STRATEGIC LOCATION MODELING OF MOBILE CLINICS IN RURAL AREAS IN SOUTH AFRICA

by

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EXECUTIVE SUMMARY

Title: Strategic Location Modeling for Mobile Clinics in Rural Areas in South Africa

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Location models have proved to be invaluable in solving complex optimization problems across various industries worldwide. The application of location theory to the healthcare industry has recently become very popular in areas such as emergency services i.e. ambulances, location of hospitals, routing of ambulances to emergency scenes, etc. These applications are mostly carried out in urban areas. In South Africa, there is a unique demand for the delivery of healthcare services in rural areas where resources are limited. Therefore it holds merit to investigate the application of location theory in rural areas and increase the service delivery to less fortunate citizens of South Africa. This project aims to address the improvement of healthcare services in rural areas by utilizing location theory to find strategic locations for mobile clinics to be stationed. Mathematical models and heuristics are used to evaluate the performance of the solutions.

Keywords: Public healthcare services, South Africa, maximal covering problems, location modeling, mobile clinics, rural areas.

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CHAPTER 1

1. INTRODUCTION

1.1 BACKGROUND OF HEALTH SERVICES IN SA

The delivery of healthcare services has been a popular point of discussion in recent history. In 2011, the National Department of Health (NDoH) published a green paper on the implementation of a National Health Insurance Scheme (NHI). Subsequently ten pilot sites were established throughout the country to test different method of delivering healthcare services to communities.

The South African health system is also faced by a myriad of challenges which includes, worsening burden of disease (BOD) and scarcity of resources. Institutions in the public sector have underperformed mainly due to, poor management, underfunding, and deteriorating infrastructure (DoH, 2011).

The burden of disease in South Africa can be divided into four main tiers according to the Lancet report (Coovadia, 2009). These are:

1. Non-communicable diseases
2. Tuberculosis (TB) and AIDS/HIV
3. Maternal, infant and child mortality
4. Violence and injuries resulting from violence

According to the World Health Organisation (WHO, 2011), non-communicable diseases (NCDs) are the main causes of deaths globally. NDCs refer to chronic diseases that are non-infectious such as heart attacks, strokes, diabetes, asthma and cancer. These diseases cause more deaths than all other causes combined and people who live in poor, vulnerable and disadvantaged populations are affected the most by these diseases. The mortality rates are also higher in low to middle-income populations compared to wealthier counterparts.

The high mortality rate is mainly due to NDCs being detected too late which results in patients needing extensive and costly hospital care which they cannot afford (WHO, 2011). These trends can be altered by providing health services which aid in the reduction of risk factors through proper education, early detection and the timely treatment of diseases.

In 2012, the Health Systems Trust (HST) conducted a South African health facilities audit. The aim of this study was to ascertain the accessibility and quality of South African health facilities. In a total of 3880 facilities included within the audit the following was found (HST, 2012):

- 96% of the healthcare facilities in South Africa are accessible by road
- 87% have access by means of taxi
- public transport accessibility is restricted with only 58% of facilities accessible by bus and 9% accessible by train
- the percentage of people that are within walking distance from the nearest healthcare facilities were not audited

A large scale problem is that the transportation cost from indigent and rural areas are high and remains a barrier to access to healthcare services. This is compounded by the limitation of resources to provide healthcare services directly within these communities.

In South Africa, the healthcare system is made up of two tiers, a large public sector and a smaller private sector that is growing by the day. Primary health care is primarily offered by the state at no cost while more specialised services are delivered by both the state and private sector. However, the public sector's resources are insufficient. The public sector should deliver services to 80% of the population while only receiving a 40% contribution of health services expenditure from the state (HST, 2012). Conversely, the private sector provides health services to middle to high class income households who are members of medical schemes. The private sector also utilises most of the health professionals in South Africa.

This two-tiered system is unbalanced and unreachable to many South African citizens, especially in rural areas. Public sector health services have become poorly managed underfunded and have deteriorating infrastructure. This has developed into a health system crisis and is worsened by the burden of diseases like tuberculosis and HIV and lack of health care professionals.

With the recent advances in medical technology and increased use of telemedicine, mobile clinics can be efficiently used to provide healthcare services to rural communities. The effectiveness of this method of health service delivery is highly reliant on the fact that the clinic must be in the right place to ensure the optimal level of demand is met.

The use of mobile clinics in rural areas in South Africa aims to relieve the pressure of the already overloaded district and sub-district health facilities. Dr. Nchaupe Mathosa, a doctor in the Makopane District, said in an interview with the Voice of America publication (voanews.com, 2013) : "Many patients travel for kilometers to the hospitals and clinics in search of medical assistance, therefore it is needed to bring mobile clinics to people in rural areas or others who are in need."

Mobile clinics offer services such as pregnancy tests, ultrasounds, diabetes and blood pressure testing. The mobile units are often, but not always staffed with general practitioners and nurses. The mobile clinics aim to visit a community in a sub-district twice a month, but generally go to where the demand is the highest. This results in many community members in the outlying areas not having ready access to healthcare.

1.2 Background of the Solution Space

The operating area chosen to model the problem is the Hlabisa Local Municipality in KwaZulu-Natal. The Hlabisa District is a sub-district of the Umkhanyakude District and is located in the northern region of KwaZulu-Natal. It is classified as one of many official rural managerial districts; it is representative of a rural area since it consists of rural villages, farm lands, small settlements and is further away from cities and towns. The district spans over an area of 1430 km^2 where the terrain varies from flat to undulating, to mountainous grasslands and thick forests (Solarsh et al, 2002).

The district population is around 210 000 and consists of predominantly Zulu speaking residents. Although some areas in the southeast near the Mtubatuba market are classified as urban and peri-urban areas, most of the population is scattered across the land forming part of multi-generational homesteads of varying size between 1 to 1000 people. The need for employment opportunities and education has driven substantial migration from the district to industrial centres (Kahn et al, 2007).

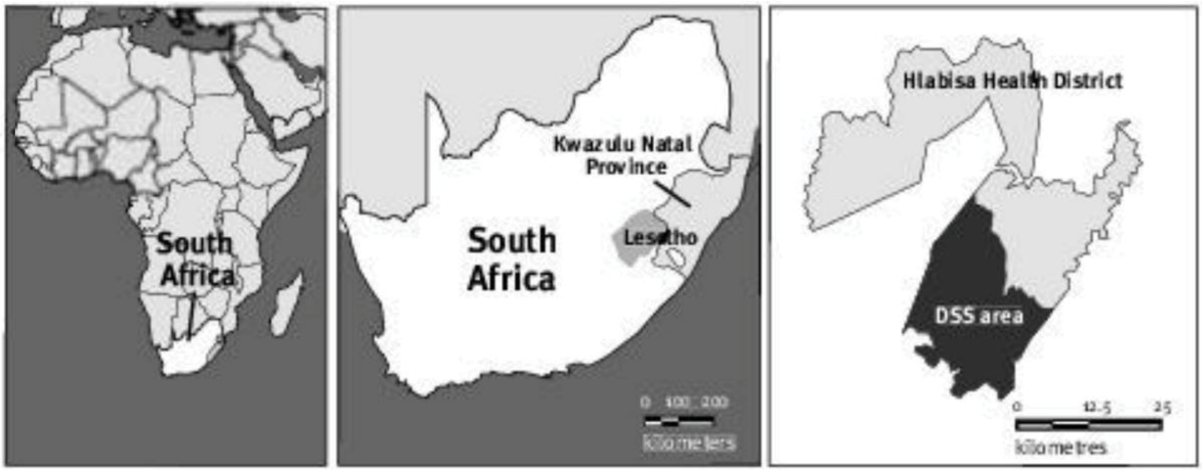

FIGURE 1: LOCATION OF THE HLABISA DSS SITE, SOUTH AFRICA SOURCE: SOLARSH ET AL, 2002

The district was built around a community or non-specialist hospital which provides the community with comprehensive primary healthcare services which is supported by a network of mobile and fixed clinics. The community hospital supervises the twelve nurse-run fixed clinics and is visited by a medical doctor bi-weekly. The clinics provide routine pre-natal, natal, and post-natal care, preventative child-health services, immunizations, TB-treatment, family planning education, sexually transmitted diseases and non-communicable conditions, such as diabetes and hypertension. The conditions which exceed the skill or capacity of the nurses are referred to the community hospital.

In the areas of the district that is not serviced by the fixed clinics, five mobile clinics are provided on a two to four week basis at defined points. The mobile clinics offer a similar range of services offered at fixed clinics, but are unable to offer any services that require short term admissions. Community health workers cover about half of the homesteads in the district and are largely responsible for nutritional and general health promotion, supervised home care, and where necessary, referral to clinic or hospital.

Table 1 depicts the current Decile distribution of the population with regard to the distance travelled to the nearest health facility. Table 1 shows that 50% of the population in the Hlabisa District resides within 5 km or less distance of the nearest healthcare facility. The average distance to the nearest healthcare facility is 5.85 km. The 50% of the population that lives further than 5 km from the nearest healthcare facility offers an opportunity to improve the distance they need to travel to a healthcare facility.

	10%	**20%**	**30%**	**40%**	**50%**	**60%**	**70%**	**80%**	**90%**	**100%**
Km	1.3	2.3	2.91	4.3	5	6	7.1	8.46	11.22	25
Populaion	24753	24095	24935	26674	27322	27892	22064	22733	24714	22115

TABLE 1: DECILE DISTRIBUTION OF BASE SCENARIO

1.3 Research Design

This model aims to assist local government and NPOs to improve the health services that they provide via mobile clinics to people living in rural areas. This is achieved by deploying the mobile clinics to an optimal location within the rural area to maximise the amount of people that are able to reach the mobile clinic within a short distance. The model provides a solution in the form of five optimal facility locations for each of the five mobile clinics to be stationed for a day.

The model is able to assist similar communities that face the same problem of service delivery with minimum alteration or adaptation to the model. The following literature regarding location-allocation models in the health care industry is incorporated in the model; accessibility, availability and adaptability.

Accessibility is measured by the ability of patients from the community as well as the mobile clinic being able to access the proposed location for the mobile clinic. Availability refers to the facility's capacity to serve patients even in changing short-term conditions such as changing weather conditions that may influence road accessibility or morbidity rates in the community. Adaptability of the models focuses on the ease of application of the model to other communities or adapting to long term changes within the present community (Berman, 2010).

1.4 RESEARCH METHODOLOGY

The model for this problem is formulated by answering the following research questions:

- What is the demand for health service delivery in rural areas?
  This question is answered by determining where fixed health services are located and the proximity of the residents from these fixed health services. The average "fair distance" for people to travel to a mobile clinic and the average "service distance" of these mobile clinics is also incorporated.

- Where are possible locations for mobile clinics to be stationed?
  This question considers the geography of the rural areas, factors that inhibit people to travel to health facilities or resistance to travel and what existing models can be used to solve the mobile clinic location problem.

The inputs to the model are taken from the 2010 Census data for a sub-district, Hlabisa Local Municipality. This municipality's population is divided into "Small Areas" defined by the 2010 Census data. A "Small Area" represents the smallest group of residents that the population has been sub-divided into. These inputs together with the accessibility constraints are taken into consideration to calculate the optimal location for mobile clinics to be positioned. Figure 2 shows what inputs are used to give the required outputs.

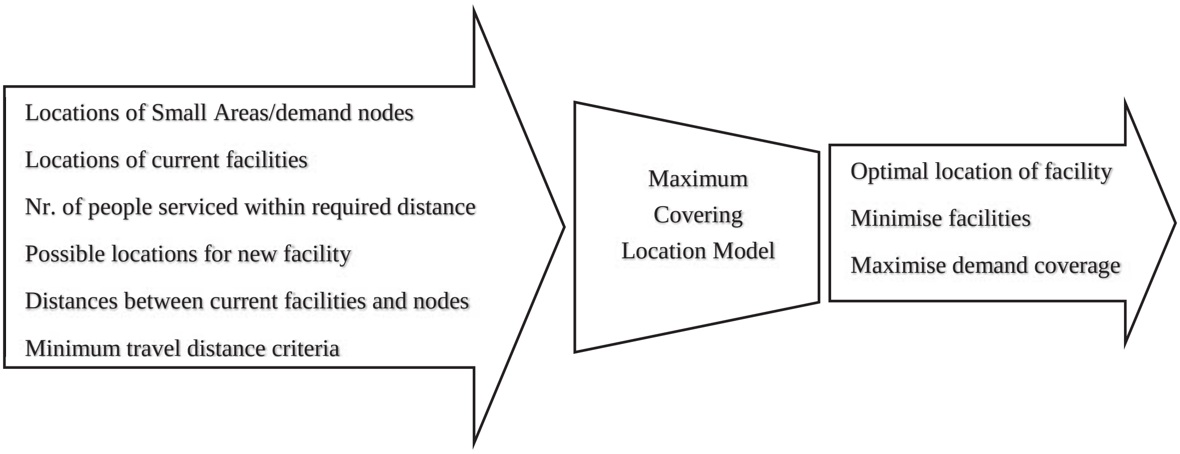

FIGURE 2: INPUTS AND OUTPUTS OF THE MODEL

The tools used in building the location model are existing facility location model theory and algorithms as well as heuristic applications to location problems as discussed in Chapter 2. The data manipulation and consolidation is done by using R-programming and MS Excel. The visualization of the problem and its solution is supported by a Geographical Information Systems (GIS) software application, QGIS and Google Fusion Tables API.

