CHAPTER 3

HEALTH DELIVERY SYSTEM IN MALAYSIA

3.1 INTRODUCTION

The vision of the Ministry of Health Malaysia (MOH) is for "Malaysia to be a nation of healthy individuals, families and communities, through a health system that is equitable, affordable, efficient, technologically appropriate, environmentally adaptable and consumer friendly, with emphasis on quality, innovation, health, promotion, and respect for human dignity and which promotes individual responsibility and community participation towards an enhanced quality of life." To achieve this, the mission of the Ministry is to build partnerships of health to facilitate and support the people to fully attain their potential in health, to motivate them to appreciate health as a valuable asset, and to take positive action to improve and sustain their health status further to enjoy a better quality of life (Annual Report MOH, 2005 page numbers vi and vii).

MOH together with the Ministry of Education (MOE) has made available university hospitals and private sectors to provide health facilities such as hospitals and clinics and specialised services such as hemodialysis centres to the country. Each of the 15 states in the country is provided with a general hospital that performs basic primary to tertiary care services. Table 3.1 summarises the number of health facilities available throughout the country. The number of health facilities in the country for 2009 as indicated by * in Table 3.1 is taken from Annual Report MOH, 2009.

Table 3.1: Health facilities in Malaysia in 2006 (Annual Report MOH, 2005)

Note: Includes Mobile Dental Teams & Clinics

Health Facilities and Types	Units (2006)	Units (2009)*
Total Number of MOH Hospitals	128	130
Total Number of Beds in MOH Hospitals	30,969	33,287
Total Number of Special Medical Institutions	6	6
Total Number of Beds in Special Medical Institutions	4,770	4,770
Total Number of Non-MOH Government Hospitals	6	8
Total Number of Beds in Non-MOH Government Hospitals	2,886	3,523
Total Number of Private Hospitals, Maternity/Nursing Homes	223	245
Total Number of Beds in Private Hospitals, Maternity/Nursing Homes	11,637	12,619
Number of MOH Health Clinics	807	808
Number of MOH Rural Clinics (Klinik Desa)	1,919	1,920
Number of MOH Maternal & Child Health Clinics	88	90
MOH Mobile Clinics	151	196

Table 3.2 summarises the ratio of the facilities to population in 2000 and 2005. The ratio has generally increased due to the increase in the population volume. However, as of 2010, a doctor patient ratio in the urban area has been 1:900 except for in the interior parts of Sabah and Sarawak (MOH webpage, July 2010). These have contributed to improvements in the speed and quality of the diagnosis as well as

enhanced patient comfort. In addition, the increasing number of private clinics and hospitals in urban areas has complemented the provision of medical care by the public sector. In the 1980's, the government contributed about 76 percent of the total healthcare expenditure. The 2007 National Health Account (NHA) reported that the total expenditure on health was 44.8 percent by the public sector and 45.2 percent by the private sector (Ng, 2010). In 2010, the private health sector looked after some 62 percent of outpatient services and 30 percent of in-hospital treatments (Annual Report MOH, 2006).

Table 3.2: Facilities provided by MOH in 2000 and 2005 (Annual Report MOH, 2005)

Type of Facilities	Number		Ratio of Facility to Population	
	2000	2005	2000	2005
Rural Health Facilities				
Community Clinics	1924	1900	1 : 4,640	1 : 5,085
Health Clinics	474	495	1 : 17,506	1 : 19,520
Mobile Units*	204	200	1 : 43,764	1 : 48,312
Mobile Dental Units	8	30		
Urban Health Facilities				
Health Clinics**	473	462	1 : 30,797	1 : 35,638
Patient Care Services				
Hospitals	119	128	1 : 197,436	1 : 204,140
Total Beds	34573	35210	1 : 679	1 : 742
Dental Units***	2597	3340	1 : 9,047	1 : 7,823

*Note: * refers to dispensary services, village health teams, flying doctor services and mobile dental services*
*** includes maternal and child health clinics*
**** refers to dental chairs in government clinics*

The public sector lost many, both general and family physicians that had opted out by opening individual clinics or by joining more established group practices; whilst specialists joined the better-paying more personalised care practices in the urban private medical centres. The private health clinics cater to most of the fee-for-service self-paying public, which include: private sector employees through panel doctor contract/insurance arrangement; thus relieving the already overloaded MOH's public clinics. In general, the choice for such private clinic consultations and treatments is due to easier access, simpler registration and appointment procedures, and shorter waiting times. In addition, there is also the possible greater continuity of care with better personal attention from one's own family physician or general practitioner.

MOH constantly strives to improve the healthcare system in the country through its Health and Planning Development division with three core businesses namely health system planning and development, health facility planning and development and health information system planning and management. The division foresees that the completion of new facilities and the upgrading of existing facilities along with the equipment will improve patients' accessibility and provide better quality of services to the community. In addition to that, in the Ninth Malaysia Plan period (2006-2010), there were activities related to capacity building, as part of the restructuring of the MOH healthcare delivery system for better service.

3.2 TYPES OF SERVICES PROVIDED BY THE PUBLIC FACILITIES

In Malaysia, the medical care services provided by the public facilities comprise of three levels: primary, secondary, and tertiary care through a wide network of health clinics and hospitals. These include outpatient and inpatient care services ranging from primary care at the health clinics to the advanced medical care at the tertiary care centres in the hospitals. Table 3.3 summarises the types of services planned for each outlet (Sixth Malaysia Plan (1991-1995) (Economic Planning Unit, 1990).

Table 3.3: Summary of types of services provided by the Malaysian public facilities

1. **Primary Care services** comprise of outpatient department as the first point of contact, including maternal child healthcare, dental services, school health services and support services such as clinical and imaging facilities, pharmacy and registration.
2. **Basic secondary care services** comprise of General Medicine, General Surgery, Obstetrics and Gynecology, and Pediatrics. The services are run by resident medical officers and visiting specialties.
3. **Full secondary care services** comprise of General Medicine, General Surgery, Obstetrics and Gynecology, Pediatrics, Orthopedics, Anesthesiology, Psychiatry, Dermatology, Medical Rehabilitation, Pathology, Imaging, Dental, Ear, Nose and Throat (ENT), Ophthalmology and Geriatrics. The services are run by medical officers and resident specialists.
4. **Tertiary care services** comprise of highly specialised care in areas such as Cardiology, Cardiothoracic Surgery, Geriatrics, Pediatric Surgery, Neurology, Neurosurgery, Respiratory Medicine, Urology and Nephrology, Plastics Surgery and Burns, Maxillofacial, Radiotherapy and Oncology, and Endocrinology.

Figure 3.1 summarises the administration levels for the type of care together with the health facilities that provide the services. The figure is adapted from the information gathered from MOH annual reports and from the presentation of MOH personnels (A.Hamidy, 2010).

3.2.1 Public Facilities Administration

The administration of the health delivery system began at the national level in which the MOH has a role, responsibility and regulatory functions to improve the mechanisms for an effective governance of the health sector. In the MOH, there are several divisions focusing on different areas of health services.

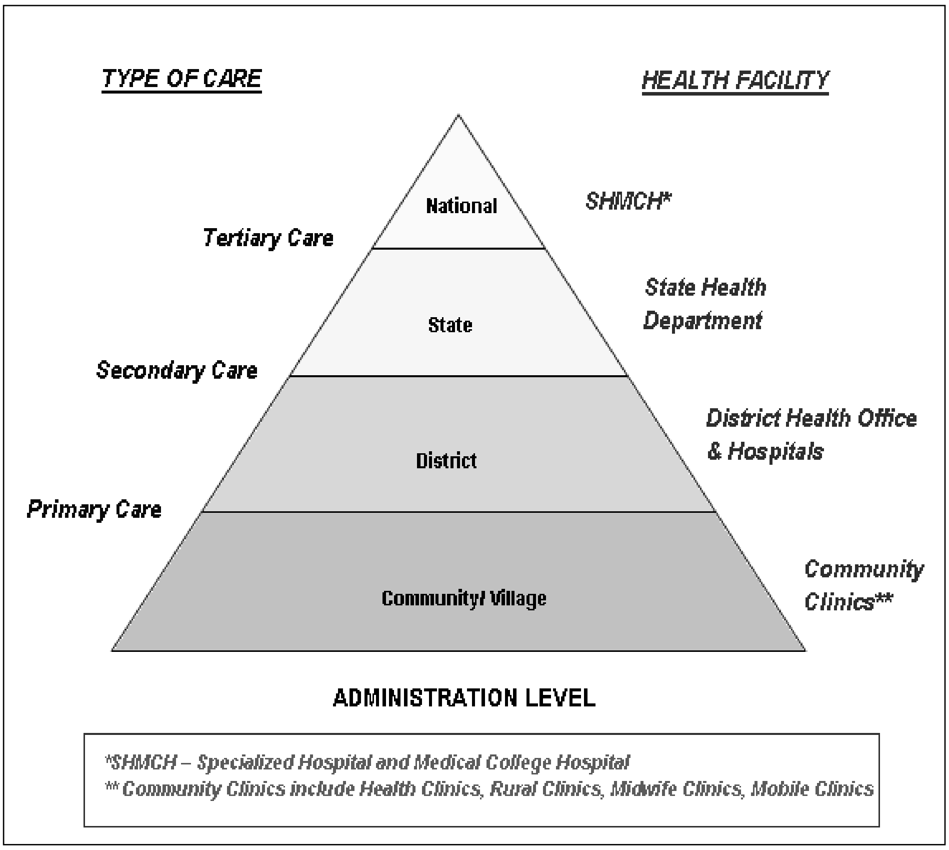

Figure 3.1: Hierarchy of public health care system in Malaysia ((At: www.moh.gov.my/v/carta_organisasi, accessed on 28 Oct., 2007)

At the state level, each state will have a State Health department headed by a Director. For example in Selangor, the Health Department is a Federal Department under the MOH. Specifically, the function of the Selangor Health Department is to execute the programmes and activities of the Health Ministry in 5 aspects, namely (i) providing medical treatment, health and dental services in the hospitals and clinics; (ii) monitoring and controlling health services in the private sector; (iii) prevention and disease control (performed together with the local Authorities); (iv) health protection for residents; and (v) promoting the residents health. All the functions are carried out in 5 Divisions, namely Medical Division, Public Health Division, Dental Division, Pharmacy Division and Management Division (Selangor State Health Office webpage, 2010).

