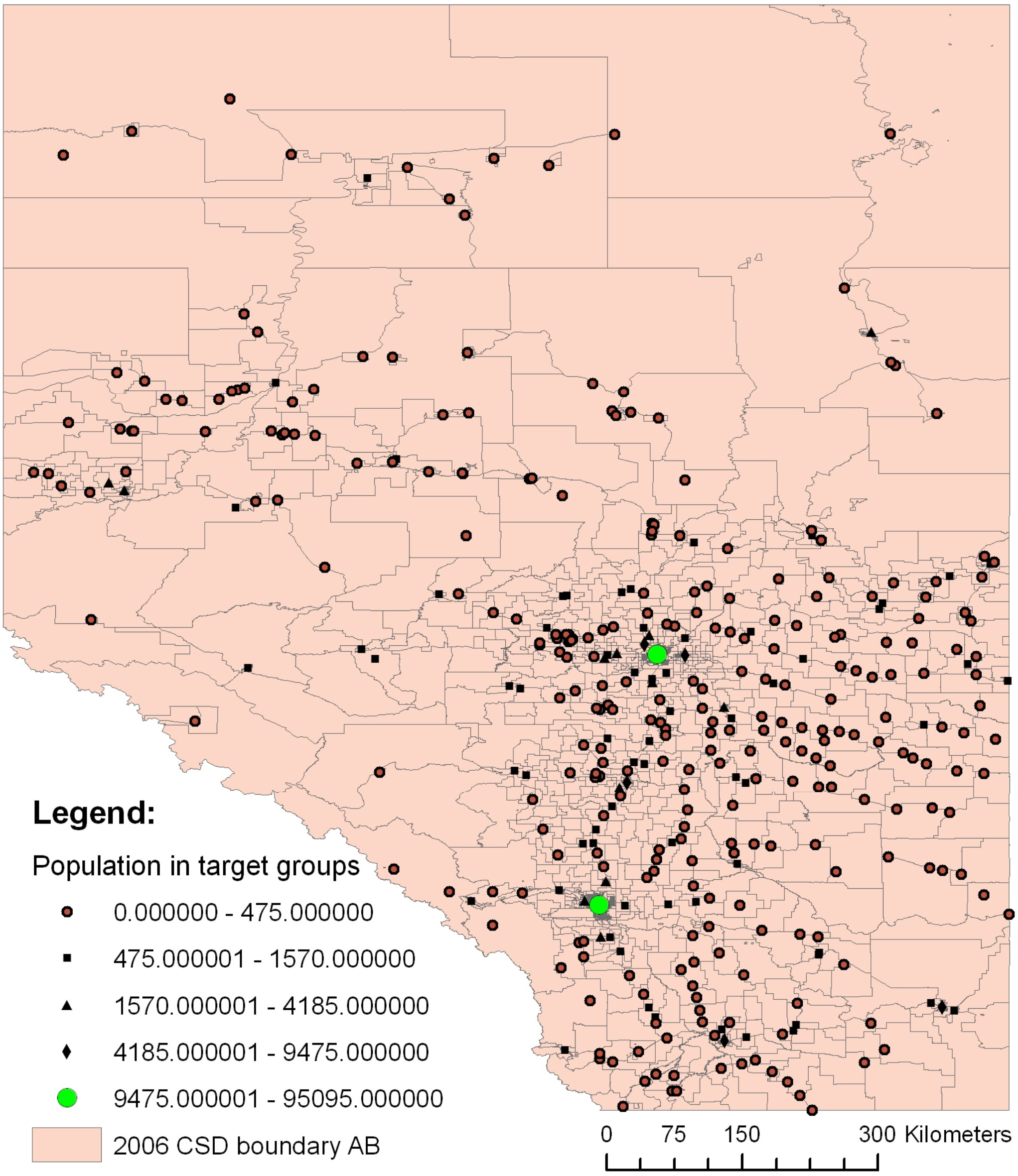


Figure 4.11 Distribution of population centers in the CSD level in Alberta

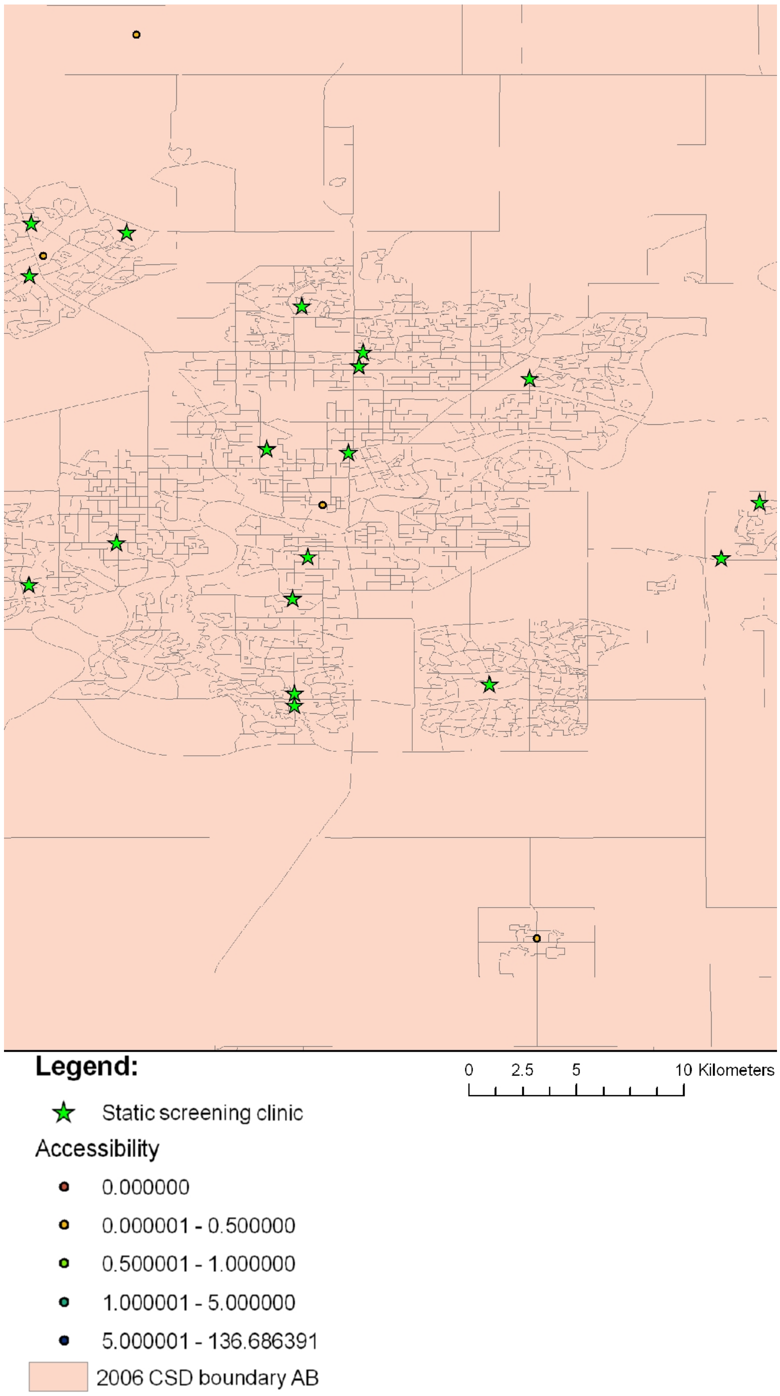


Figure 4.12 Accessibility measurement on the optimized screening clinic configuration in the Edmonton metropolitan in the CSD level

- As for the breast cancer screening program investigated in the thesis, there is a need for analyzing screening records of breast cancer in order to understand clients' behaviour. The clients' behaviour would help us to set the factors in the method precisely, such as how long a mobile screening unit should stay in a place and its influence, the service radius of static screening clinic and mobile screening unit. In addition, the cost associated with the health care planning, e.g., the capital cost and the land price would be considered in the next step.
- During the past thirty years, Geographical Information Systems (GIS) have evolved in the field of location model development and in terms of the applications to which these models are applied. By integrating a wide range of facility location models and optimizing algorithms, GIS is becoming an indispensable tool for conducting facility location decision-making. Thus, combining the methods in the thesis with GIS is potentially very useful. The combination would assist users to search useful location information (e.g., identify where candidate sites are located), to conduct spatial constraints (e.g., prohibit facilities being located in some region), and to visualize geographic and location-based information.

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APPENDIX: PUBLICATION DURING THE PROGRAM

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