1.5 RATIONAL FOR THE PROJECT

Rural areas in South Africa are seriously deprived of health care services. This can be attributed to the high rates of immobility of the inhabitants, lack of socio-economic resources and the far distances people have to travel to health facilities. To reach these people who fall outside medical coverage zones in rural areas, mobile clinics have been deployed to provide them with primary health care services. Mobile clinics provide decentralised tuberculosis and HIV treatment, immunisation services, reproductive health support and support to survivors of sexual violence.

FIGURE 3: TRUCK CONVERTED INTO A MOBILE CLINIC SOURCE: MEDIFIT.COM, 2014

To increase the effectiveness of the service delivery of mobile clinics, it is imperative for these clinics to be stationed at an optimal location. The mobile clinics should be stationed in an area which can serve the most amounts of people living far away from fixed health services such as clinics or hospitals. The accessibility of the mobile clinic is also important as most of the residents of rural areas in South Africa live along rocky and bumpy roads.

Facility location theory as a branch of operations research has been used to solve complex problems for years in many industries. Location models aid in the decision making process of determining the optimal location or site for a facility to support a required function. Examples of location modeling include locating a supermarket in a community, locating distribution centres for retailers or the optimal positioning of ambulance dispatch points. Location modeling is a favourable solution to locate a site for a mobile clinic in order to maximise the patients covered within a rural community.

1.6 Document Structure

This chapter provided the introduction and background of the research problem and the current status of healthcare services in South Africa. The reasons behind embarking on the investigation of possible solutions to the problem are also explained. The rest of the dissertation is organised as follows:

Chapter 2: A comprehensive literature review of location modeling problems

Chapter 3: The model formulation and analysis

Chapter 4: The model results and validation

Chapter 5: The conclusion and recommendations

CHAPTER 2

2. LITERATURE REVIEW

This chapter is a study of the relevant location theory required to solve the mobile clinic location problem. In section 2.1, a broad overview of the possible types of location models are discussed. In section 2.2 a more in depth analysis is done on the maximal covering problem and the variations of the problem.

2.1 LOCATION MODELING

The pioneer of location modelling, Alfred Weber, developed a model to position one facility with the objective to minimise the distance between customers and the facility. Later, Harold Hotelling studied and developed a model to strategically position vendors close to customers and in return increasing their market share. Walter Isard then found regional science, which is a combination of economics and location theory (Daskin, 2008).

Location models can be subdivided into four categories as depicted in Figure 4.

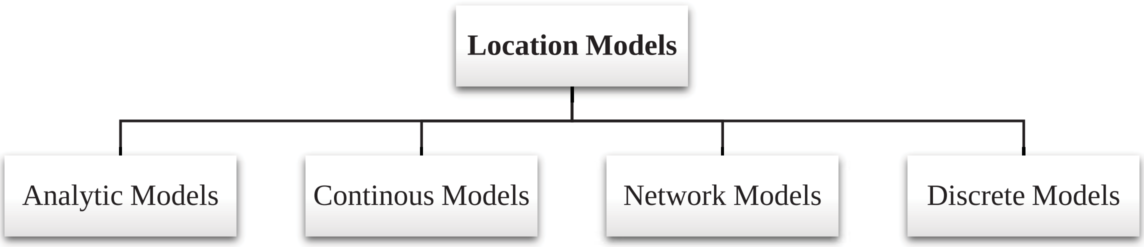

FIGURE 4: TYPES OF LOCATION MODELS. SOURCE: DASKIN, 2004

Analytic models use the assumption that the demand is spread over an area and that a facility can be located anywhere in that area. This model is relatively easy to solve with calculus or other simple techniques. Continuous models, as opposed to analytical models, assume demand is located at specific demand points or nodes and the location of the facility will be sited among these points. Network models consist of a framework made up of nodes and links and assume that the demand arises at each node. There are no limitations as to where the facilities can be located on the network and in order to solve a network problem, the polynomial time algorithm must be found (Daskin, 2004).

The final model category is discrete models; these models assume that the individual demand points can be grouped together to form selected discrete demand points. This means that we can represent a geographical area by several demand points or nodes (small areas). The demand arises on nodes and the location of facilities is limited to a predetermined set of locations (Daskin, 2008).

Discrete location modeling can further be classified into three general groups according to the type of location problem namely: covering-based models, median-based models and other models (Figure 5).

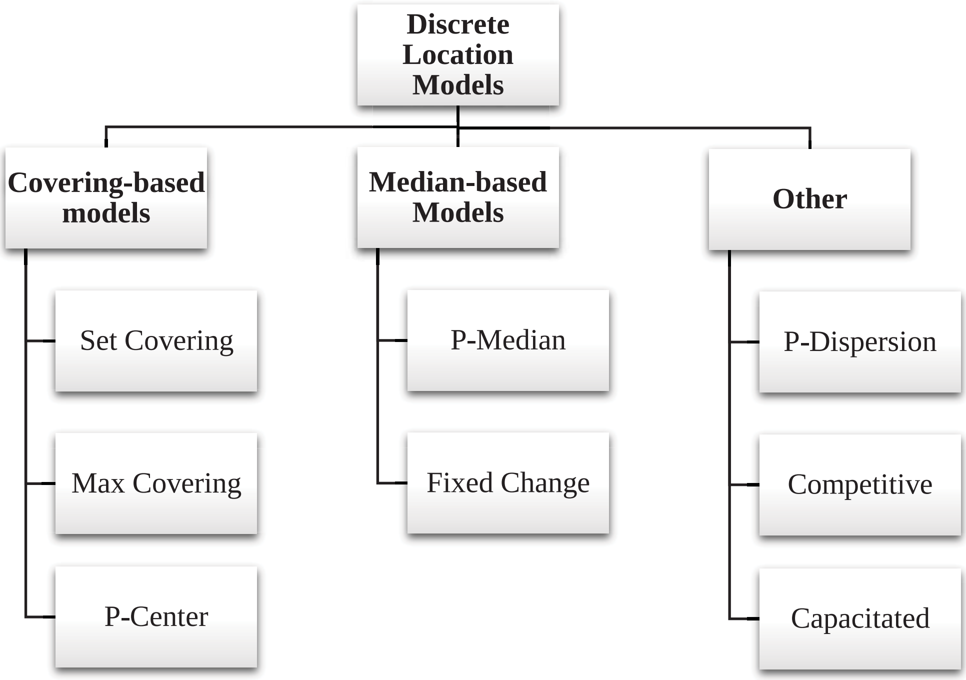

FIGURE 5: TAXONOMY OF DISCRETE LOCATION MODELS. SOURCE: DASKIN, 2004

Covering-based models, also called maximum service distance problems, site facilities with the objective to maximise the demand coverage within certain proximity from the facility. Covering models assume that there exists a minimum covering metric, time or distance, within which demands need to be served or covered. Models based on covering are usually used in emergency services due to the fact that practical and in some cases statutory procedures govern the coverage of an area.

There are three models that are prototypes of the covering model namely: set covering model, maximal covering model and the P-centre model. Below we will discuss the set covering model and the maximal covering model. The P-centre model will not be considered for this dissertation.

To explain the workings of such models an indicator variable can be defined, a_{ij}:

$$a_{ij} = \begin{cases} 1 & \text{if demand of node } i \text{ can be covered by a facility at candidate site } j \\ 0 & \text{otherwise} \end{cases}$$

The purpose of the set covering model is to minimise the cost of the selected facilities with the objective to cover every demand node. To parameterise the model, the following inputs are required:

$\boldsymbol{I}$ = set of demand nodes

$\boldsymbol{J}$ = set of candidate facility sites

$\boldsymbol{F_j}$ = fixed cost of locating a facility at candidate site j

A decision variable is defined as follows:

$$X_j = \begin{cases} 1 \text{ if we locate at candidate site } j \\ 0 \text{ otherwise} \end{cases}$$

With the above variables defined, it is necessary to define the set covering problem:

Minimize (Objective function, facility costs)

$$\min \sum_{j \in J} f_j X_j \qquad (1)$$

Subject to

$$\sum_{j \in J} a_{ij} X_j \geq 1 \qquad \forall i \in I \qquad (2)$$

$$X_j \in (0,1) \qquad \forall j \in J \qquad (3)$$

The objective function (1) seeks the minimum cost to locate the selected facilities. Constraint (2) ensures that each demand node is covered by at least one of the facilities. The left hand side of equation (2) represents the sum of selected facilities that can cover the demand of node i. Constraint (3) is the decision variable as defined above.

In location problems it is often required to minimise the quantity of facilities that are located rather than the cost of locating them. This type of model is typically used when the fixed facility cost is approximately equal.

Minimize (Objective function, number of facilities)

$$\min \sum_{j \in J} X_j \qquad (4)$$

In practice there are two main disadvantages of using the set covering model. The objective function (1) results in exorbitant costs in order to cover all demands. Constraint (4) as objective function results in a very large number of facilities that should be located in order to meet the demands. The second concern is that the model is unable to differentiate between high level demand nodes and demand nodes that have lower levels of demand (Daskin, 1995).

If the cost of meeting all demands is prohibitive it would be preferred to cover the nodes that generate higher levels of demand. The two concerns above was the primary motivation for Church and Revelle (1974) to create the maximal covering location problem. The following inputs should be added to the previous model:

h_i = demand in node i

P = number of facilities to locate

We also require an additional decision variable:

$$Z_i = \begin{cases} 1 \text{ if demand in node } i \text{ is covered} \\ 0 \text{ otherwise} \end{cases}$$

The **maximal covering location model** is adjusted with the additional decision variable, the formulation given below:

Maximise

$$\max z = \sum_{i \in I} h_i Z_i \qquad (5)$$

Subject to

$$Z_i - \sum_{j \in J} a_{ij} X_j \leq 0 \qquad \forall i \in I \quad (6)$$

$$\sum_{j \in J} X_j = P \qquad (7)$$

$$X_j \in (0,1) \qquad \forall j \in J \qquad (8)$$

$$Z_i \in (0,1) \qquad \forall i \in I \qquad (9)$$

The objective function (5) maximises the demand nodes covered. The significance of this model is that it not only maximises the demands at nodes but ensures that all demands are served at the nodes. Constraint (6) stipulates that at least one facility, that can meet the demand of the node, must be allocated to a node before the demand of node *i* can be covered. Constraint (7) stipulates that precisely P new facilities are sited.

The models discussed above simply ascertain whether a demand node is covered or not. It is often a requirement to optimize the average distance a person has to travel to be serviced or a provider has to travel to provide the service. Median-based models site facilities with the objective to minimise the average distance from users to the facility. As seen on Figure 4, there are two types of median models namely: *P*-median and uncapacitated fixed charge models. The p-median problem is considered, which minimises the demand weighted total/average distance. An additional input is needed to formulate the problem;

d_{ij} = distance between the demand node i and the location j

Including the following decision variable

$$Y_{ij} = \begin{cases} 1 \text{ if demands at node } i \text{ are assigned to a facility at site } j \\ 0 \text{ otherwise} \end{cases}$$

By including the above decision variable, the ***P*-median problem's** formulation is shown below:

Minimise

$$min \sum_{j \in J} \sum_{i \in I} h_i d_{ij} Y_{ij} \qquad (10)$$

Subject to

$$\sum_{j \in J} Y_{ij} = 1 \ \forall i \in I \qquad (11)$$

$$Y_{ij} - X_j \leq 0 \qquad \forall i \in I; \forall j \in J \qquad (12)$$

$$\sum_{j \in J} X_j = P \qquad (13)$$

$$X_j \in (0,1) \qquad \forall j \in J \qquad (14)$$

$$Y_{ij} \in (0,1) \qquad \forall i \in I; \forall j \in J \qquad (15)$$

The demand weighted total distance is minimised by (10), the objective function. This is the same as minimising the demand weighted average distance because the total demand remains constant. Constraint (11) ensures that only one facility is allocated to a demand node. Constraint (12) was formulated to ensure that demand nodes are only allocated to open facilities

Other facility location models include capacitated, completion and p-dispersion models. Capacitated facility problems take into account that there are limitations to a facility. For example, the demand that can be served, number of units stored in a warehouse and is therefore typically used in the location of storage facilities. A competition facility problem determines where a facility should be located to gain a competitive edge over competitors in a certain area evaluating areas where the competitor is under servicing its customers. Finally the P-dispersion model looks at a pair of facilities and maximised the minimum distances between the two facilities. This model can be applied in the determination location of a franchisee relative to the franchise (Church, 1999).

According to Daskin and Dean (2004), the set covering model, the maximal covering model and P-median model are the foundation for all healthcare facility location models. Further evaluation of these models is required for the nature of the dissertation. These models are chosen due to their discrete model characteristics, hence restricting the area wherein a facility can be located.

2.2 Variations of covering models: Maximal Covering Models

2.1.1 Network Maximal Location Covering Problem

This section will deal with facility location problems where the facilities can be located at any point on the network as is the case for this project. The problem that will be discussed is the Network Maximal Location Covering Problem (NMLCP).