In every state, there will be districts in which each district will have one district health office. However, some districts may have more than one district health office depending on the need. In Selangor for example, there are 9 districts. However, there are 11 district health offices, one for each district, one for the Kuala Lumpur International Airport (KLIA) and one for Port Klang. The health offices in KLIA and Port Klang have specific functions mainly based on the operations at the site, which are the main entrance and exit doors to the country.

3.3 GOVERNMENT POLICY AND LOCATION OF HEALTH FACILITIES

The need for a National Health Policy (NHP) was identified at the midterm review of the Sixth Malaysia Plan (Economic Planning Unit, 1990). In 2005, the existing draft containing policies was revised with the assistance of an external consultant to develop the NHP framework. Several workshops were planned in 2006 to finalise the NHP and circulate it to the stakeholders. The department of the Health Planning and Development is responsible for the NHP. As the policy is endorsed, standards and norms will be further refined and new ones developed for the purpose of benchmarking of the health facilities and to accommodate new policies and service requirements. The location of the facilities and the distribution of the scope of the services will be identified based on the concept of an integrated holistic planning approach in order to enhance optimisation of resources and their utilisation among service providers.

In the Seventh Malaysia Plan (Economic Planning Unit, 1996), under the rural health programme, comprehensive coverage of basic health services for rural and remote areas are given priority. This was planned through the construction of new primary healthcare clinics and upgrading the rural and midwife clinics into health clinics. The health clinics are equipped in basic imaging and laboratory diagnostic facilities and teleprimary IT systems. The scope of the services at the health clinics are maternal and child health service, and provide antenatal and post-natal care for mothers; child immunisation; child development charting and monitoring; family planning; medical outpatient treatment; wellness clinic – health screening for risk factors like hyperlipidaemia and obesity and chronic diseases like diabetes and hypertension; smoking counseling; nutrition counseling; nutrition and health promotion; elderly care; mental healthcare; and adolescent health (Selangor State Health Office webpage, 2010).

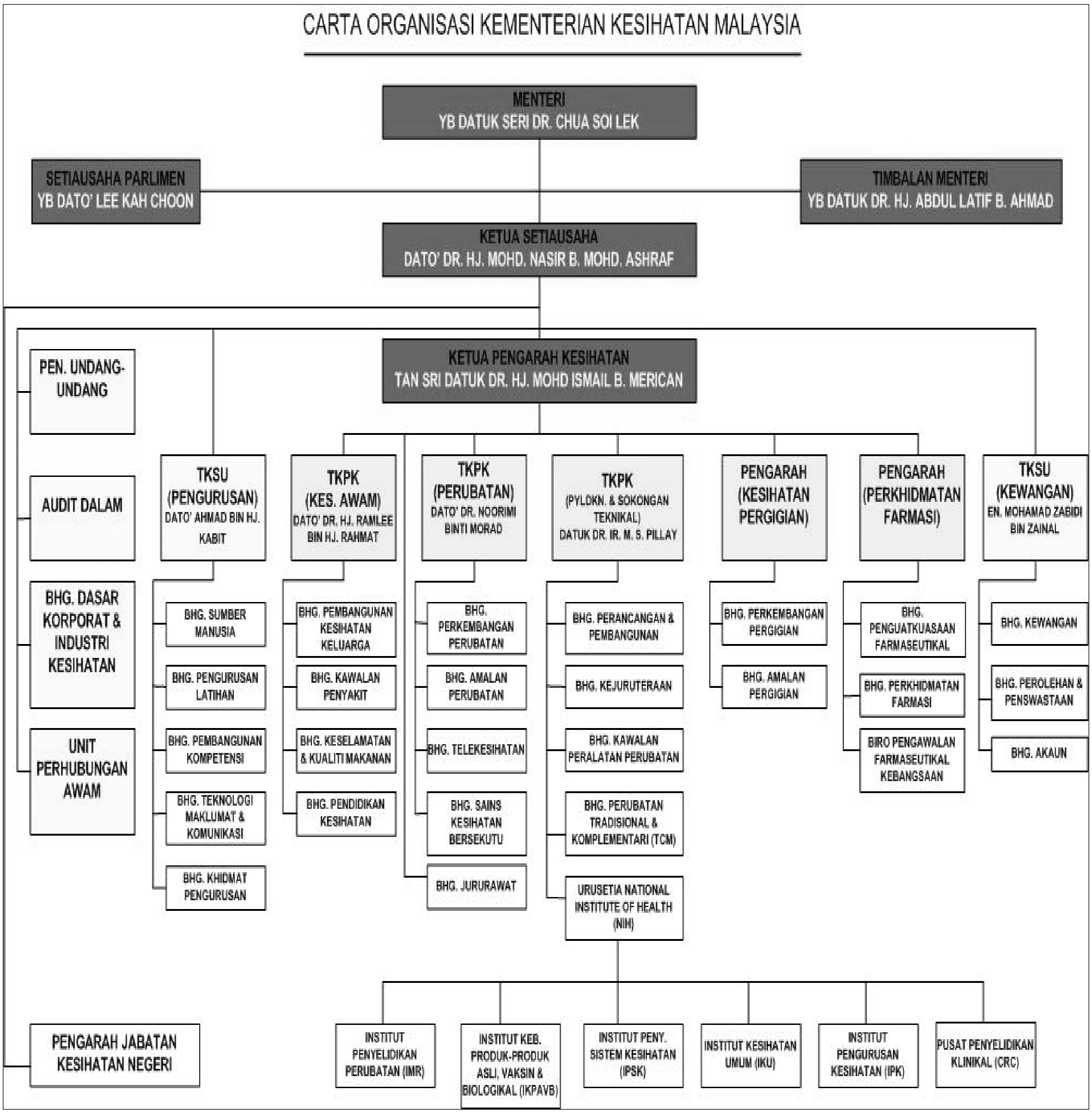

Figure 3.2: Structure of the public facilities administration (At: www.moh.gov.my/v/carta_organisasi, accessed on 28 Oct., 2007)

In the Ninth Malaysia Plan period (2006-2010) (Economic Planning Unit, 2005), the emphasis continues to be on the provision of client-focused services and community needs in order to fulfill the demand for a better healthcare system. The delivery of healthcare will be further improved through greater integration, enhancement in the quality of services and resource optimisation. The medical and health service programmes that provide primary, secondary, tertiary and rehabilitative care will be consolidated to improve the delivery of healthcare. During this period, greater efforts will be undertaken to strengthen the services provided at the primary care level. Existing facilities will be upgraded while new facilities will be built to provide a comprehensive package of services. In a further effort to increase accessibility, mobile clinics will be provided in densely populated areas where suitable land is unavailable for construction of health facilities. Access to health care in the remote and underserved areas will be improved through the provision of more mobile clinics equipped with the necessary diagnostics equipment.

Primary healthcare service in Malaysia is among the best in the developing countries (Annual Report MOH, 2005; Quek, 2010). In 2005 the statistical analysis showed a decreased trend in mortality rates as compared to in 2004. This continued to reduce in 2006 for some measurements while maintaining at 4.4 percent for crude death rates. For communicable diseases, the incident rate of dengue fever remained to be on top in 2006, with 64.37 percent and 0.01 percent mortality rate. Tuberculosis followed closely with 62.56 percent incident rate and 5.37 percent mortality rate. Among the 10 principal causes of hospitalisation in MOH hospitals in 2006, the diseases of the respiratory system (including tuberculosis) were the fourth with 7.30 percent. It is important to note here that most of the communicable diseases could be controlled through immunisation programmes, health education and better management of diarrheal diseases (Annual Report MOH, 2006). These are among the important components of primary healthcare.

At present, there are more than 800 health clinics and about 1920 community clinics (CCs) with 90 stand alone maternal and child clinics nationwide. The norm is to have one primary health clinic (PHC) for every 15,000 to 20,000 people and one CC for every 5000 in the population. From the MOH records, 88.5 percent of the population lives within 5 km of a health facility and 81 percent within 3 km (Merican, 2007). The performance of the healthcare delivery system is based on health indicators such as Infant Mortality Rate (IMR) (per 1000 live births), Life Expectancy at birth and Under 5 (years of age) Mortality Rate (per 1000 live births). In fact, the life expectancy for both males and females has risen from 68.8 years for males and 73.5 for females in 1999, to 71.56 years for males and 76.40 for females in 2008 (Health Facts, 2009). The IMR of Malaysia has improved tremendously since the 1970s. It has been decreasing from 10.4 per 1000 in 1995 to 5.8 in 2003 (WPRO, 2005). Table 3.4 shows that the IMR of Malaysia is now comparable to the developed countries such as the United States of America (USA), Australia, and the United Kingdom (UK). In 2008, the IMR increased a bit to 6.4 and the Under 5 Mortality Rate was at 8.1 per 1000 live births (Health Facts, 2009).

Table 3.4: Comparison of mortality indicators of selected nations (Source: UNDP, 2004)

Country	Infant Mortality Rate (per 1000 live births)		Under 5 Mortality Rate (per 1000 live births)	
	1970	**2002**	**1970**	**2002**
Malaysia	46	8	63	8
Thailand	74	24	102	28
USA	20	7	26	8
UK	18	5	23	7
Japan	14	3	21	5
Australia	17	6	20	6
India	127	67	202	93
China	85	31	120	39

3.3.1 Comparison to Other Developing Countries

According to the report by WHO (World Health Organization), nearly 14.5 million people die annually from preventable communicable diseases. Tens of millions more have their lives impaired by these diseases on a daily basis. More than 90 percent of the world's communicable disease burden, and 90 percent of the related deaths, occur in the poorest populations of developing countries. Hence the health global programs that focus in preventing or controlling communicable diseases becomes the high priority. However, in developing countries the global priorities with local needs in a situation of extreme resource scarcity must be reconciled. Disease prevention and control is part of the public health agenda, rather than a separate one (Lele et al., 2005)

Though still being categorized as developing countries, Malaysia as part of Southeast Asia countries has tremendously improved its control on the communicable diseases. Figure 3.3 summarizing the population distribution by age in Southeast Asia shows that Malaysia has increased age longevity comparably. These trends are, in turn, affected by economic, social, cultural and political developments. With increasing longevity, the pace of increase in numbers of the oldest old (aged 80 years and older) in Southeast Asia is projected to exceed that of East Asia over the period 2025–2050 (Chongvivatwong et al. 2011). The increase implies on the management of the burden of disease and healthcare provision for elderly people. This is because increasing longevity is a result of diminishing burden from communicable, maternal and perinatal diseases, whereas countries with aged populations will have a higher burden of non-communicable diseases. Interestingly, mortality rates from these two groups of diseases, as well as from injuries, are correlated. Countries with high mortality rates from communicable diseases also have high death rates from chronic diseases. Deaths from communicable diseases are still prominent in Cambodia, Myanmar and Laos. Injuries are an important cause of death in all countries, though less so in Singapore and Brunei. Figure 3.3 depicts the population distribution by age in Southeast Asia.