Covering models require the assumption that there are a predetermined set of possible facility locations. Possible facility locations usually refer to the some or all demand nodes on the network. Extensions of covering models have formulated the problem with a pre-specified and finite set of possible facility locations even if the possible facilities are located anywhere on the network (Church and Meadows, 1979).

The objective of NMLCP is to maximise the coverage of the finite set of p-facilities. The p-facilities are part of a network intersect point set (NIPS). The NPIS is composed of a predetermined set of locations identified on the network of potential facility sites. As previously stated, the nodes on the network refer to demand points and in addition every node, i, has an related weight a_i. Possible sites for facilities not only include the nodes and pre-specified points on the arcs but any points on the network. Figure 6 below illustrates that node 1 and node 2 are connected by an arc. The maximal service distances S1 and S2 are also indicated on the figure. The section of the line between node 1 and point B is restricted by the service distance S1 and therefore potential facility locations can be located anywhere along that line segment and covers the demand of node 1.

The same applies to the section of the line between point A and node 2. Line segment AB illustrates the overlapping of coverage for node 1 and node 2. Line segment AB is referred to as a segment of equal coverage (SEQ) as every point positioned on the line can cover an equal amount of demand as every other point on the section AB. The definition of a SEC given by Church and Meadows (1979) is: “A line segment of an arc is a segment of equal coverage (SEC) if each point lying solely within that segment covers exactly the same demand nodes as any other point lying solely within that segment.”. Thus any point on an ARC which lies within S units from a demand node i is a network intersection point (NIP) and the set of NIP’s with all the demand points is called the NIPS. In Figure 6 the NIPS will consist of nodes 1 and 2 as well as the NIP’s A and B.

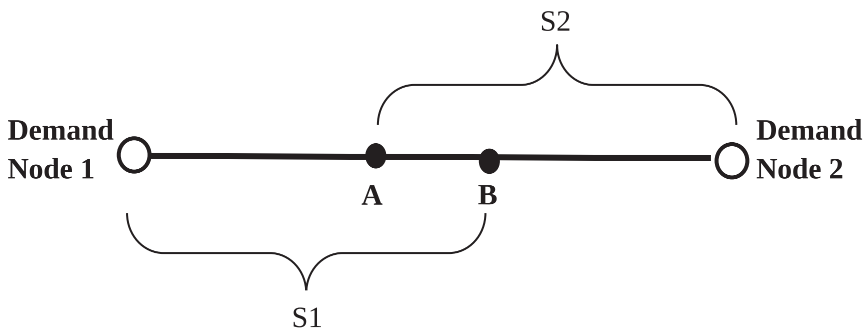

FIGURE 6: COVERAGE REPRESENTATION

The NMLCP generally locates more potential facilities than the number of demand points in the network. To address this problem, augmented networks are used. The second type of variant of the maximal covering problem that will be discussed is the maximal covering problem with a equal weight factor. The weight factor in this case is the same for all demand points without considering the demand sized at the nodes. The objective is thus to maximise the coverage of demand points (Case and White, 1974).

The maximal covering with mandatory closeness problem is another variant of the maximal covering problem which addresses the demand not covered inside the maximum service distance, S. This problem includes another, less stringent, service distance parameter, T where T > S, to cover the uncovered demand points. The objective is therefore to ensure the nearest facility is no further than T units from the demand points while still maximising the demand points covered within S units from a facility (Case and White, 1974).

The mathematical model for the MCLP can be adjusted with the following two constraints:

$$\sum_{j \in N_i} X_j \geq Y_i \qquad \forall i \in I \qquad (16)$$

and

$$\sum_{j \in M_i} x_j \geq 1 \qquad \forall i \in I \qquad (17)$$

Where

$$N_i = \{ j | d_{ij} \leq S \}$$

$$M_i = \{ j | d_{ij} \leq T \}$$

N_i is the set of facility sites that is able to cover demand node i within the determined service distance S. M_i includes the set of N_i because T>S. Constraint (17) will ensure that each demand point will be located inside the T units, the secondary service distance. Contrasting to the regular maximal covering problem, only certain values of P, the number of facilities, will offer a feasible solution.

An example solution for this problem is given in Figure 7. A network with 55 nodes is used to represent the problem where all the demand must be covered within a service distance, S=15. The five sites chosen as potential facilities are circled with the solid line in the Figure 7. The nodes were grouped into sets as each node was allocated to its nearest facility. The dashed line represent demand points within a S=10 radius from the nearest facility and the solid line represent the demand points within a S=15 radius from the facility. The solution represents the desire to cover as much population within a S=10 radius while maintaining total coverage within T=15. Since the set location model's objective is to cover all demand points, the maximal covering with mandatory closeness problem could be used as an alternative to the set location problem (Case and White, 1974).

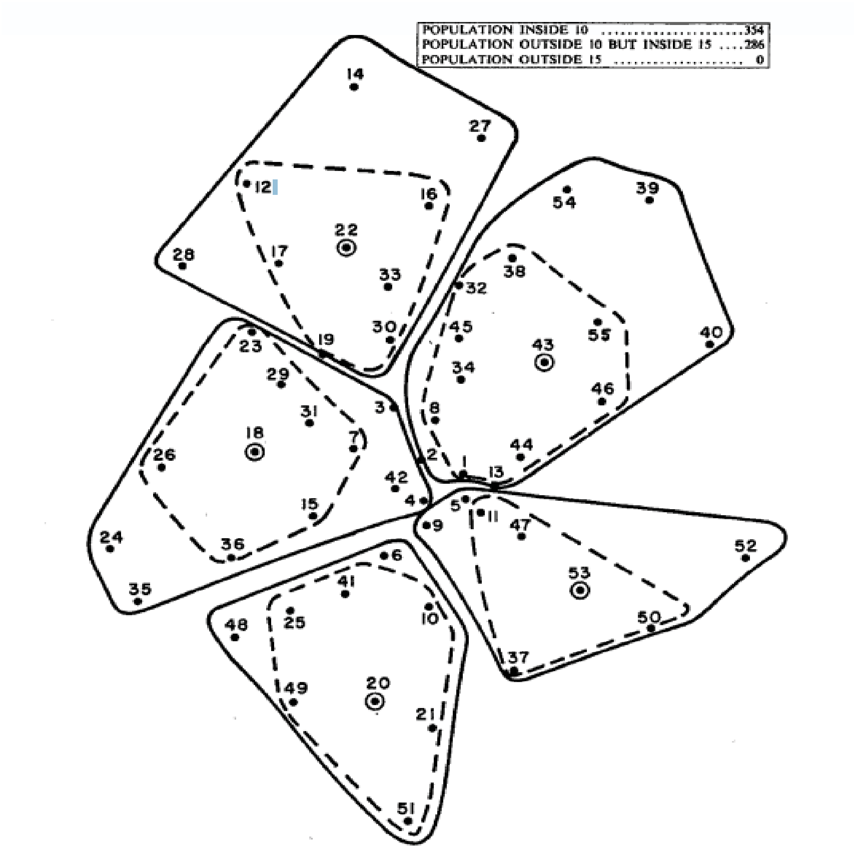

FIGURE 7: EXAMPLE SOUTION TO A 55 NODE PROBLEM. SOURCE: CASE AND WHITE, 1974

Church and ReVelle (1974) have proved that the MCLP with mandatory closeness provides a more desirable solution to the problem. They have shown that more population can be covered with less facilities in the MCLP with mandatory closeness problem than in the set covering model and is thus a better decision making model to locate public facilities.

2.1.2 RELATIONSHIP BETWEEN THE P-MEDIAN AND MCLP

Daskin (1995) has shown that the MCLP can also be adapted to show that it is a variant of the p-median problem and yield an appropriate solution for MCLP. The p-median approach is appealing since it minimises the total travel distance to facilities and in return the system is more accessible to its users.

Consider the adjustment of the P-median problem to the real distances:

$$d'_{ij} = \begin{cases} 0 \; if \; d_{ij} \le S \\ 1 \; if \; d_{ij} > S \end{cases}$$

The real distances to travel from node i to node j is given by d_{ij} and the modified travel distance is given by d'_{ij}, with S the determined service distance. When the actual travel distances are used, the P-median problem gives an output of locations that minimises the total weighted distance. When the modified distances are used the objective function is modified to minimise the demand/population that is not serviced within the service distance S. Each demand node i with population a_i, should be allocated to the nearest facility. If a demand node i is covered by a facility inside S units, the associated weighted distance $a_i d'_{ij} = 0$, because $d'_{ij} = 0$. Conversely, when a facility covers a demand node i outside S units, the related average distance $a_i d'_{ij} = 1$, because $d'_{ij} = 1$. Hence, when using the modified distances and the minimisation of the amount of population outside the service distance S, the objective changes from minimising the total weighted distance to minimising the population serviced outside the service distance S. Thus the minimisation of the population outside S is equivalent to maximising the population within S and equivalent to the MCLP. This transformation was used by Daskin (1974) to construct a multi-objective model that evaluates the maximising covered demand against the minimisation of demand weighted total distance.

Since the MLCP is proved to be a special type of P-median problem, the MCLP can be solved using the same approaches developed to solve the P-median problem. Thus in addition to Church's heuristics and linear programming, the MCLP can also be solved using the Maranzana heuristic used to solve the P-median problem. Although the previous statement is true, it is noted that linear programming (LP) approaches to solve the MCLP is much more effective than the P-median LP approaches. The two heuristic solutions developed by Church are the Greedy Adding Algorithm (GA) and the Greedy Adding Substitution (GAS). Both the heuristic's solutions were proved to be optimal 30-50% of the time. The heuristics used to solve P-median problems are Maranzana and Teitz and Bart (Daskin, 1995).

The performance of the different heuristics, Maranzana and Teitz and Bart versus GA and GAS must be considered before choosing the heuristic which best aids as a decision making tool. To compare the Maranzana heuristic, it must be adjusted to handle distorted distance matrices. The Maranzana routine should be adjusted to include the actual distances in the partitioning step and the modified distances in the facility-location step in order to improve its performance.

Teitz and Bart opts to find a non-facility location that provides an improved function value as it replaces the current facility location. GAS algorithms use a p-1 solution and add the next best facility location to yield a p-facility solution. The solution is improved by searching for a adequate replacement site (ARS). The performance of Teitz and Bart and GAS is estimated to be the same as they attempt to improve the solution in the same way. The only difference between them is the way the solution is started. Teitz and Bart requires an initial start from the user and GAS uses the p-1 solution as a beginning solution. Piggybacking is also used in the heuristic solutions in order to improve the performance. Piggybacking refers to when the results from the beginning solution is used to start a second solution technique. An example of piggybacking for MCLP heuristics would be to use the results of a GA algorithm in order to initiate a Teitz and Bart routine.

2.3 Chapter 2 Summary

This chapter discussed the methodologies and various approaches available to solve the mobile clinic location problem. It is clear from the information above that the maximal covering problem will form the foundation for a possible solution. In the next chapter, the formulation of a mathematical model and a guide to use to use the model are outlined.

CHAPTER 3

3. MODEL FORMULATION

This chapter will discuss the methods used to formulate a maximum covering model for the location problem by using heuristic techniques. The Maximum Covering Location Problem (MCLP) developed by Church and ReVelle (1974) is used to formulate an appropriate mobile clinic location model. As discussed in the literature review, the maximal location problem is used when the resources available are insufficient to cover all the demand nodes. Linear programming solutions are too cumbersome to solve large instances of MCLP and thus heuristics are employed to deal with the large scale of the MCLP.

3.1 MODEL CONDITIONS

The model is formulated based on the restrictions of the environment that the mobile clinics operate in. The model is applicable to the following conditions:

- When the optimal site for a mobile clinic to be dispatched to a rural area is unknown
- When the population is grouped into small settlement areas
- When limited resources (mobile clinics) are available

The following assumptions are made regarding the inputs to the model:

- The population of the small area is proportionate to the demand for healthcare services.
- Due to the lack of regular transportation services in rural areas the maximum service distance from the small area to the mobile clinic is assumed to be a walking distance.
- The centroid of the small area's latitude and longitude were used as the reference to the demand node.
- Due to the nature of the MCLP, not all demand will be covered. Optimal facility locations will be determined based on the maximum amount of people that can be serviced by the mobile clinic within the required service distance.
- The nodes on the network represent the position of the mobile clinic.
- The demand point is covered when the distance between the demand node and the sited facility is less than or equal to the service distance, S.

The remainder of the chapter will demonstrate the techniques used to obtain the inputs to the model and the execution and programming of the model.

3.2 THE MATHEMATICAL MODEL

An exogenous version of the MCLP was adapted and formulated with the following variables, parameters and objectives:

$\boldsymbol{I}$ The set of demand node i,

$\boldsymbol{J}$ The set of possible facility sites j,

a_i The population/demand for node i

d_{ij} The minimum distance between demand node i and facility at node j,

S The maximum service distance within which coverage is expected,

N $\{ j \mid d_{ij} \leq S \}$ = the set of nodes j that fall within the service distance of S to node i,

p The number of facilities to be sited,

x_j $\begin{cases} 1 \text{ if facility is sited at } jth \text{ node} \\ 0 \text{ otherwise} \end{cases}$

y_i $\begin{cases} 1 \text{ if node } i \text{ } is \text{ covered by one or more facilities sited within } S \text{ units} \\ 0 \text{ otherwise} \end{cases}$

Objective function:

$$\text{Maximize } z = \sum_{i \in I} a_i \, y_i \qquad (1)$$

Subject to:

$$y_i \leq \sum_{j \in N_i} x_j \qquad \forall i \in I \qquad (2)$$

$$\sum_{j \in J} x_j = p \qquad \forall j \in J \qquad (3)$$

$$0 \leq y_i \leq 1 \qquad \forall i \in I \qquad (4)$$

$$x_j \in \{0, 1\} \qquad \forall j \in J \qquad (5)$$

The objective function (1) maximises the demand covered. Constraint (2) ensures that the number of facilities that are sited doesn't exceed the number of demand points. Constraint (4) ensures that the values for y_i remain binary. Constraint (5) is the binary variable for x_j.

3.3 Model Execution

The following diagram describes tasks that need to be completed in order to use the mathematical model.

Task 1
Define and map area and set up area as a network

Task 2
Plot demand nodes/small area population on map

Task 3
Plot current facilities on map

Task 4
Determine distance matrix

Task 5
Determine the set of covered demand nodes

Task 6
Redo reduced distance matrix

Task 7
Generate random sample of initial potential facility locations

Task 8
Programme the mathematical model

Task 9
Interpretation of results

FIGURE 8: TASK DIAGRAM

Task 1: Define map area and set up area as a network

The owner of the mobile clinic is required to select the operating area for which the model will be used. The capability of the model should be considered when determining the size of the operating area. The physical capability of programming software and hardware may constrain sample sizes, computation time and performance of the solution.

The area is geographically represented on a map to display the locations of healthcare facilities and the representative population of the area. Figure 9 below shows the operating area, Hlabisa Local Municipality, which was selected to be used in the model.

FIGURE 9: HLABISA LOCAL MUNICIPALITY. SOURCE: GOOGLE MAPS

Task 2 and 3: Plot demand nodes/small area population and current healthcare facilities on map

The Figure 10, depicts the demand nodes and current healthcare facilities that are plotted on the map of the operating area. Each Small Area as defined by the 2011 Census data represents a demand node on the map. There small area's demand node is centered at the centroid of each Small Area as seen on Figure 10. There are 308 demand nodes, 17 clinics and one hospital in the Hlabisa Local Municipality.

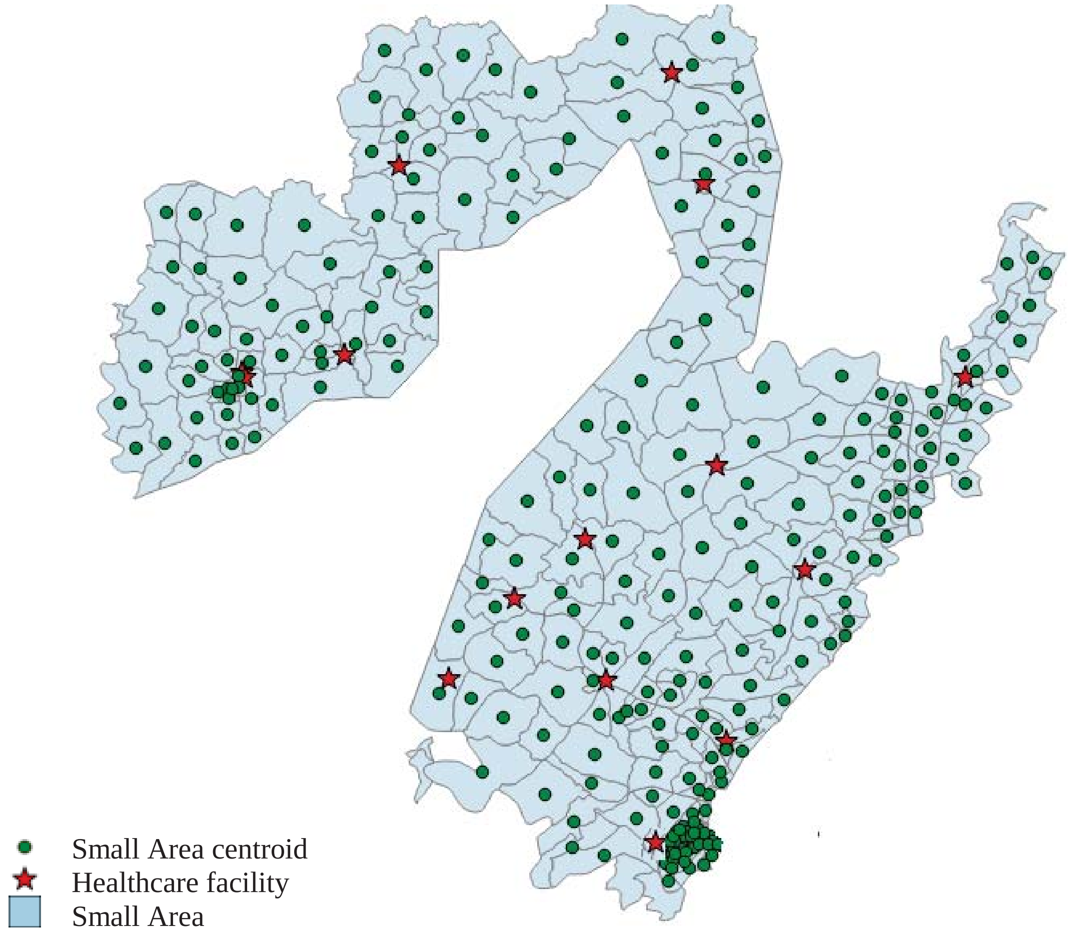

FIGURE 10: HLABISA LOCAL MUNICIPALITY, SMALL AREA WITH CENTROID AND HEALTHCARE FACILITIES VIEW. SOURCE: QGIS 2.10.1

Figure 11 shows the population density represented by the intensity of the color in the heatmap, the darker colors represent the bigger the population and lighter colors a smaller population. As the Small Area's size differs, the population density was calculated by dividing the population of a Small Area by the size of the area. The figure shows that some areas are more densely populated than others and that there are areas where the inhabitants live very far from the nearest healthcare facility. The figure also shows that some Small Areas lie in very secluded areas. These secluded nodes will be excluded from the model as they are inaccessible by mobile clinics due to constraints such as boundaries of the Hluluwe National Park and poor road conditions leading to the areas.

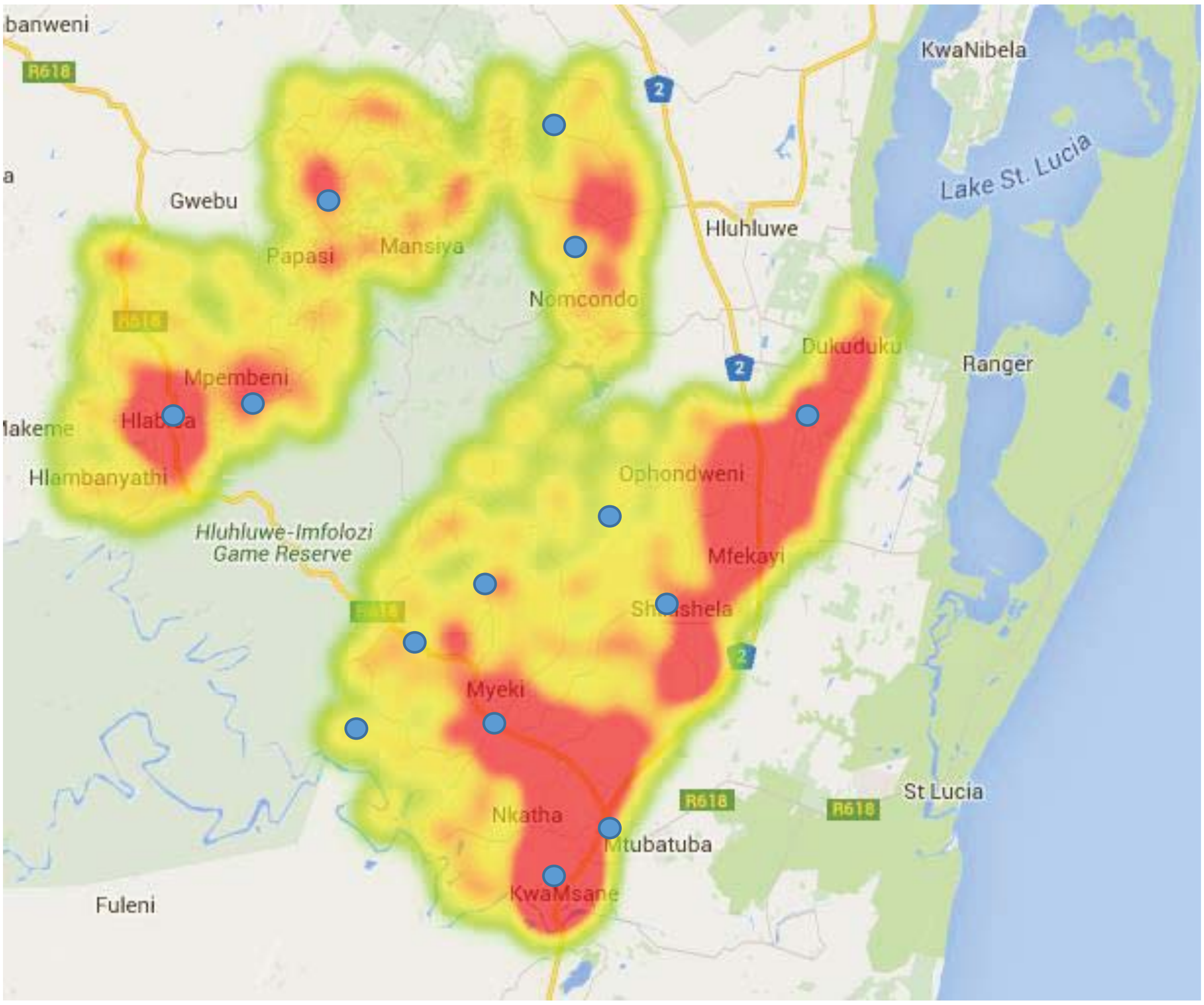

FIGURE 11: HLABISA LOCAL MUNICIPALITY, POPULATION DENSITY WITH HEALTHCARE FACILITIES VIEW. SOURCE: GOOGLE FUSION TABLES

Task 4: Determine the distance matrix

The latitudes and longitudes of each small area, clinic and hospital were used to calculate a distance matrix (See Appendix B). The distance matrix represents the distances from each Small Area to each healthcare facility in the sub-district. The distances calculated are the Euclidian distances and actual driving distances calculated using Google API. For the purpose of this project, the actual driving distances will be assumed to be the walking distance for residents to walk from their home to a healthcare facility. Table 2 shows the outcome of a sample with 10 Small Areas and 18 healthcare facilities. The minimum distance in a row of the matrix represents the facility closest to the small area.

		Calculated distances to facility n						Min Distance		
Small AreaID	Centroid Location	1	2	3	…	17	18	Euclidean Distance	Google Distance	> 5 km
5850038	-28.23272734,31.9547077	51	57.5	32.7	37.4	38.1	53.6	9.61	25	1
5860092	-28.22768378,32.28953733	55.7	49.2	35.9	29.1	29.8	52.9	8.21	4.1	0
5850044	-27.95511366,32.15310011	20.1	88.5	75.3	68.5	69.1	17.5	1.52	2.8	0
5860017	-28.27911311,32.32549703	78.3	31.5	38.6	31.8	32.5	75.5	10.13	3.6	0
5860002	-28.36259903,32.24546952	90.8	19.9	24.2	17.3	7	88	7.9	15.9	1
5850067	-28.04792478,32.04437777	13.7	99	85.8	78.9	79.6	11.9	8.26	4.5	0
5850021	-28.186423,31.83155771	49.4	81.2	56.4	61.2	61.8	51	6.63	14.7	1
5850052	-28.04669913,31.85023406	29.7	88.1	63.3	68	68.7	34.3	9.7	0.3	0
5850071	-28.01868028,32.07072005	12.2	92.7	79.5	72.7	73.3	10.4	9.45	7.4	1
5850068	-28.04493872,31.83262324	29.5	87.9	63.1	67.9	68.5	34.1	10.65	1.9	0
										42%

TABLE 2: SAMPLE OF DISTANCE MATRIX

Task 5: Determine the set of covered demand nodes

In order to reduce the distance matrix, the demand nodes which are already covered by a current healthcare facility within the required service distance, can be eliminated from the matrix. In this model we will chose the maximum service distance S= 5 km. Thus all shortest distances from a specific Small Area to the nearest facility that fall within a 5 km radius can be eliminated. Table 3 shows the highlighted distances of already covered demand points. This reduction will reduce computation time of the model.