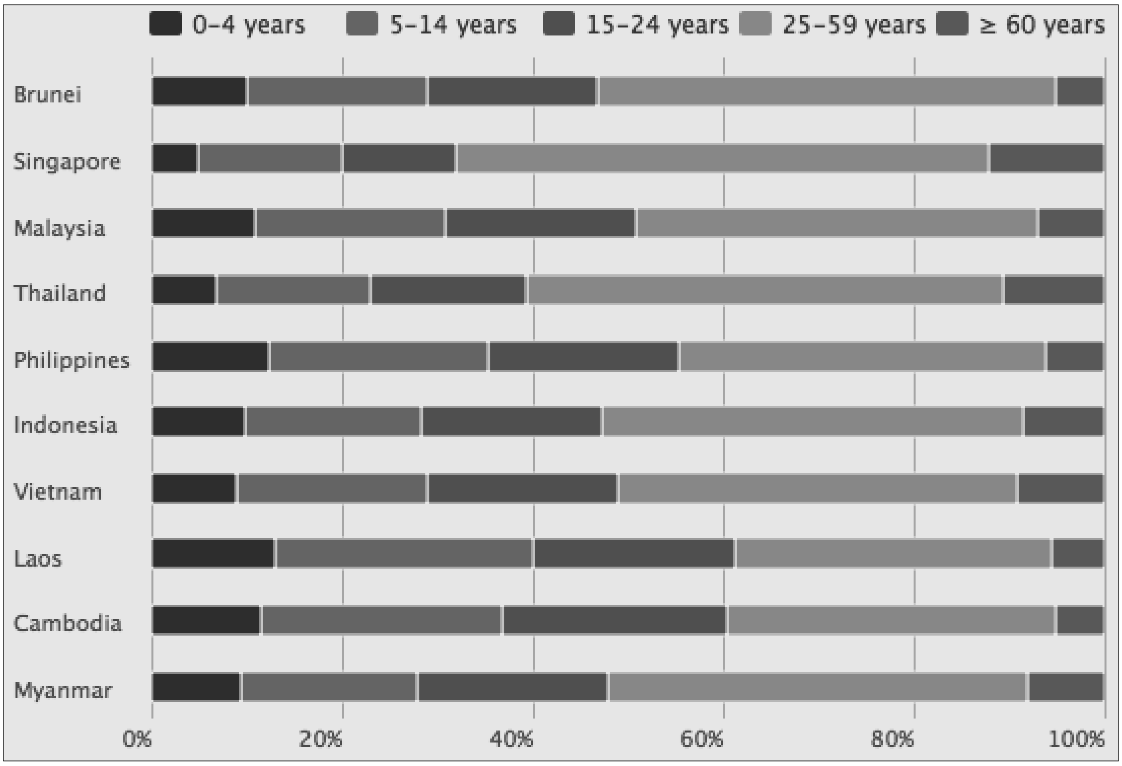

Figure 3.3: Population distribution by age in Southeast Asia, 2005 (Chongvivatwong et al., 2011)

Thus, our present system is effective in delivering good healthcare to the people in Malaysia. However, as mentioned in Chapter 1, most of the clinics especially in the urban areas are highly congested and have a high average waiting time. The primary health care services must be strengthened (Hsu, 2005). A good primary care system with easy accessibility is the most effective way to contain the escalation of health cost and maintain a good healthcare for the nation. Hence, the scope of this study will be on determining the location of the CCs and the maternal and child clinics which provide the primary healthcare, the main entrance to the public health care system.

3.4 DATA PROFILE

In order to study the suitability of the models and measure the effectiveness of method in solving the location model, two sets of real-world data to represent the Malaysian primary healthcare delivery service are utilised. The data profiles will be detailed in the following section. The first one is a small data set of 179 nodes whilst the second comprises of a larger set of 809 nodes.

3.4.1 Small data set – Mukim Telok Panglima Garang

Mukim Telok Panglima Garang (MTPG) is located about 27 km southeast of Shah Alam (the capital state of Selangor) and comprises a small town centre, a few medium-sized residential areas and villages, as well as small to medium workshops and factories. At present, the area is served by two Health Clinics, which are Klinik Kesihatan Telok Panglima Garang (KK TPG) and Klinik Kesihatan Sijangkang (KK S) and 4 Rural Clinics. These Rural Clinics or Klinik Desa, also known as maternal and child clinics, serve mainly mothers and children aged between 0 and 6 years old. The services range from pre-natal check-ups for the total nine months of pregnancy, to post-natal check-ups after the delivery including family planning. KK TPG has two sections, one is for maternal and child and the other for outpatients. KK S on the other hand only consists of the outpatient department. This study will only consider the homogeneous types of facilities, which is the location of Rural Clinics. Therefore, there are 5 units (1 KK and 4 KDs, namely TPG, Kampung Medan (KM), Kebun Baru (KB), Sijangkang Dalam (SD) and Sijangkang Luar (SL)) for consideration. Figures 3.4 and 3.5 illustrate the various districts in Selangor and the location of the area under study, respectively.

Figure 3.4: Map of Selangor indicating all the districts

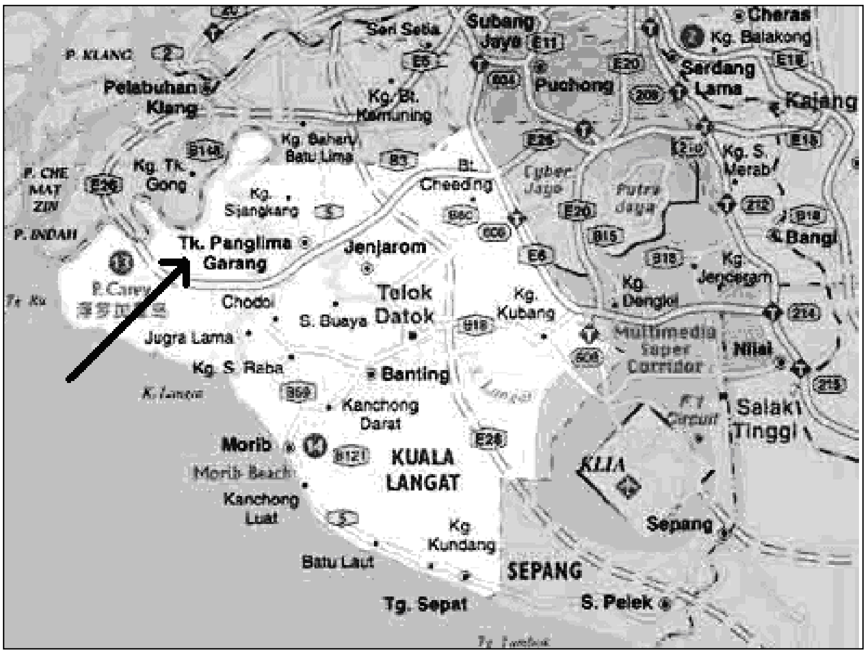

Figure 3.5: Map of Kuala Langat indicating Mukim Telok Panglima Garang

The area of study covers 8071 hectares in size, with a total population of 66240 situated within a rectangular area of $2^{o}54'$ N to $2^{o}58'$ and $101^{o}26'$ E to $101^{o}30'$ E (or 80.71 km^{2}). The population in the study area is sparsely distributed with approximately 18 hectares or 24 percent of the area is unpopulated as there are chicken (poultry) and oil palm farms situated in this area.

The population service coverage and the service boundary for each of these clinics have been determined by the higher management in the District Health Office in Kuala Langat and is monitored by the Staff in Charge (SIC) based in KK TPG. The boundaries are determined based on the population density, distance as well as accessibility. Each clinic is assigned a target population to service per year. For example in 2007, the target was 5 clinics to serve a total of 66240 people, with individual clinics serving between the minimum population of 6000 and the maximum of 23000. Some clinics are operating above their capacity. For example, KD SL is still operating in the old building which is the old midwife's clinic building (Rumah Bidan Kerajaan (RBK) status) that can only accommodate a maximum of 4000 patients per year. However, the unit was targeted to serve approximately 13000 patients in 2007 (JM KD Sijangkang, personal communication, 15 October, 2007).

Table 3.5 summarises the target population breakdown for the five clinics under study in Mukim TPG. It also describes the breakdown of target service volume for every clinic, showing, for instance, the number of babies and the number of pregnant mothers that should go to clinics and family planning provision. As mentioned earlier, RCs only serve mothers and children under six years old. Hence, instead of the total population of 66240 in Table 3.5, only 30458 are potential visitors to RCs.

Each RC is located 7 to 11 km apart from each other and situated on a car track with very good road conditions. Although there is no public transport available except for in TPG, every other clinic is accessible via other means of transportation. Figures 3.6 and 3.7 indicate the service boundaries and the roads and tracks passable by car in the area under study.