		Calculated distances to facility n						Min Distance		
Small AreaID	Centroid Location	1	2	3	…	17	18	Euclidean Distance	Google Distance	< 5 km
5850038	-28.23272734,31.9547077	51	57.5	32.7	37.4	38.1	53.6	9.61	25	0
5860092	-28.22768378,32.28953733	55.7	49.2	35.9	29.1	29.8	52.9	8.21	4.1	1
5850044	-27.95511366,32.15310011	20.1	88.5	75.3	68.5	69.1	17.5	1.52	2.8	1
5860017	-28.27911311,32.32549703	78.3	31.5	38.6	31.8	32.5	75.5	10.13	3.6	1
5860002	-28.36259903,32.24546952	90.8	19.9	24.2	17.3	7	88	7.9	15.9	0
5850067	-28.04792478,32.04437777	13.7	99	85.8	78.9	79.6	11.9	8.26	4.5	1
5850021	-28.186423,31.83155771	49.4	81.2	56.4	61.2	61.8	51	6.63	14.7	0
5850052	-28.04669913,31.85023406	29.7	88.1	63.3	68	68.7	34.3	9.7	0.3	1
5850071	-28.01868028,32.07072005	12.2	92.7	79.5	72.7	73.3	10.4	9.45	7.4	0
5850068	-28.04493872,31.83262324	29.5	87.9	63.1	67.9	68.5	34.1	10.65	1.9	1
										58%

TABLE 3: SAMPLE OF DISTANCE MATRIX

Task 6: Generate a sample of initial potential facility locations

A random sample of latitude and longitude (x;y) points are generated as an initial input for possible facility locations in the model. The range of the operating area, $(A_x - B_x\ ; A_y - B_y\ )$ was used as boundaries wherein the random samples were generated. Thus an individual sample k (x ; y) will consist of x-values between A_x and B_x and y-values between A_y and B_y . Figure 12 depicts an example of possible facilities generated using a random sampling technique.

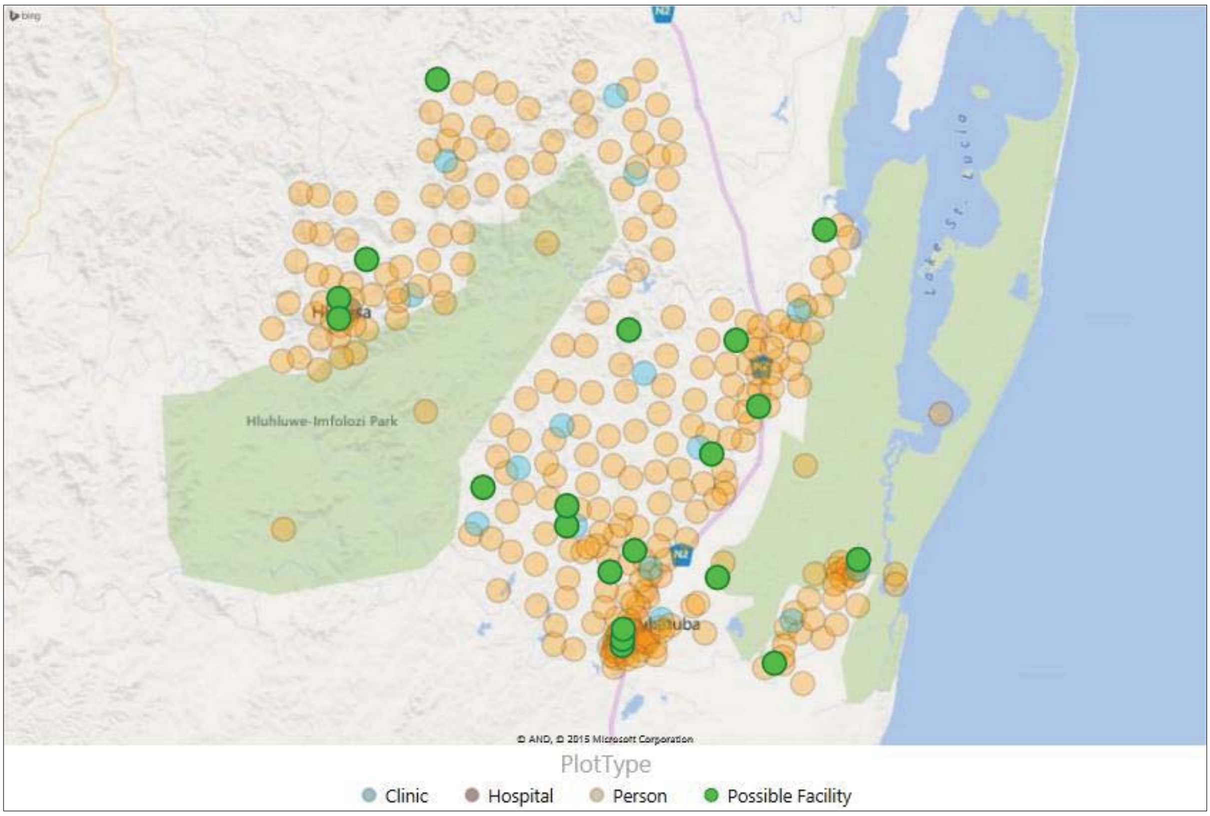

FIGURE 12: MAP WITH RANDOM SAMPLES SOURCE: GOOGLE FUSION TABLES

Task 7: Redo reduced distance matrix

After the possible facility locations have been generated, the distance matrix should be recalculated to ascertain whether facilities are located within the distance constraints of the facility location problem. This process will be repeated until an optimal solution is found. If an optimal solution is not found within the current parameter specification, the model can be altered, i.e. the distance constraint can be relaxed, number of facilities can be increased, or a demand covering estimation can be introduced. This process will be facilitated by a programmed mathematical model.

						Calculated distances to facility n								
	Small AreaID	Centroid Lat	Centroid Long	ESIY01_ Lat	ESIY01_ Long	1	2	3	...	16	17	18	MinDist (km)	>5 km
1	5850035	-28.1174	31.86249	-28.329	32.0049	25.50	57.11	27.74	...	33.24	61.67	3.34	6.15	1
2	5850054	-28.1151	31.84818	-28.329	32.0049	26.67	58.60	29.26	...	34.64	63.22	4.61	8.68	1
6	5850053	-27.9721	32.05512	-28.329	32.0049	34.20	50.38	26.02	...	34.24	51.61	25.34	18.99	1
7	5850077	-27.9584	32.03363	-28.329	32.0049	35.18	52.80	27.71	...	35.94	54.19	24.49	17.14	1
8	5850079	-27.9501	32.0135	-28.329	32.0049	35.85	54.77	29.04	...	37.24	56.33	23.62	15.32	1

TABLE 4: REDUCED DISTANCE MATRIX

3.4 Chapter 3 Summary

This chapter reviewed the steps required to build the model and the alterations required to the MCLP in order to solve the location problem. The mathematical model together with the heuristic alterations will determine the optimal solution. The programming of the mathematical model and the interpretation of the results (Task 8 and Task 9) will be discussed in Chapter 4 of the dissertation.

CHAPTER 4

4. DATA ANALYSIS

This chapter discusses the data used as inputs for the mobile clinic location models. This is followed by an explanation of the model results and validation analyses to determine the functionality of the models.

4.1 MAXIMUM DEMAND COVERING MODEL

This section describes the method to transform the input data into results. The model was programmed in R version 3.0.3 (R Core Team, 2013), using the 'Orloca' package (Munoz, 2014). The problem was solved in under two seconds. The model code can be viewed in Appendix B. The data sets and parameters are discussed in the following section, followed by the results and a sensitivity analysis of the model.

4.1.1 PRE-PROCESSING PROCEDURE

The small area geographical locations is grouped into defined sets. An R package, Orloca, is used to calculate possible facility locations for each segment in the grid. A grid is superimposed over the map of the area containing the demand nodes. The grid divided the area into 24 segments, Figure 13. The Orloca application calculated an optimal location for a candidate facility in each segment and as a result provided 24 candidate facilities that will be utilized as seed/input values for the model. The Orloca application is based on the P-median algorithm, discussed in Chapter 2, whereby facilities are located based on the mean average distance between nodes and facilities.

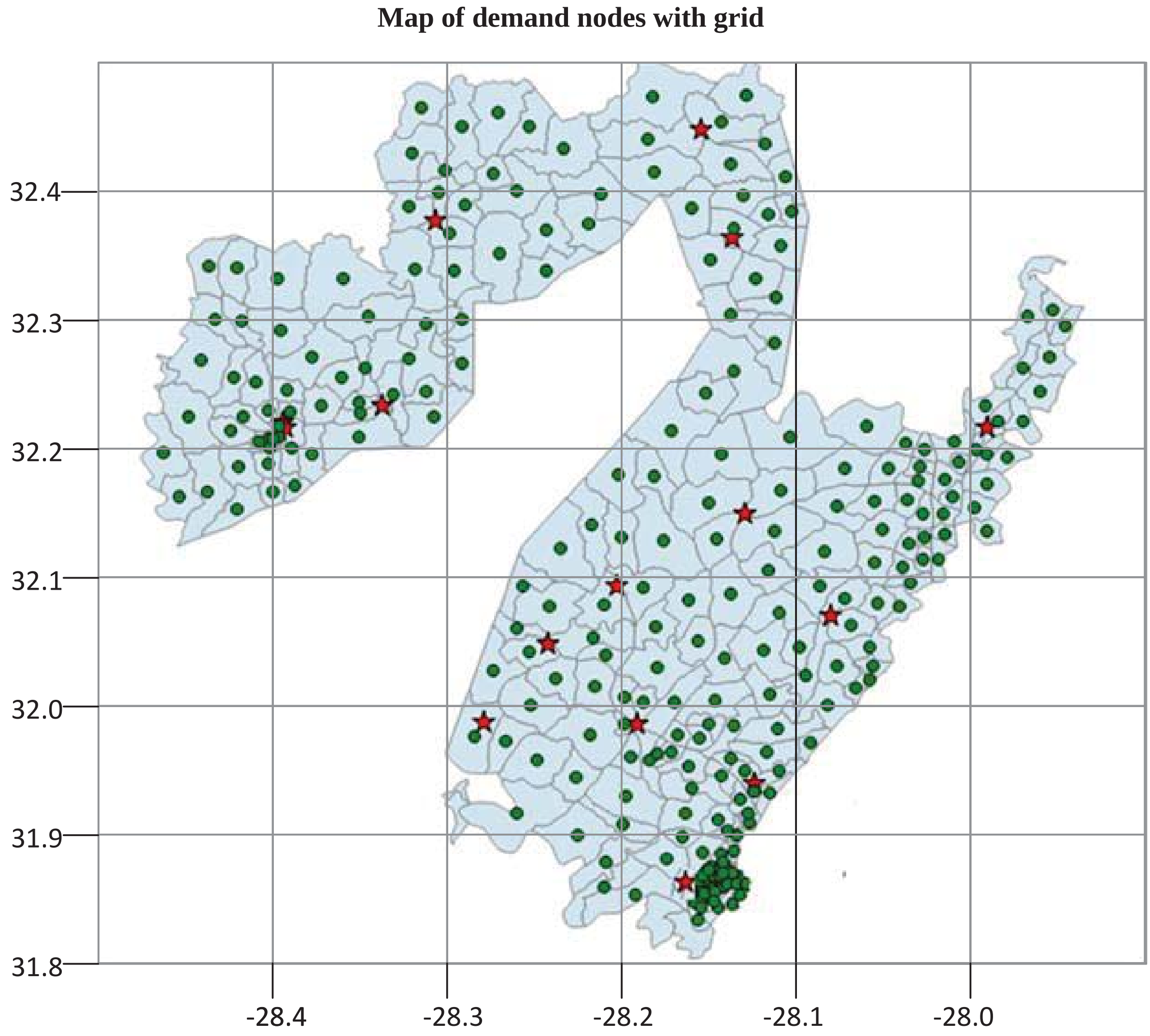

FIGURE 13: PLOT OF DEMAND NODES WITH GRID. SOURCE: QGIS 2.10.1

The table below shows the list of 24 candidate facilities and the impact they have on the coverage of demand nodes compared to only having the existing healthcare facilities. The following list describes the definitions of the column headings of Table 5:

1. The "IsCloser" column refers to the amount of demand nodes that is closer to a healthcare facility if a specific candidate site is located.

2. The "IsCovered" column refers to the amount of demand nodes that is closer to a healthcare facility and located within the required 5km radius.

3. The "Cover Included" column refers to the additional population that is covered if the specific candidate site is located.

4. The "New Distance" column refers to the newly calculated average distance to a healthcare facility if a specific candidate site is located.

5. The "Km Difference" column refers to the decrease or increase in the average distance to healthcare facility when compared to the existing healthcare facility locations.