Table 3.5: Targets for consultations and health provision in 2007 (Telok Panglima Garang Health Clinics)

	KKTPG	KD K/B	KD S/D	KD K/M	KD S/L	Total
Births in 2006	440	179	104	210	196	1129
Total Population	22722	11128	5696	14109	12585	66240
% of total	34.3	16.8	8.6	21.3	19	100
Live Birth	425	206	105	262	233	1231
No of Babies	639	311	159	395	352	1856
Children 0-1 yrs	598	291	149	370	330	1738
Children 1-2 yrs	1182	578	296	733	653	3442
Children 1-4 yrs	2271	1111	568	1408	1256	6614
Children 5-6 yrs	856	443	227	562	554	2642
Pregnant Mothers	483	238	121	306	269	1417
Birth at Residence	3	1	1	2	2	9
Family Planning (New)	98	47	24	61	53	283
Family Planning (Repeat)	1510	790	404	1016	988	4708
Pap Smear	280	144	73	183	180	860
Women (15-44 yrs)	5178	2691	1377	3412	3364	16022

Table 3.5 : Continued

Milk Powder Recipients	50	24	12	31	31	148
House Visit	4003	2681	1065	2038	2601	12388
Potential Population That Should Go to KD	10085	5114	2617	6485	6157	30458

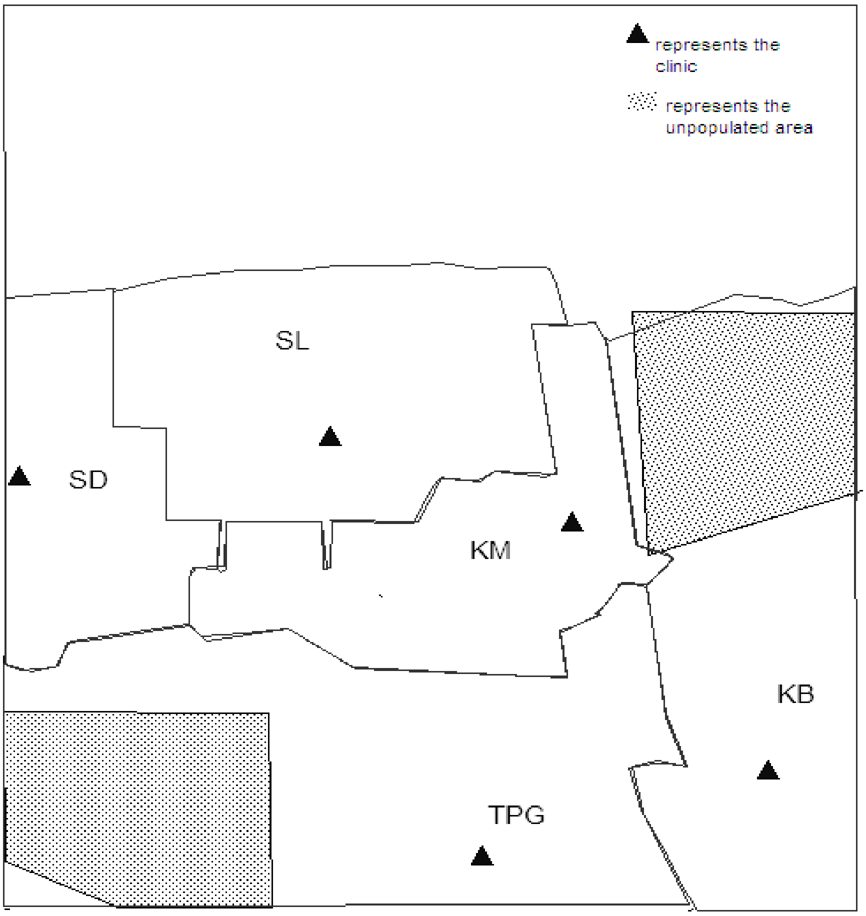

Figure 3.6: Map of Telok Panglima Garang indicating the service boundaries for all 5 rural clinics and the unpopulated regions

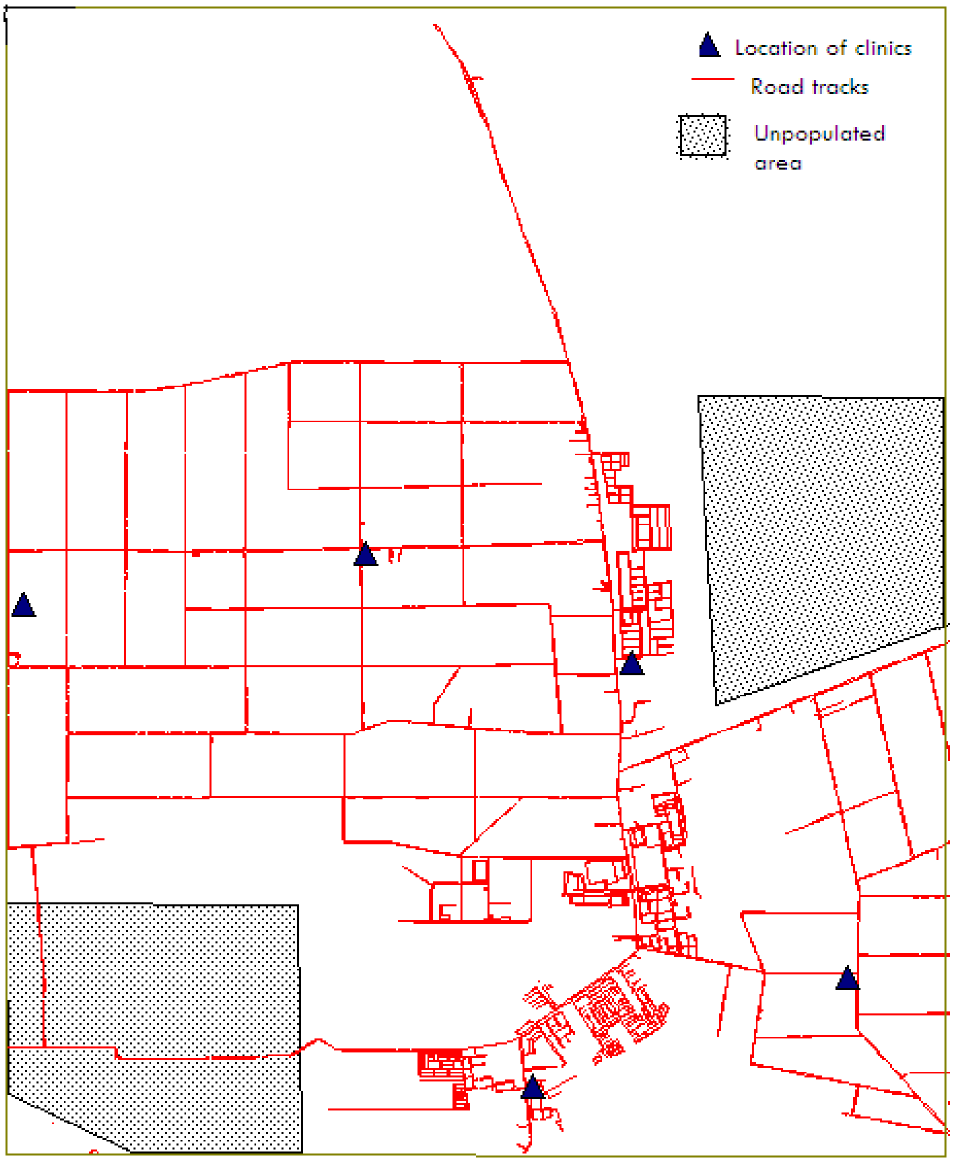

Figure 3.7: Map of Telok Panglima Garang indicating car roads and tracks together with the location of 5 rural clinics

3.4.2 Large data set – Kuala Langat

Kuala Langat is a district in Selangor, Malaysia. It is situated in the southwestern part of Selangor. It is bordered by the districts of Klang to the north and Sepang to the east. Its southern border forms part of Selangor's border with the state of Negeri Sembilan. The Straits of Malacca forms its western border. It is supported by very good road infrastructure connected to Kuala Lumpur, Petaling Jaya, Shah Alam, Klang, Port Klang, Putrajaya and KLIA.

The district of Kuala Langat covers the area of 87,704 hectares with a total population of more than 200,000. The majority races are Malay, Chinese and Indians followed by some minority of the aborigines (orang asli). Among the major towns in Kuala Langat are Banting, Bandar Jugra, Telok Datok (district capital), and Morib (refer to Figure 3.3). Morib is famous among the locals for its beach. Since the early days, Kuala Langat district was known for the beauty of its beaches especially the Morib beach which is the main recreational centre in Kuala Langat.

Besides that, there is also a historical site namely the omission of Sultan Of Selangor ruling era in Bukit Jugra. There are also places which possess tourism attraction based on the culture and local traditions such as the aborigines' village and the traditional Malay village. There is one Free Trade Zone in TPG in which factories and vehicle spare-parts (KAYABA) are located. The main plantation is oil palm. The town of Banting is the administration, commerce and industrial centre of the Kuala Langat district which is situated 30 minutes from KLIA and 45 minutes from Klang (refer to Figure 3.3).

Table 3.6: Targets for consultations and health provision in 2008 (Kuala Langat Health Clinics)

Facilities	Facility Code	Population Volume
KK Telok Datok	**1**	**28279**
KD Sg Kelambu	2	1719
KD Kg Sg Lang	3	3437
KD Telok Bunut	4	5625

Table 3.6 : Continued

KK Tg Sepat	**5**	**7408**
KD Tumbuk Darat	6	1988
KD Kundang	7	2733
KD Batu Laut	8	3401
KK Bandar	**9**	**11660**
KD Sg Buaya	10	4560
KD Permatang Pasir	11	3780
KKBukit Changgang	**12**	**13092**
KD Labohan Dagang	13	6294
KD Olak Lempit	14	5791
KK Kanchong Darat	**15**	**13862**
KD Kg Endah	16	2582
KD Kanchong Tengah	17	2108
KD Kelanang	18	3954
KD Morib	19	3848
KK Telok Panglima Garang	**20**	**25509**
KD Sijangkang Dalam	21	6616
KD Sijangkang Luar	22	13536
KD Kampung Medan	23	14323
KD Kebun Baru	24	12723
KK Jenjarom	**25**	**27135**
KD Kg Jenjarom	26	5325
KD Sri Cheeding	27	4012
Total		235300

Table 3.6 summarises the target population breakdown for the twenty seven clinics under study in Kuala Langat. This work is based on the primary and secondary source of data. Data on population size and number of potential

visitors to the clinics are collected from the Kuala Langat District Health Office in Banting.

As mentioned earlier, the boundaries are determined based on population density, distance as well as accessibility. Each clinic is assigned a target population to service per year. For example in 2008, the target for the 27 clinics serving mother and children was to serve a total of 235300 people, with a minimum of 1719 (KD Sg Kelambu) to a maximum of 28279 (KK TPG) population size.

3.5 SUMMARY AND CONCLUSION

This chapter outlines the Malaysian National Health Policy and the public healthcare delivery system in the country. The health policy on ensuring health service for everyone in the country or full coverage is emphasized in every five year plans; and that every one in the country is within 3 to 5 km distance away from the basic healthcare facility. It also highlights the nominal capacity of each type of healthcare facility. Despite the improvement in health measures in the recent years, public healthcare delivery in Malaysia still needs some development in decision making of its facility location. The data on primary healthcare are collected from selected areas and summarized to suit the need of decision models applied and introduced in the following chapters.

CHAPTER 4

UN-CAPACITATED MODELS

4.1 INTRODUCTION

The Un-capacitated Facility Location Problem (UFLP) is one of the most widely studied discrete location problems, and its applications arise in a variety of settings. The UFLPs take a variety of forms, depending on the nature of the objective functions (*minisum*, *minimax*, problem with covering constraints), the time horizon under consideration (static, dynamic), the existence of hierarchical relationships between the facilities, and on the inclusion or not of stochastic elements in their formulation (deterministic, probabilistic). Numerous different types of problems can be defined if the possible combinations of the categories are considered. The location problems initially studied in the literature were related to industrial contexts referring to the supply of a single commodity from a set of potential locations, where facilities may be placed at clients of known locations and demands, at a minimum cost. These problems consisted of determining the locations of the facilities and the flow of commodity from the facilities to the clients, such that the sum of fixed (establishment) and variable (operational and transportation) costs were minimised. However, un-capacitated problems assume that each facility can produce and ship unlimited quantities of commodity under consideration. In the context of this study, the assumption is each health facility can serve an unlimited number of patients or customers.

In this chapter, a preliminary study applying both the *p*-median and MCLP models is carried out to locate the public health facilities in Malaysia by examining the existing facilities in MTPG, situated in the district of Kuala Langat, Selangor. The efficiency and the effectiveness of the past location decision is studied and analysed. This chapter is organised as follows: both the *p*-median and the MCLP models together with their solutions are described in Section 4.2 and 4.3 respectively. Section 4.4 presents the results and recommendations whilst the conclusion and proposals for future work are presented in the last section.

4.2 The *p*-median problem

The *p*-median problem was first introduced by Hakimi in 1964 and was formulated as a minisum objective function. Several methods have been developed to solve the *p*-median problem. One of the earliest heuristic algorithms developed for solving the location problems was the vertex substitution algorithm by Teitz and Bart (1968). The algorithm swapped facilities from the non-selected set to the selected set until a local optima was reached. Local optimum is a solution that is optimal within a neighbouring set of solutions, but it is not an optimum solution among all solutions. The vertex substitution algorithm is not guaranteed to find the global optima solution, and it does not have a mechanism to break out of the local optima. Usually, the mechanism to break out of the local optima requires the algorithm to first move to worse solutions than the local optima in hope to later find a better solution. Because of these reasons, the vertex substitution algorithm is often run multiple times using different randomly generated initial sets of selected facilities, which increases the chances of reaching the global optima solution. Jarvinen et al. (1972) constructed a branch and bound algorithm for solving the *p*-median and making comparisons with the vertex substitution method of Teitz and Bart (1968). They showed that the vertex substitution method could lead to local optima by choosing a good initial solution. Densham and Rushton (1992) developed a two-phase search heuristic (Global/Regional Interchange Algorithm (GRIA)) for implementing the Teitz and Bart (1968) vertex substitution.

Re Velle and Swain (1970) structured the *p*-median as an integer linear programming programme and solved it optimally. Swain (1974) presented the approach of determining the optimal facility locations for the un-capacitated location problems in two stages. First, it was shown that a subset of all the solutions to the un-capacitated public facility location problem could be obtained by considering a closely related private location problem. The results were then used in the second stage. Narula et al. (1977) proposed a mathematical programming-based heuristic, which used the Lagrangian relaxation. The bounds were obtained by solving the Lagrangian relaxation of the *p*-median problem using the sub gradient optimisation method. Galv**ã**o (1980) presented a dual bound algorithm to solve the *p*-median problem which was also based on the Lagrangian relaxation based procedure. The dual algorithm was used to calculate a lower bound on the overall optimal solution to the *p*-median problem ranging from 10 to 50 vertices, for several values of *p*. The dual bound was then embedded into a tree search algorithm and guaranteed an optimal solution for every possible value of *p* for a network of up to 30 vertices within a reasonable amount of computing time.

All these problems considered did not exceed the size of 55 nodes network (55 demand nodes x 55 potential facility sites), either because the bounds were not tight enough or because the very large linear programmes that resulted could not be solved efficiently due to the very degenerate nature of the corresponding formulations (Galvão et al., 1996).

Daskin (1995) applied the greedy adding algorithm which finds the first facility that optimises the objective. It adds the facility to the selected set, and chooses the second facility. The second facility is the one which when combined with the first facility will optimise the objective. It then adds that facility to the selected set, and repeats this until the desired number of facilities is chosen. The algorithm is referred to as a greedy algorithm because it selects a facility based on what is best at each iteration without looking ahead to see how the current selection would impact later selections and alternatives. A variation of the greedy algorithm, the greedy adding with substitutions was also introduced in the same paper. After adding a facility, the greedy with substitutions heuristics algorithm will try to substitute other facilities in the selected set with facilities from the non selected set. If such a substitution improves the solution, the algorithm keeps the substitution. The author considered locating 5 facilities for 88 node problem.

The tabu search is a meta-heuristics that includes a core search heuristic and incorporates adaptive memory during the searching process. Adaptive memory inhibits certain moves based on the short term memory to make the search more efficient and economical. To break out of the local optima, the tabu search employs a long term memory to diversify the search into other areas of the solution space. Rolland et al. (1997) designed a tabu search algorithm to solve the *p*-median problem. The algorithm used short term and long term memory, as well as strategic oscillation and random tabu list series. The proposed heuristics was found to produce superior quality solutions compared to the well-known interchange heuristics and a hybrid heuristics (node substitution) in up to 500 node-networks.

Rosing and Re Velle (1997) showed that the results from the multiple runs of an exchange heuristic could be combined to construct a solution that is better than any of the best local optima previously found. Heuristics concentration is a two stage meta-heuristics that can be applied to a wide variety of combinatorial problems. It is particularly suited to location problems in which the number of facilities is given in advance. In such settings, the first stage of the Heuristics concentration applies repeatedly some random-start interchange (or other) heuristic to produce a number of alternative facility configurations. A subset of the best of these alternatives is collected and the union of the facility sites in them is called a concentration set (CS). Among the component elements of the CS are those sites which are members of the optimal solutions which are likely to be included. Multistage algorithms that utilise the idea of the Heuristics concentration have been applied to solve the *p*-median problem. The gamma heuristics developed by Rosing et al. (1999) uses the concept of Heuristics concentration to narrow down the candidate facilities to a CS. In earlier studies, the second stage of Heuristics concentration consisted of an exact procedure to extract the best possible solution from the CS. In the gamma heuristic, two additional layers of heuristics to improve the solutions found in the first stage of Heuristics concentration are utilised in sequence. The algorithm can provide comparable solutions in comparable amount of time given that the number of best solutions is small.

The simulated annealing is based on the process of annealing, in which metal cools and freezes into a crystalline structure of minimum energy state. In the annealing process, the crystal structure tends to move to lower energy states, but at times also moves to higher energy states to avoid being trapped at a local minimum. Minimisation problems based on simulated annealing also tend to move toward solutions that decrease the objective function. Based on the probability functions similar to the annealing process, the search would sometimes move to solutions that increase the objective function to avoid local minimum. Chiyoshi and Galvão (2000) applied the simulated annealing to the *p*-median problem as well. The computational results were given for OR – Library (Beasley, 1990) test instances. The optimal solutions were found for 26 of the 40 problems tested. Al-Khedairi (2008) proposed an improved simulated annealing meta-heuristics for the *p*-median by using the initial solution provided by the greedy descent algorithm and this improved the results to 33 out of the 40 problems.

Hansen and Mladenovic (1997) used another meta-heuristics called the Variable Neighbourhood Search (VNS) for the *p*-median, as an addition to the extensive literature. The VNS proceeds by a descent method to a local minimum, then explores systematically or at random, increasingly distant neighbourhood of this solution. Each time, one or several points within the current neighbourhood are used as an initial solution for a local descent. One jumps from the current solution to a new one if and only if a better solution has been found. It is not a trajectory method and does not specify forbidden moves. The performance of the VNS is analysed on several OR – Library (Beasley, 1990) test problems and the effects of its parameters. The results show that it will depend on the local search subroutine used and the number of initial points for descent in each neighborhood. Despite the ability to produce comparable solutions, the VNS consume high computational effort and time.

The few algorithms mentioned above, such as the tabu search, simulated annealing, vertex substitution or VNS, all started with at least one set of selected facilities. Through certain mechanisms such as substitutions, the algorithms try to improve on that solution. In contrast, Genetic algorithm (GA) works with a population of solutions and is a technique designed to imitate the selection of breeding of organisms (such as animals or plants) in the context of problem solving. It employs components like chromosome, crossover, and mutation and utilises the survival-of-the fittest principle. GA has also been used to solve the *p*-median by many authors. Hosage and Goodchild (1986) were the first to implement the GA to solve the *p*-median problem. They encoded the chromosome solutions as a string of n binary digits, with 1 representing a facility that was built at the corresponding location. Since such encoding did not guarantee that *p* number of facilities was being selected, a penalty function was used to impose the fixed facility constraint.

Estivil-Castro and Velazquez (1999) described a hybrid GA as one that combined GA and vertex substitution. The technique was useful for preventing local optima that the vertex substitution was prone to locate. Bozkaya et al. (2002) described a GA that modeled solutions with chromosomes where each gene was an index of a *p*-median vertex. The GA has improved slowly but steadily and was compared to the earlier work on GA by Hosage and Goodchild (1986). Alp et al. (2003) also used GA to solve the *p*-median problem, but they encoded the solution differently. In their encoding, a solution was represented by *p* number of candidate facilities, which ensured that *p* number of facilities was always selected. Instead of using a standard crossover operator, they used the greedy deletion heuristics to generate child solution or chromosomes. They reported that the performance of their GA compared favourably against the other heuristic algorithms, such as simulated annealing and the gamma heuristic.