Solution No	Solution Location	IsCloser	IsCovered	Cover Included	New Distance	Km Difference
1	-28.02443,32.05219	6	2	2037	8.34	-0.27
2	-28.05153,32.17683	6	3	3270	8.38	-0.23
3	-28.07385,32.36189	4	3	2849	8.44	-0.17
4	-28.14940,31.84858	9	0	0	8.51	-0.09
5	-27.96249,32.00579	8	2	1822	8.41	-0.20
6	-28.42870,32.33983	0	0	0	8.61	0.00
7	-28.41591,32.07836	7	4	3446	8.45	-0.15
8	-28.42668,32.15017	3	2	1166	8.55	-0.06
9	-28.40098,32.22067	2	0	0	8.59	-0.02
10	-27.95917,32.03350	6	2	1840	8.41	-0.20
11	-27.96939,32.15858	5	3	2470	8.48	-0.13
12	-28.05334,31.84922	6	3	2439	8.35	-0.26
13	-28.06330,31.96497	3	1	859	8.55	-0.06
14	-28.25399,32.05381	4	1	596	8.49	-0.12
15	-28.26532,32.14780	6	4	3102	8.50	-0.11
16	-28.26532,32.14780	6	4	3102	8.50	-0.11
17	-28.36375,32.06310	6	0	0	8.49	-0.12
18	-28.35581,32.14779	6	5	5000	8.45	-0.16
19	-28.37940,32.21266	3	0	0	8.59	-0.02
20	-28.37883,32.35499	4	2	1526	8.54	-0.06
21	-28.12168,31.95063	5	1	723	8.55	-0.06
22	-28.14790,32.14609	7	3	1646	8.48	-0.13
23	-28.17687,32.27010	21	5	5696	7.84	-0.76
24	-28.13897,32.33897	7	2	2478	8.48	-0.12

TABLE 5: LIST OF CANDIDATE FACILITY SITES

The candidate sites were calculated with the aim to reduce the run time of the model. If random coordinates within the solution space were used as seed values, it increased the run time of the model and exceeded the processing capacity of the computer used to run the model. Figure 13 depicts the superimposed grid with the calculated candidate sites in each section. The map below, Figure 14, shows the calculated optimal site for a candidate facility in each segment of the grid as shown in the Figure 13 above.

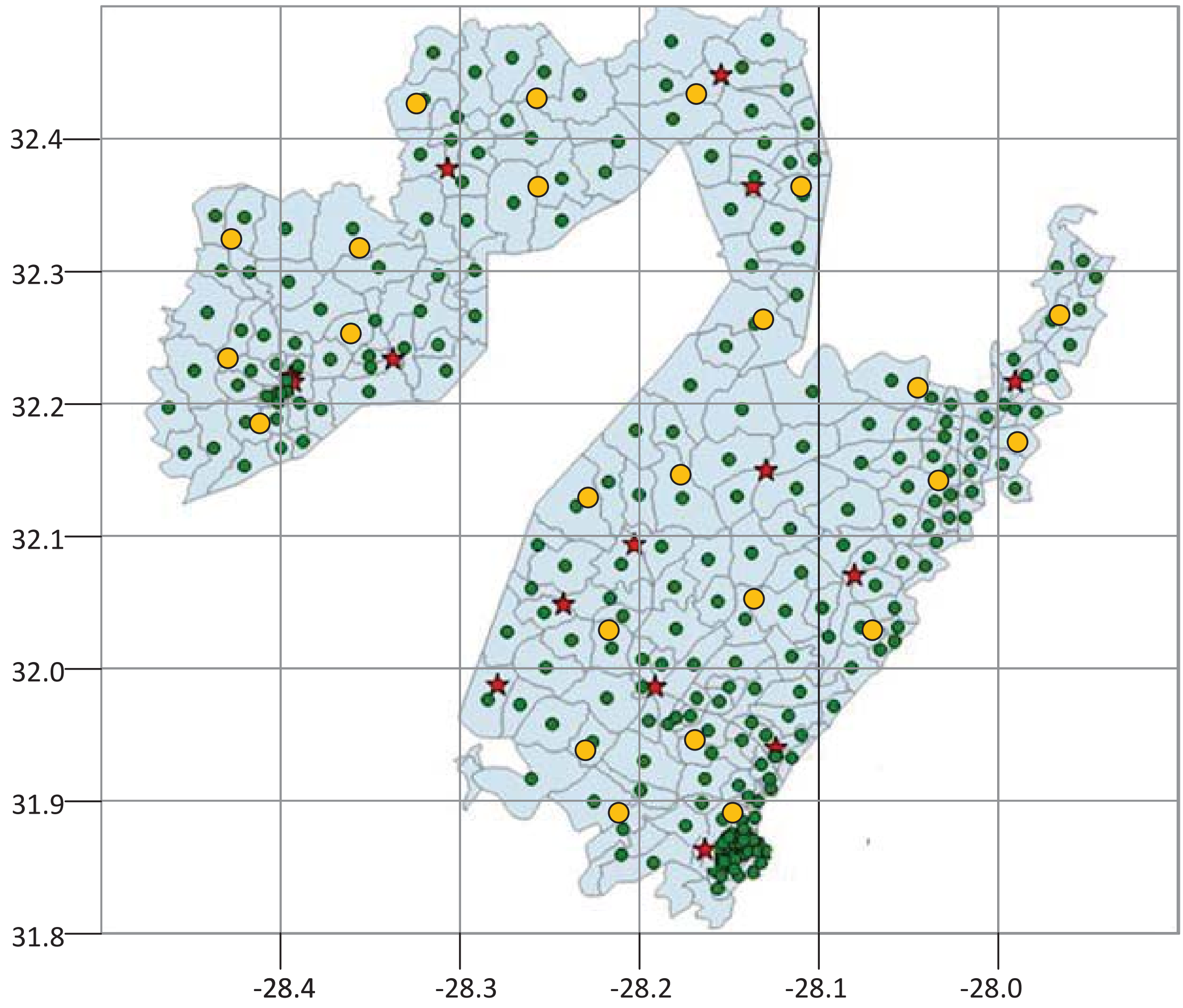

FIGURE 14: 24 CANDIDATE FACILITY SITES. SOURCE: QGIS 2.10.1

4.1.2 Model Assumptions

- The covered nodes were not included in the model. Demand nodes refer to nodes that are located outside a 5 km from the nearest existing facilities.
- A weighting factor was applied to each demand node based on the population size at the node. This was done to ensure that the maximizing purpose of the model is achieved by rating demand nodes with higher populations above locations with lower populations.
- The objective of the model is to determine the best combination of 5 possible locations for mobile clinics to be located that will maximize the population demand covered.

4.1.3 Model Results

Using the heuristic principles and the maximising covering location problem, the model was built using R (R Core Team, 2013) and Visual Basic for Applications (VBA). The candidate values generated in the previous phase were used as inputs to the model. The walking distance from each demand node to the nearest current facility was calculated using the Google Application Programming Interface (API). These distances determined whether a demand node was covered or not. The definition for a demand node to be covered is that the demand node is located within a 5 km walking distance from the nearest healthcare facility.

The distance from each demand node to each of the 24 candidate sites were again calculated by the model using Google API algorithms. The model was programmed to determine whether one or more candidate sites provided a shorter distance to the demand nodes compared to the existing healthcare facilities. The minimum value of the recalculated distances to the candidate sites were used to determine whether one or more of the candidate sites are closer to a demand node than an existing healthcare facility.

The model provided 42 205 possible combinations of 5 optimal facility locations out of the 24 candidate sites. The success of the 5 potential facility locations were ranked according to the maximum amount of population that could be covered. The top 3 combinations of the 5 facilities are shown in Table 6 below.

Combination No	Site 1	Site 2	Site 3	Site 4	Site 5	Population Increase	Percentage Increase	Average Km
A	2	7	15	18	23	20515	8%	7.22
B	7	15	16	18	23	20346	8%	7.45
C	2	3	7	18	23	19262	8%	7.15

TABLE 6: COMBINATIONS OF SOLUTIONS

The objective of the model is to maximise the population who can be covered if only five sites identified in the candidate sites list are located. The model therefore takes into account the demand at each node and identifies the five best sites to use for the mobile clinic locations. These five sites are depicted in Figure 15.

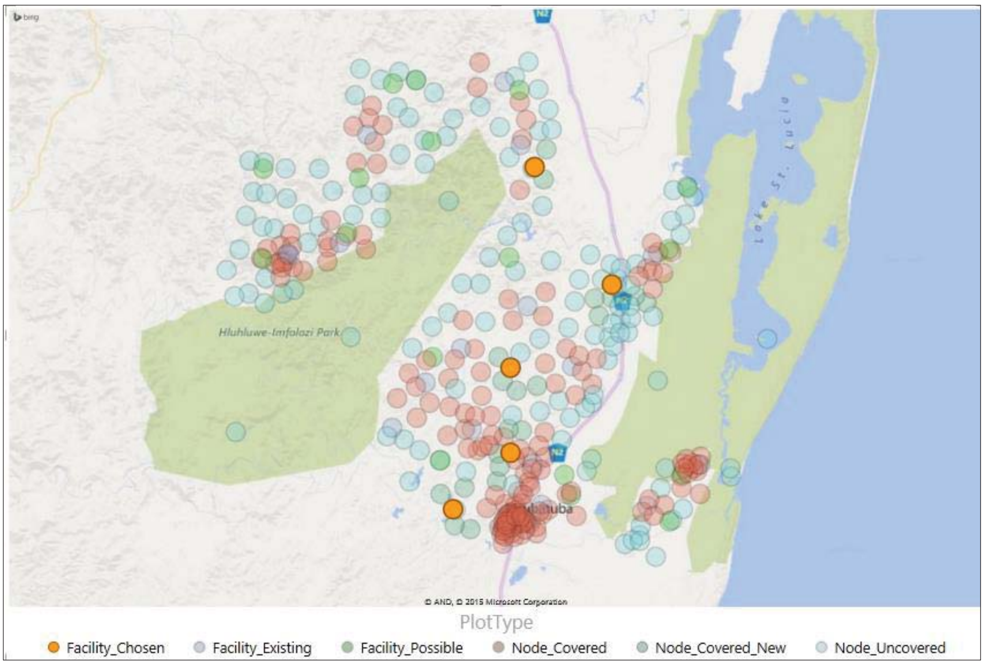

FIGURE 15: 5 CHOSEN FACILITY SITES. SOURCE: GOOGLE MAPS

The following map depicts the increase in 27 demand nodes that are covered due to the placement of the optimal 5 candidate sites.

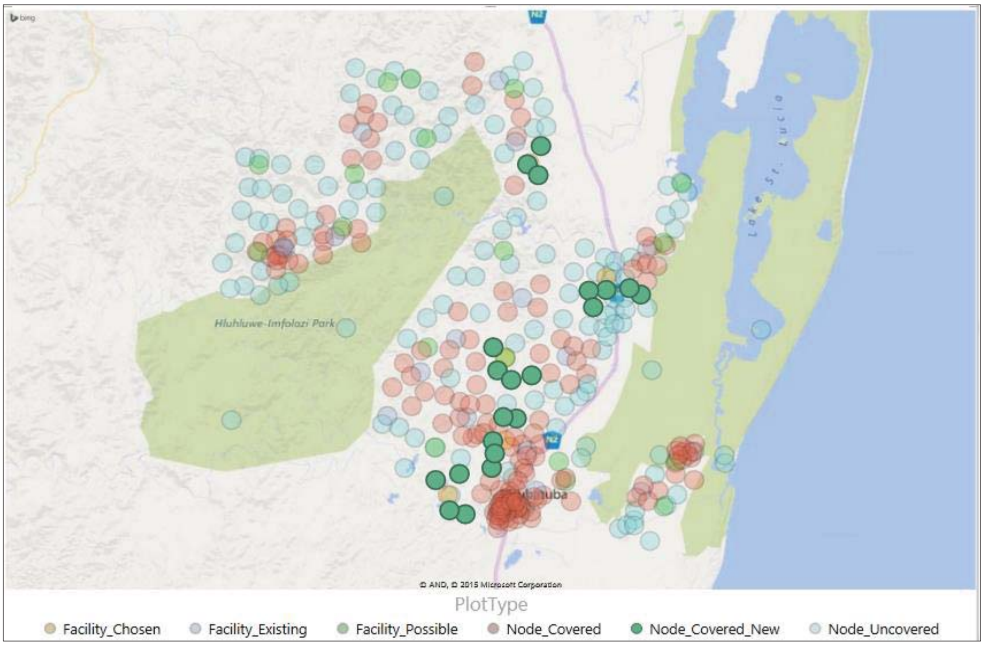

FIGURE 16: EXTRA DEMAND NODE COVERAGE. SOURCE: GOOGLE MAPS

The population that lives within a 5 km radius from a healthcare facility could be increased by 8% if the sites in solution number 1 are located. The average distance to a healthcare facility improved from 5.6 km to 4.93 km.

Solution Metrics	Base Scenario	Max Cover
Population:		
Base Population	247 296.12	247 296.12
Population Covered	127 779.02	148 293.52
%Population Covered	52%	60%
Small Areas/Nodes:		
Number of Nodes	308	308
Number of Nodes Covered	157	178
% Node Covered	51%	58%
Distance:		
Average Distance to Facility (km)	5.60	4.93
% Reduction in Average Distance	0	12%

TABLE 7: RESULT SUMMARY MAXIMUM DISTANCE MODEL

4.1.4 Model Validation

The model was tested by increasing and decreasing the service distance parameter within which the facilities must be located from the demand nodes. This was done to verify that as distance parameter is changed, the model would give the optimal amount of coverage required. This ensures that the model does not choose the optimal five sites without taking the demand into account. The resulting scenarios that are identified are indicated in Figure 17.