Aside of the *p*-median problem, GA has also been applied to solve other location problems. For instance, Jaramillo et al. (2002) applied the GA to solve a few location problems, including the fixed charge location problem, the maximum covering problem, the centroid (optimise total demands that falls into the set of *p* facilities of the leader knowing that the follower will position *r* facilities) and the medianoid (a Maximum Capture Problem in which given that the leader currently operates *p* facilities in a market, the follower considers locating *r* facilities so as to maximise its market share) problems. They compared the performance of the GA with other heuristics algorithms, such as the Lagrange heuristic. They concluded that for the fixed charge and maximum covering problem, the GA tended to take a lot more time than the specialised heuristics, but they produced solutions that were no worse, and sometimes better that those produced by other methods. They also reported the GA performed well for the centroid and medianoid problems in terms of computation time and solution quality. The GA based heuristics will be discussed in more detail in the later chapters.

4.3 THE MAXIMAL COVERING LOCATION PROBLEM (MCLP)

There are not as many studies done in solving MCLP compared to *p*-median. More studies are on the related covering location problems such as Location Set Covering Problem (LSCP) (refer to: Gunawarde, 1982; Cornuejols and Thizy, 1989; Fisher and Kedia, 1990; Rosing et al., 1992; Hoffman and Padberg, 1993; Alminana and Pastor, 1994; Church and Gerard, 2003; Hwang, 2004; Gouwanda and Ponnambalam, 2008). Early solution methods proposed for MCLP to include the Linear Programming (LP) relaxation of the 0-1 integer formulation of the problem and a greedy-interchange heuristics (Church and Re Velle, 1974). The first heuristic considered by the authors was the Greedy Adding Algorithm. The algorithm started with an empty solution set and then added the best facility sites to this set one at a time. It picked the first facility that covered most of the total population, followed by the second facility that also covered the most but which was not covered by the first facility. The process continued until either the p facilities were selected or all the population was covered. The second heuristics was called the Greedy Adding with Substitution. The algorithm determined a new facility location and sought to improve the solution at each iteration by trying to replace each facility with another "free" facility. Both algorithms automatically calculated the maximal coverage for problems with one to p facilities. However, the global optimality was not guaranteed. The authors then used the LP to obtain global optimal solutions. The LP terminated fractionally as only 80 percent of the solution was all zero-one. Hence, all integer solutions were obtained using the method of branch and bound. The programme also generally took quite some time and it ended up with only nearly optimal solution. All the algorithms were tested on the largest set of 55 node networks described in Swain (1971).

Another earlier application of the Greedy Adding Algorithm was by Chvatal (1979) who implemented the greedy algorithm to solve the set covering problem. The author compared the value of the objective function at a feasible solution found by a simple greedy heuristic to the true optimum. It turned out that the ratio between the two grew at most logarithmically in the largest column sum of A where A was a binary matrix of size m x n, and the set-covering problem was to minimise $c^T x$ subject to $Ax \geq e$ and x binary.

An exact method that included the branch and bound algorithm was developed by Dwyer and Evans (1981) for the particular case where all the demands had equal weight. The algorithm solved the maximal covering problem (MCP) well for small problems only and was computationally expensive or even impossible to solve certain large problems. Downs and Camm (1996) developed a robust, exact algorithm for the MCP as well as using dual-based solution methods and greedy heuristics in branch and bound. The authors presented an extensive computation evaluation of their method, in terms of both variety of applications and problem sizes.

Recently, modern heuristic algorithms have been applied to solve location problems. Most of these algorithms have mechanisms to break out of the local optima, so that there is a better chance for them to obtain global optimal solution. Many of these algorithms incorporate the vertex substitution algorithms as the heuristic search. Particularly useful is the Lagrangian relaxation embedded within a branch and bound algorithm (Daskin, 1995). Daskin also provided mathematical programming formulations for the UFLP and MCLP, and presented an Excel based software called SITATION to solve five classes of location problems including: *p*-median, *p*-center, Set Covering, Maximal Covering, and Incapacitated Fixed Charge Problems. The software can solve up to 300 nodes for MCLP.

Galv**ã**o and Re Velle (1996) developed a Lagrangian heuristics for the problem that attempted to improve both the upper and lower bounds at each iteration of the algorithm. However, the test was restricted to problems not larger that the 55-vertex network. Galv**ã**o et al. (2000) continued to work on using the Lagrangian relaxation heuristic to solve the MCLP. The Lagrangian relaxation was obtained by dualising the cover constraint and comparing it to the surrogate relaxation obtained by combining the cover constraint into a single knapsack constraint. They reported comparable performance but the computing times depended on the problem size.

Espejo et al. (2003) defined a combined Lagrangian-surrogate (L-S) relaxation to solve for a hierarchical covering location problem (HCLP). The difference from the MCLP was that two different types of facilities were involved in HCLP and the order in which the facilities were introduced was potentially important. The authors incorporated the L-S relaxation using the sub-gradient-based heuristics and tested using the test problems in the literature ranging from 55 to 700 nodes. They reported that the algorithm was competitive in terms of the time~~s~~ in solving the problems.

Senne et al. (2010) presented a cluster relaxation technique to solve large scale MCLP. The proposed approach required the identification of graph related to a set of constraints where MCLP was considered as a covering graph. If some of these constraints were relaxed, this graph could be partitioned into sub-graphs (clusters), corresponding to smaller problems that could be solved independently. However, the quality of the bounds depended on the application, as the processing time~~s~~ needed to solve instances with only a few clusters could be longer if the best quality was to be assured.

Aside from the heuristics mentioned above which is similar to the *p*-median problem, the GA based heuristics is also used to solve MCLP. There is an example on the implementation of GA by Beasley and Chu (1996) to solve the set covering problem. Unlike the *p*-median or maximum covering problem which requires a fixed number of facilities in the solution, the set covering problems attempts to minimise the number of selected facilities while ensuring that all the demands are covered. Because of this, Beasley and Chu (1996) encoded the solution with the usual binary representations, with a bit of 1 at the *i*th bit implying facility *i* being selected, and a bit of 0 at the *j*th bit implying the facility *j* is not selected. The fitness function is simply the number of 1 bit in the solution, and solutions with lower fitness functions are considered better solutions. They also designed a new crossover operator, a variable mutation rate and a heuristics feasibility operator to adapt the GA to the set covering problem. In order to measure the performance of the new operators, the problem dependent parameters like the population size and the choice of initial population are modified so that the initial population covers the high probability optimal solutions. Hence, only a small population size of 100 is necessary to provide adequate coverage. In their findings, their implementation of GA was able to generate optimal solutions for small size problems, and good solutions for large size problems.

In addition to the development of the solution techniques, commercial software that represents the mathematical model and solves it with far less effort than general-purpose programming languages is also developed. IBM ILOG CPLEX Optimisation Studio (originally referred to be ILOG CPLEX) provides the fastest way to build efficient optimisation models and state-of-the-art applications for the full range of planning and scheduling problems. It includes tools and interfaces for building analytical decision support applications using the optimisation technologies implemented in the IBM ILOG CPLEX Optimisers for mathematical programming and constraint programming (IBM ILOG Optimization page, 2011). The Optimisation Programming Language (OPL) provides a natural, descriptive representation of mathematical optimisation models, producing substantially a simpler and shorter code. Its powerful syntax supports all expressions needed to model and solve problems using mathematical programming and constraint programming-based approaches. ILOG OPL

Development Studio is built as an extension of the object oriented interfaces to ILOG CPLEX, providing a tight efficient link between the model and the engine. As a result, the OPL models take maximum advantage of the ILOG CPLEX optimisation engine and deliver relatively short computational performance in solving mathematical programming (MP) problems. The software is used widely to solve the facility location problems (for examples see Galvão et al., 2000; Verter and Lapierre, 2002; Espejo et al., 2003; Senne et al., 2010). In this initial study, the ILOG OPL DEVELOPMENT STUDIO 5.2 with optimisation engine CPLEX 10.2 is used to solve the location allocation problem of the study area.

4.4 MODEL

The need for the National Health policy was first identified in the midterm review of the Sixth Malaysia Plan, 1991—1995 (Economic Planning Unit, 1990) which gave the priority to comprehensive coverage of basic health services for rural and remote areas (Annual Report MOH, 2005). In view of this, the MCLP is first considered.

The following formulation, adapted from Pirkul and Schilling (1991) is used to model the problem. As mentioned in Section 2.2.3, the sets *I* and *J* represent the clients and sites for facilities respectively. Variable x_{ij} is 1 if client i is assigned to facility *j*, y_j is 1 if a facility is sited at *j* and c_{ij} is 1 if the demand volume a_i is assigned to a facility within the coverage distance *S*, where *S* is the maximum service distance or time. a_i is the demand volume at demand node i and d_{ij} is the distance between demand node i and facility *j*. The objective maximises the total population assigned to a facility within the coverage distance *S*. The mathematical expression, equation 2.17, is given again (Section 2.2.3) as follows:

Maximise $$Z_7 = \sum_{i \in I} \sum_{j \in J} c_{ij} a_i x_{ij} \tag{4.1}$$

Subject to

$$\sum_{j \in J} y_j \leq p, \qquad \forall \quad j \in J \tag{4.2}$$

$$\sum_{j \in J} x_{ij} = 1, \qquad \forall \quad i \in I \tag{4.3}$$

$$x_{ij} \leq y_j \qquad \forall \quad i \in I, j \in J \tag{4.4}$$

$$y_j = 1 \qquad \text{for all existing facilities} \tag{4.5}$$

$$x_{ij}, y_j = [0,1] \qquad \forall \quad i \in I, j \in J \tag{4.6}$$

Constraint (4.2) limits the total number of facilities to no more than p, while Constraint (4.3) ensures that all demand nodes are assigned to a facility. The level of service provided to covered demand is obviously controlled by S; however, an uncovered demand node could be assigned to any available facility, regardless of its proximity. Constraint (4.4) guarantees that a demand node is only allocated to an open facility. Constraints (4.5) and (4.6) fix the locations of the facilities that already exist and impose the integrality restriction respectively. Note that the value of p is the total number of facilities, including both existing facilities and facilities that are to be located.

Another important factor that is always considered in any location allocation model for public health is minimising the total travel distance between demand nodes and the facilities, as in the p-median problem. The following formulation is used (Re Velle and Swain, 1970) in which the objective of the problem is to minimise the total distance which people must travel to the facilities to get the service.

Minimise $$Z_8 = \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \tag{4.7}$$

$$\sum_{j \in J} y_j = p, \qquad \forall \quad j \in J \tag{4.8}$$

All the above Constraints (4.3), (4.4) and (4.6) apply to this model with the change of Constraint (4.2) to Constraint (4.8). Instead of limiting the total number of facilities to no more than *p* as in the MCLP, Constraint (4.8) fixes the number of facilities to while Constraint (4.5) is not applicable to *p*-median problem.

4.5 DATA ANALYSIS (MTPG)

The area comprises five service boundaries (SD, SL, KM, KB and TPG) with different target population volume with a total population of 30458. The whole area is divided into 179 smaller sub regions, with their demand nodes located centrally and are approximately 1 km apart from each other. The same methods of having the demand nodes located centrally have been used in several other studies (Yeh and Hong, 1996; Jia et al., 2007). Figure 3.5 displays the locations of the five clinics within the study area, together with the service boundary and the unpopulated regions. There are 47 nodes that fall into the unpopulated regions situated within the service areas of KB and TPG. It is also noted that the nodes, located in KM, are assigned very high demand volume of more than 240 per node.

In order to reduce the high demand volume, the regions are further divided into smaller regions which are within approximately 0.5 km each and this result in an increase of the demand nodes from 179 to 221 nodes. Table 4.1 summarises the profile of the demand nodes distribution in the study area whilst the situation is described in Figure 4.1.

Table 4.1: Demand Nodes Distribution

Service Area	Number of Demand Node	Volume per Demand Node
SD	20	131
SL	32	192*
KM	26	249
KB	46	111
TPG	55	183
Total	**179**	
SD	20	131
SL	32	192*
KM	45	144
KB	46	111
TPG	78	129
Total	**221**	

The assumption made for the initial study is that the demand is uniformly distributed. This is due to the unavailability of data of the demand breakdown by nodes and only the demand breakdown by the service area is obtained. The detailed analysis on the demand breakdown found that some areas were actually more dense compared to the others. An important consideration of sitting facilities is to ensure an equitable distribution of services. This may be done by putting in certain weights into the more dense area (Murray and Gerard, 1997). Note that from Table 4.1, despite the high volume per demand node at 192 for SL, it is not split due to the size of the SL service area. SL service area is comparably small for more split.

To analyse the effect of the demand distribution and its allocation to each existing facility, the assignment of demand nodes are done in two ways:

1. The population demand is uniformly distributed *within its own service boundary.*

2. The population demand is uniformly distributed *within the whole area of study.*

As there are five service areas (SD, SL, KM, KB and TPG), it is assumed that one facility will be opened for each area, hence the analysis will base on five potential facility sites.

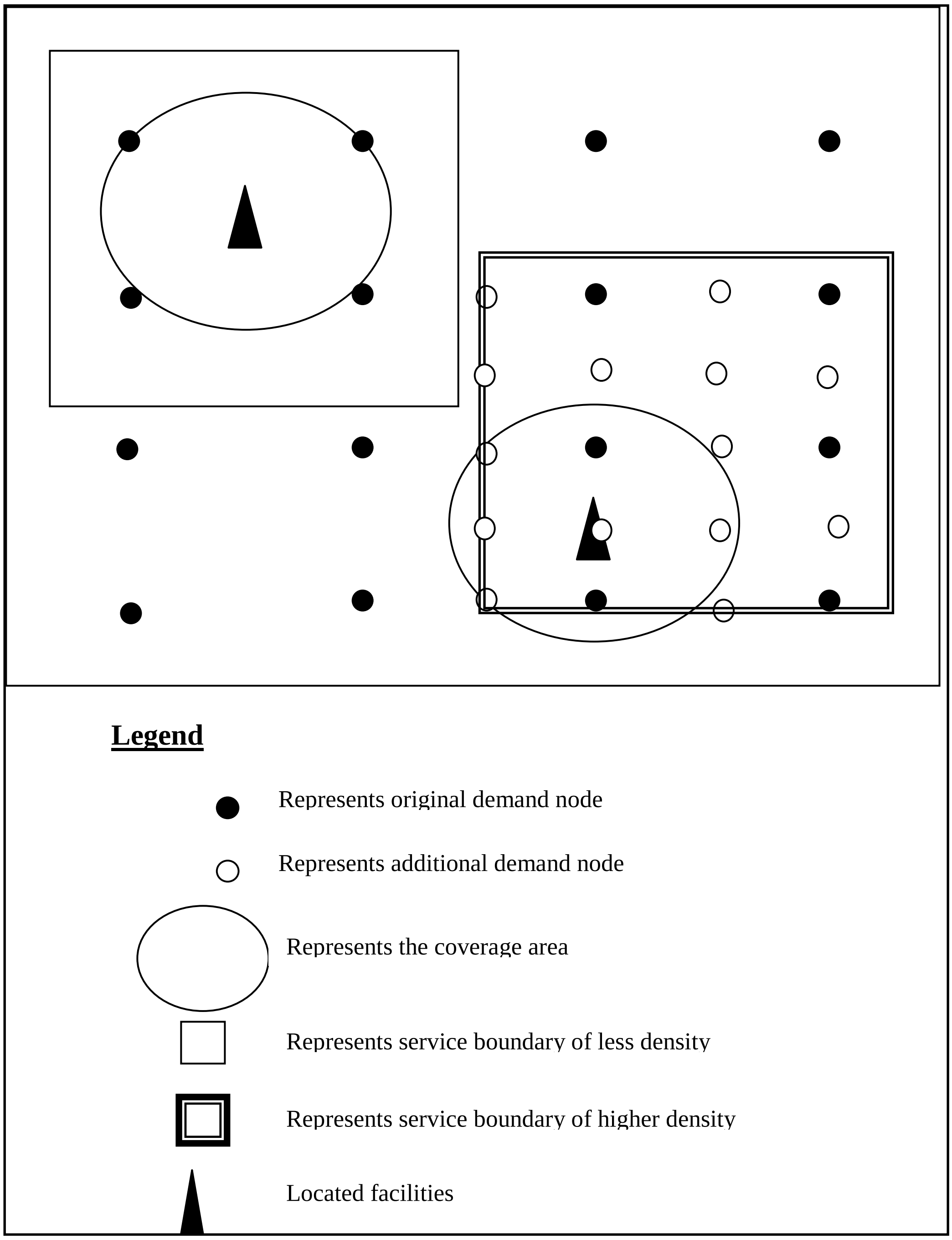

Figure 4.1: Distribution of two areas with different densities and their nodes distribution

4.5.1 Locational Efficiency Based On Percentage of Population Coverage

The locational efficiency is analysed by using the MCLP where the objective function is to maximise the percentage of population covered within some maximum allowable distance, *S*. As mentioned earlier in Chapter 3, from the MOH records, 88.5 percent of the population lives within 5 km of a health facility and 81 percent within 3 km (Merican, 2007). Although the national health policy does not specify any maximum allowable distance, the two values are recorded and considered by MOH, which are 3 and 5 km, respectively. This can be deduced that the efficiency of road system in Malaysia that allows easy access within these distances.

Tables 4.2 and 4.3 tabulate results for the first case where the population demand is distributed uniformly within the service boundary area. It is observed that the choice of facilities to be opened is exactly the same for the 179 and 221 nodes. In the 221 nodes, due to smaller demand at each node, the population coverage is higher at 99.4 percent when only two facilities are open. This might be due to the demand volume being more scattered at the facility area (as shown in Figure 4.1).

Table 4.2: Coverage Percentage when demand nodes are uniformly distributed within service boundary only (*S*=5km)

Total No of Nodes	Number of Facilities	Objective Function Value	Coverage Percentage	Open Facility
179	1	26963	88.5	KM
	2	30085	98.8	SL,KB
	3	30458	100.0	SD,KM,TPG
	4	30458	100.0	SD,SL,KM, TPG
	5	30458	100.0	SD,SL,KM,KB,TPG
221	1	26587	87.3	KM
	2	30270	99.4	SL,KB
	3	30458	100.0	SD,KM,TPG
	4	30458	100.0	SD,SL,KM, TPG
	5	30458	100.0	SD,SL,KM,KB,TPG

Table 4.3: Coverage Percentage when demand nodes are uniformly distributed within service boundary only (*S*=3km)

Total No of Nodes	Number of Facilities	Objective Function Value	Coverage Percentage	Open Facility
179	1	12809	42.1	KM
	2	23273	76.4	SD,KM
	3	27437	90.1	SD,KM,TPG
	4	29144	95.7	SD,SL,KM, TPG
	5	30458	100.0	SD,SL,KM,KB,TPG
221	1	12146	39.9	SL
	2	23251	76.3	SL,TPG
	3	27417	90.0	SL,KB,TPG
	4	29124	95.6	SD,SL,KB, TPG
	5	30318	99.5	SD,SL,KM,KB,TPG

Figures 4.2, 4.3 and 4.4 illustrate the coverage trend for this case. It is worth noting that 100 percent coverage is achieved for $S = 5$ km when only 3 facilities are open for both numbers of nodes. When S is reduced to 3 km, the number of facilities required to achieve full coverage increases to 5. If only one facility is open, 100 percent coverage can only be realised when $S = 7$ km.