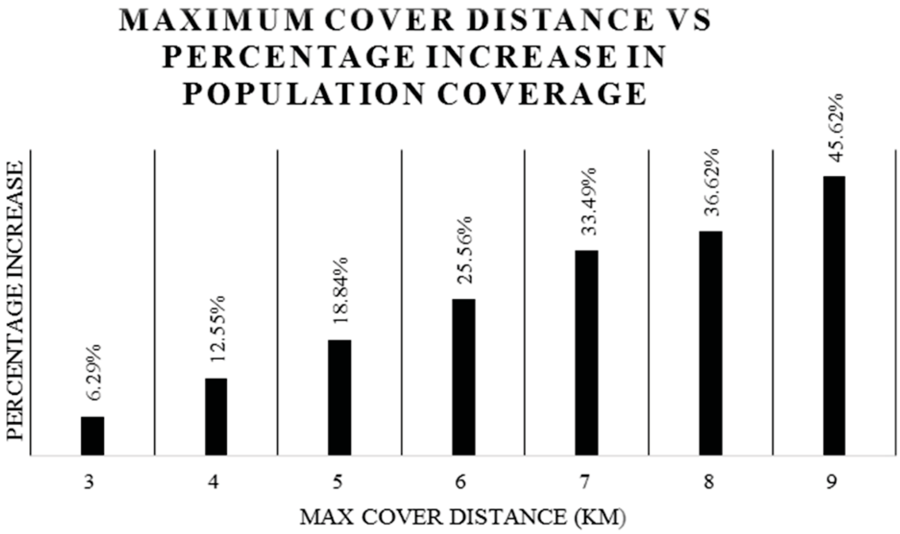

FIGURE 17: PERCENTAGE INCREASE IN POPULATION COVERAGE

The current constraint of a 5 km coverage proximity could be relaxed since the average distance to an existing healthcare facility is 8.84 km. For each kilometer the coverage constraint is increased, on average 6.8% or 8 127 of the population could be covered. A significant increase of 25.56% or 30 544 of the population could be reached if the maximum covering distance is increased to 6 km. The relaxation of the service distance constraint indicates that there is a possibility for further increase in population coverage if the number of mobile clinics can't be increased in the short term.

4.2 Alternative analysis

An alternative analysis was done as an attempt to verify the results of the previous model. The objective of the model was shifted to minimise the distance traveled instead of maximising the demand.

4.2.1 Minimum distance traveled model

The same results obtained from the pre-processing procedure in Section 4.1.1 is used as an input for this model. A weighted average of distance multiplied by population, was incorporated in this model to ensure that the demand is taken into account when the decision is made to locate the optimal facility locations. In this model, there is no parameter for the maximum service distance within which the facility must be located. Alternatively, the model located facilities that minimises the distance from all of the demand nodes to the nearest facility.

4.2.2 Model results

The objective of the model is to minimise the weighted distance from each demand node to the nearest facility and generating the 5 best combinations of candidate sites to achieve this. The top three solutions of the model are shown in Table 8 below.

Combination No	Site 1	Site 2	Site 3	Site 4	Site 5	Population Increase	Percentage Increase	Average Km
A	1	2	3	12	23	15090	6.1%	4.79
B	1	2	12	18	23	14925	6.0%	4.93
C	1	2	7	12	23	14294	5.8%	5.02

TABLE 8: MINIMUM DISTANCE TRAVELED RESULTS

The minimum distance traveled model reduces the average distance traveled to the nearest facility from 5.6 km to 4.79 km. The placement of the facilities can be seen on the map, Figure 18, below.

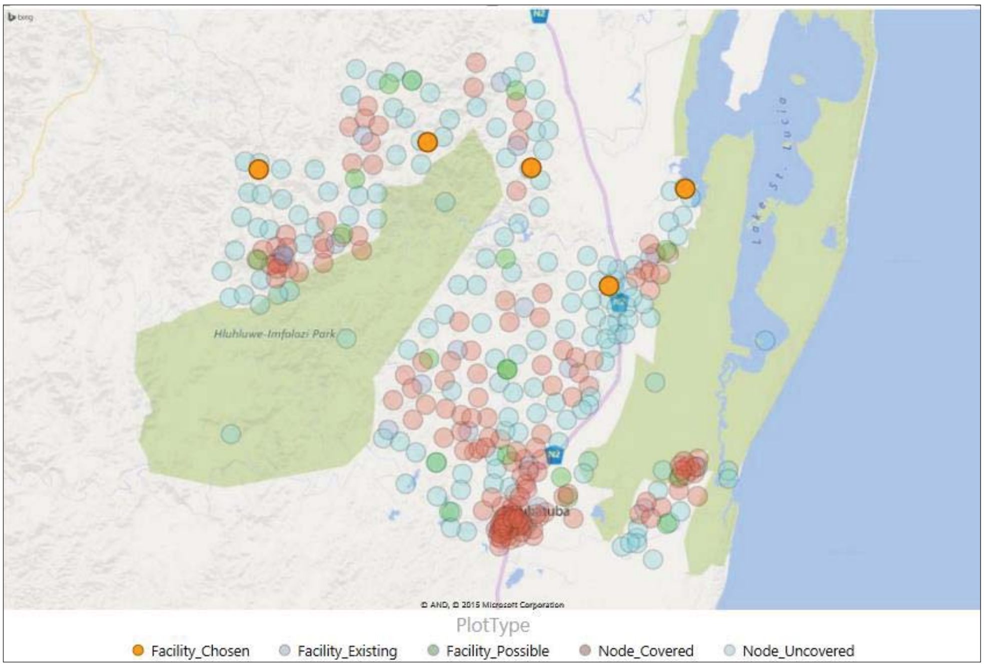

FIGURE 18: 5 CHOSEN FACILITY SITES (MINIMUM DISTANCE). SOURCE: GOOGLE MAPS

However, the coverage for the selected 5 facilities is only 58% or 15090 of the population that represents 16 extra demand nodes that are covered. (See Figure 19)

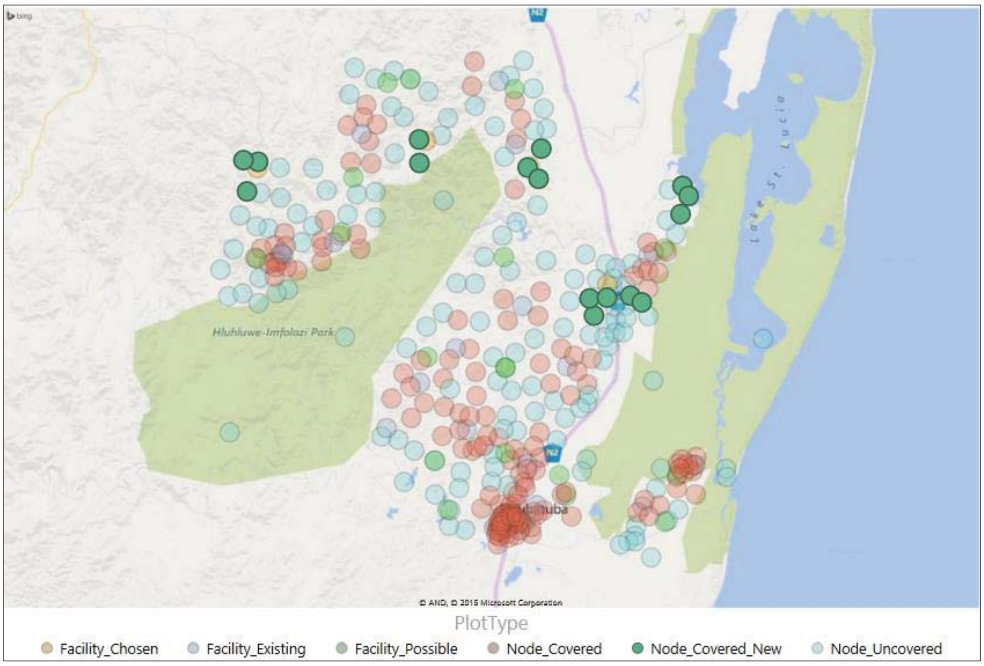

FIGURE 19: EXTRA DEMAND NODE COVERAGE (MINIMUM DISTANCE). SOURCE: GOOGLE MAPS

4.3 Meso-Zone Input Analysis

In this section, an alternative method to Section 4.1.1 is used to calculate the candidate sites as an input to the model. As an alternative to superimposing a grid over the operating area to divide the population, Meso-zones were used to divide the operating area. A Meso-zone represents the division of a piece of land according to administrative and physiographic boundaries, e.g. roads, rivers, municipal boundaries. The CSIR demarcated South Africa into 52 000 Meso-zones, which are approximately equal in size and similar in socio-economic character (CSIR, 2007). The demarcation of Meso-zones enables a finer scale to do geographic specific analysis such as comparative analysis of bio-physical and socio-economic data. The Hlabisa Local Municipality is divided into 32 Meso-zones as seen in Figure 20. The corresponding Small Areas can be seen inside each Meso-zone.

FIGURE 20: MESO-ZONE DEMARCATION SOURCE: QGIS 2.10.1

4.3.1 Maximum Covering Model

Using the R package, Orloca, an optimal site for a mobile clinic to be located in a Meso-zone was calculated. This resulted in a list of 32 candidate facility locations as seen in Figure 21. The constraints for this model is similar to the previous model, Maximum Covering Model, in Section 4.1. The service distance remains 5 km and the objective of the model is to maximize the population coverage.

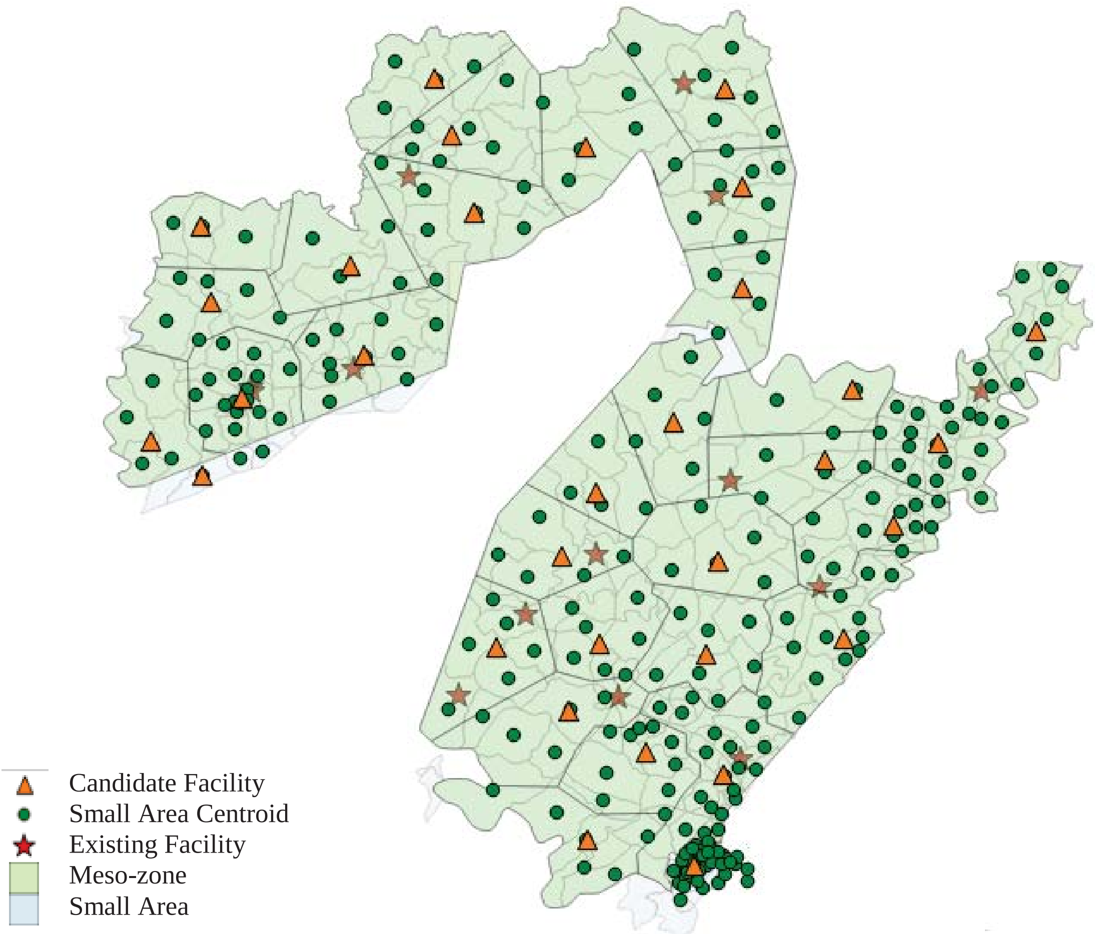

FIGURE 21: MESO-ZONE DEMARCATION WITH CANDIDATE SITES SOURCE; QGIS 2.10.1

The results for this model can be seen in Table 9. This model yields an 11.1% or 27 844 increase in population coverage and improves the average distance travelled from 5.6 km to 4.86 km.

Combination No.	Site 1	Site 2	Site 3	Site 4	Site 5	Population Increase	% Population Increase	Avreage Km
A	9	18	20	22	25	27 844	11.1%	4.86
B	8	9	13	14	18	26 885	10.9%	4.98
C	10	17	18	20	22	25 953	10.8%	5.01

TABLE 9: MESO-ZONE MAXIMUM DEMAND RESULTS

4.3.2 Minimum Distance Traveled Model

The same results obtained from the pre-processing procedure in Section 4.3.1 is used as an input for this model. In this model, there is no parameter for the maximum service distance within which the facility must be located. Alternatively, the model located facilities that minimises the distance from all of the demand nodes to the nearest facility. The results for the model can be viewed in Table 9. This model increased the population coverage by 9.1% or 22 378 people and improved the average travel distance from 5.6 km to 4.86 km.

Combination No.	Site 1	Site 2	Site 3	Site 4	Site 5	Population Increase	% Population Increase	Avreage Km
A	5	16	19	22	25	22 378	9.1%	4.86
B	5	17	20	25	28	22 045	9.0%	4.98
C	10	13	14	17	22	21 975	8.9%	5.01

TABLE 10: MESO-ZONE MINIMUM DISTANCE TRAVELED RESULTS

4.4 Chapter 4 summary

A comparative analysis of the different models as discussed in the chapter is carried out in this section. Table 11 below provides a summary of the models and their solutions.

	Section	4.1	4.2	4.3.1	4.3.2
Solution Metrics	**Base Scenario**	**Maximum Coverage**	**Distance Minimisation**	**Meso Maximum Coverage**	**Meso Distance Minimisation**
Population:					
Base Population	247296.12	247296.12	247296.12	247296.12	247296.12
Population Covered	127779.02	148293.52	144070.14	155623.23	153608.80
%Population Covered	52%	60%	58%	63%	62%
Small Areas/Nodes:					
Number of Nodes	308	308	308	308	308
Number of Nodes Covered	157	178	173	185	184
% Node Covered	51%	58%	56%	60%	60%
Distance:					
Average Distance to Facility	5.60	4.93	4.79	4.86	4.79
% Reduction in average distance	0	12%	14%	13%	15%

TABLE 11: RESULTS SUMMARY

Table 11 indicates that the Meso-zone Maximum Coverage Model is the most favorable model in addressing the objective of maximising the demand covered. The Meso-zone Maximum Covering Model increased the amount of the population living within 5 km radius of a healthcare facility by 11% or 27 844 residents and decreased the average travel distance to a healthcare facility from 5.6 km to 4.86 km. Figure 22 shows graphically how the populations have increased for each model based on the percentage of the population as well as the amount of the population.

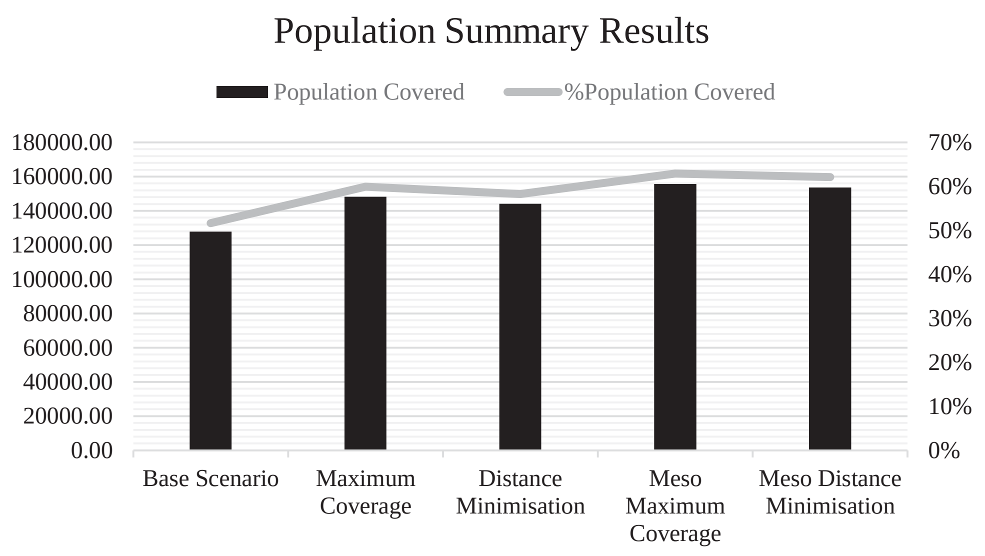

FIGURE 22: POPULATION RESULTS SUMMARY

The Minimum Distance Traveled Model is the most optimal model to minimize the average distance travelled to the nearest healthcare facility. This model improved the walking distance from all demand nodes from 5.6 km to 4.79 km but this only included an extra coverage of 6% or 22 378 of the population. Figure 23 depicts the summary of the average distance to a facility for each model as well as the percentage reduction each model offers in the average distance.

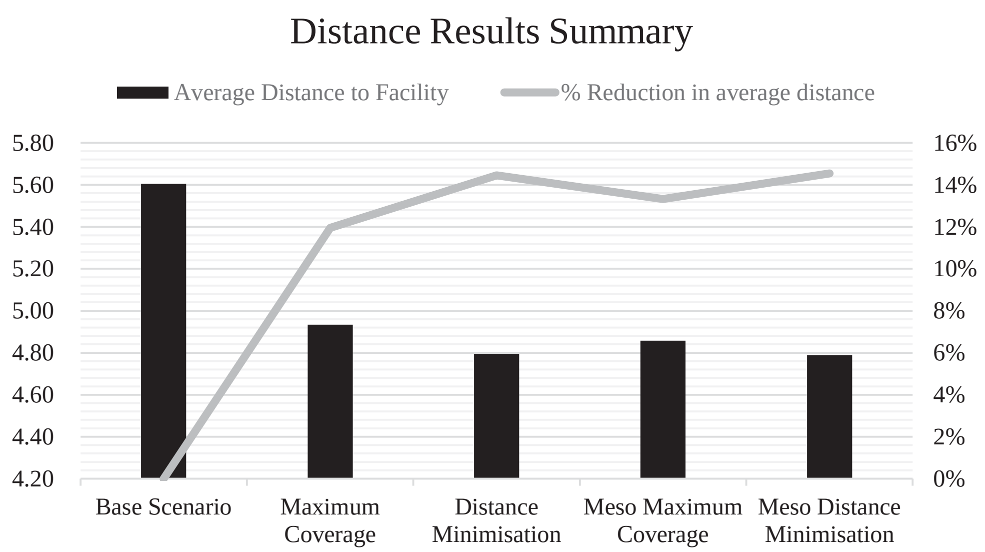

FIGURE 23: DISTANCE RESULTS SUMMARY

At the same distance that the Minimum Distance Traveled Model optimises the distance traveled to the nearest facility, 4.79 km, the Meso-zone Maximum Covering Model can cover a higher percentage, 12.43%, of the population. This is a significant improvement from the previous 6% and therefore will the Meso-zone Maximum Covering Model be favored in this analysis.

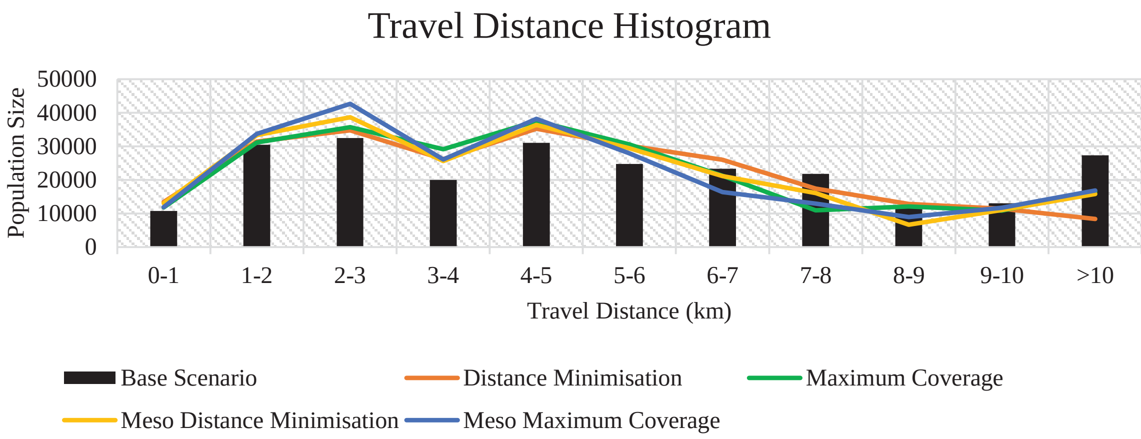

FIGURE 24: TRAVEL DISTANCE HISTOGRAM

From Figure 24, it is noticeable that the population who used to travel more than 10 km to a healthcare facility has reduced 45% if the Meso-zone Maximum Covering Model is chosen. The amount of the population who live between 0 and 5 km from a healthcare facility has improved with 11%.

CHAPTER 5

5. OPTIMISATION OF RESOURCE ALLOCATION

This chapter investigates the results found in Chapter 4 and attempts to optimize the resource allocation. Thus far the objective of the dissertation was to find the optimal location for 5 mobile clinics to be stationed for a day in the rural area of Hlabisa Local Municipality. This chapter will address the mobility aspect of a mobile clinic and determine whether the 5 mobile resources are able to increase their service delivery if they travel between more than 5 optimal locations. The optimal solution validated in Chapter 4 is the Meso-zone Maximum Covering Model and is the basis for this analysis. This analysis will investigate the ability of a mobile clinic to service the maximum demand over a period of 30 days and the demand for healthcare services in the area of Habisa. An analysis is done to verify the mobile clinic's capacity and its ability to cover the demand for healthcare in the area.

5.1. CAPACITY CONSTRAINT ESTIMATION

The capacity calculation of a mobile clinic is based on the amount of nurses traveling with the clinic, the service time per patient and the clinic service hours. The table below shows the assumptions made based on a standard size mobile clinic. Standard size mobile clinics are repurposed vehicles from small, high roof panel vans such as a Toyota Landcruiser 4x4.

Number of Mobile Facilities		5	
Workdays per month		30	
Patients per hour		8	
Hours per day		8	
	Total	**9600**	patients per month

TABLE 12: MOBILE CLINIC ASSUMPTIONS

The number of mobile clinics remain 5 as this is the current resources available to the area. The workdays per month are estimated at 30 days, this will constitute 100% utilization of the 5 resources in a month. The patients per hour are calculated based on two nurses per vehicle with the service rate of 15 minutes per patient. It is assumed that each mobile clinic will be open for 8 hours per day. These assumptions yield a service capacity of 9 600 patients per month or 320 patients per day.

5.2 HEALTHCARE DEMAND ESTIMATION

Demand for healthcare related services in Hlabisa Local Municipality was estimated using national prevalence rates for non-communicable diseases as in the National Burden of Disease document (Actuarial Society of South Africa, 2010). The demand was estimated by taking into account that on average, only 60% of people are aware of their disease and actively consume health care services and making allowances for people with multiple conditions. The calculation was done on a high level not taking into account age and gender distribution of the underlying population. Table 13 below summarizes the prevalence rates obtained from the National Burden of Disease document.

	Prevalence Rates	Monthly Consumption
HIV	20.5%	1
Diabetes	6.5%	0.75
Hypertension	17.0%	0.6
Hyperlipidemia	9.0%	0.6
Asthma	4.5%	0.9
Emergency	1.5%	1

TABLE 13: PREVELANCE AND MONTHLY CONSUMPTION RATES

The HIV prevalence in the Hlabisa Local Municipality is extremely high at 20.5%. HIV/TB co-infected patients are included in this prevalence rate. The monthly consumption rate for HIV is 1 as patients are dispensed a month's supply of medication at a time. Hypertension, Diabetes, Hyperlipidemia and Asthma are common chronic diseases in the area and are not frequently diagnosed. The monthly consumption rate for these diseases are therefore less than one. The prevalence rate for emergencies are relatively low at 1.5% as mobile clinics are not equipped to provide emergency services. The total demand requirements is summarized in Table 14.

Demand Coverage	Population
Covered Demand: Existing Facilities	51 613
Covered Demand: 5 Mobile Clinics	9 820
Uncovered Demand	25 785
Total Demand	87 218

TABLE 14: DEMAND FOR HEALTHCARE BASED ON PREVELANCE RATES

The 5 mobile clinics are only able to service 9 820 of the prevalence population, the percentage of the population in need of healthcare services. A further 25 785 people need to be serviced by mobile clinics. The demand for healthcare services is much more than the capacity that the 5 mobile clinics can provide even when they are stationed at the most optimal locations. The mobile clinics has therefore no spare capacity to travel to other locations and increase the service delivery in the area. Based on the calculations above, additional mobile clinics are required in order to increase the service delivery in the area.

5.3 Resource Allocation Model

To increase the service delivery for the areas which aren't covered by the 5 mobile clinics specified in the Meso-zone Maximum Covering Model, it is necessary to determine how many additional mobile clinics are required. The 32 candidate sites obtained from the Meso-zone Maximum Covering Model are used in this model to determine how many additional population can be serviced by adding additional mobile clinics. Figure 25 shows the cumulative increase in the population coverage with the addition of mobile clinics.