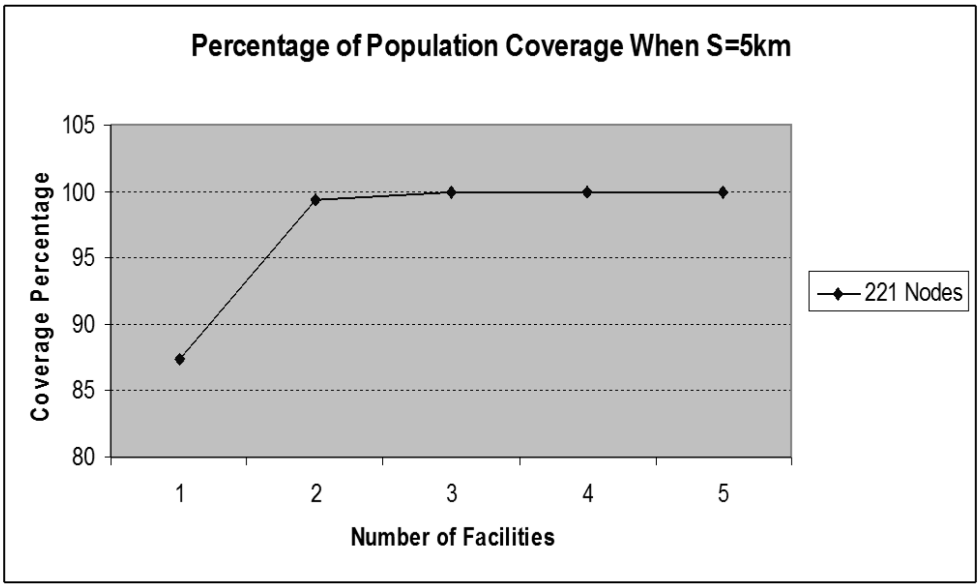

Figure 4.2: Trend in Coverage Percentage (when demand is distributed uniformly over its own service area) when S= 5km

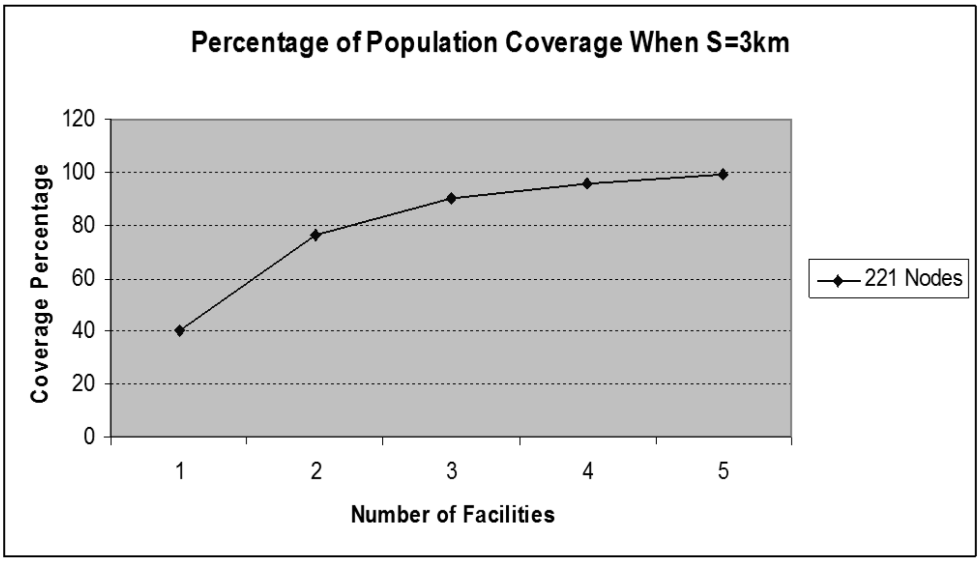

Figure 4.3: Trend in Coverage Percentage (when demand is distributed uniformly over its own service area) when S= 3km

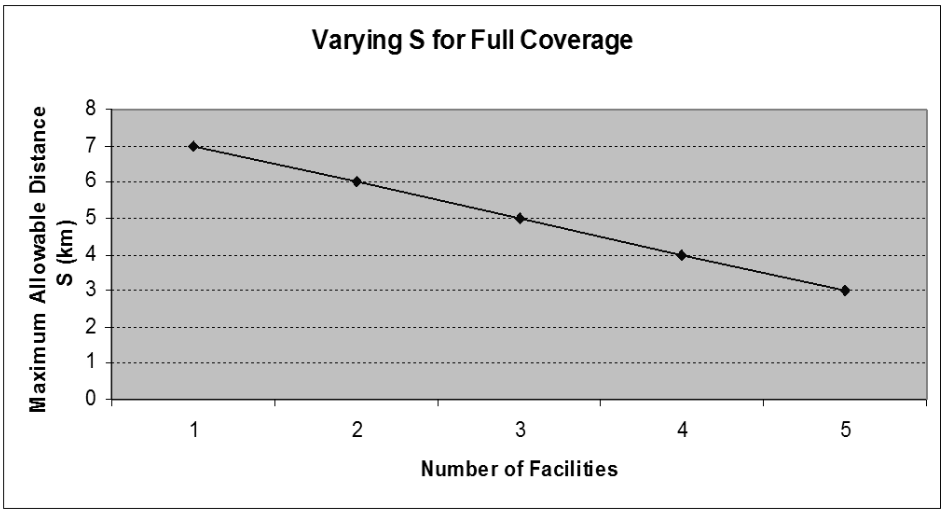

Figure 4.4: Trend in Coverage Percentage (when demand is distributed uniformly over its own service area- when S varies)

When the population is distributed uniformly over the whole area of study as shown in Tables 4.4 and 4.5, the highest coverage of only 99.4 percent is achieved. Further analysis shows that all the uncovered nodes fall in the unpopulated areas. Consequently, full coverage is obtained when the nodes in the unpopulated area are assigned a demand of zero. There remain 132 nodes with positive demands. Figures 4.5, 4.6 and 4.6 illustrate the trend in the number of facilities and maximum allowable distance S in achieving full coverage. As in the first case, full coverage is achieved if only one facility is open when the maximum allowable distance S is 7 km. When S equals to 3 km, the highest coverage achieved is only 98.5 percent with opening of 5 facilities, even after assigning zero demand to the unpopulated nodes (where number of nodes is 132 nodes instead of 179 nodes).

Table 4.4: Coverage Percentage when demand is uniformly distributed over the whole study area (*S*=5km)

Number of nodes	Number of Facilities	Objective Function Value	Coverage Percentage	Open Facility
179	1	22788	74.8	KM
	2	28925	95.0	SD,KM
	3	30287	99.4	SD,KM,TPG
	4	30287	99.4	SD,SL,KM, TPG
	5	30287	99.4	SD,SL,KM,KB,TPG
132	1	25157	82.6	KM
	2	29997	98.5	SD,KM
	3	30458	100.0	SD,KM,TPG
	4	30458	100.0	SD,SL,KM, TPG
	5	30458	100.0	SD,SL,KM,KB,TPG

Table 4.5: Coverage Percentage when demand is uniformly distributed over the whole study area (*S*=3km)

Number of nodes	Number of Facilities	Objective Function Value	Coverage Percentage	Open Facility
179	1	11560	38	KM
	2	17868	58.7	SD,KM
	3	23138	76	SD,KM,TPG
	4	25009	82.1	SD,SL,KM, TPG
	5	26709	87.7	SD,SL,KM,KB,TPG
132	1	13143	43.2	SL
	2	21228	69.7	SD,KB
	3	25612	84.1	SD,KM,TPG
	4	28379	93.2	SD,SL,KB, TPG
	5	29996	98.5	SD,SL,KM,KB,TPG

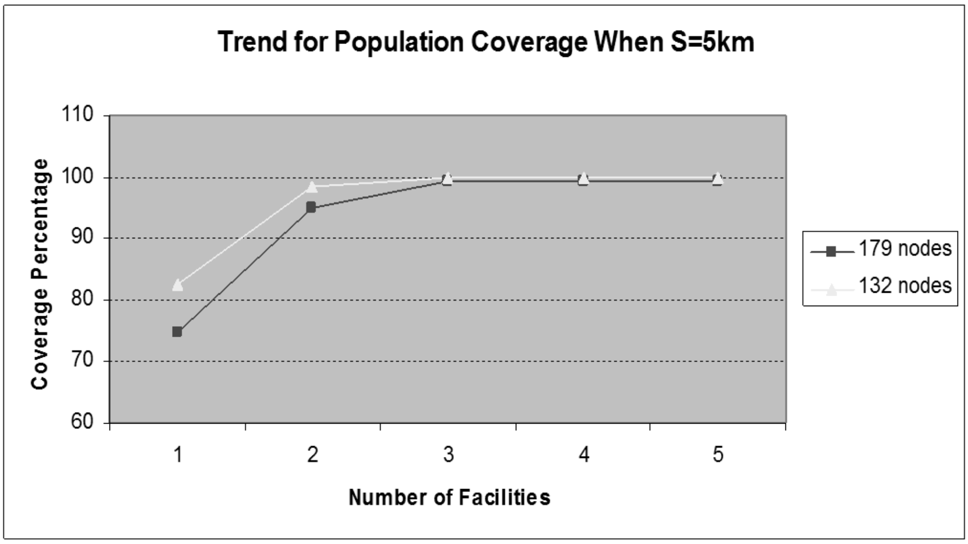

Figure 4.5: Trend in Coverage Percentage (when demand is distributed uniformly over the whole service area) when S=5km

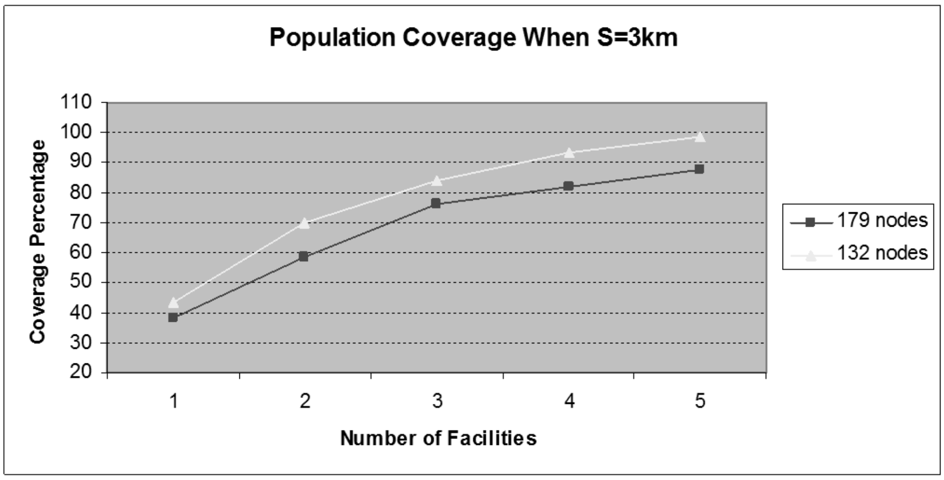

Figure 4.6: Trend in Coverage Percentage (when demand is distributed uniformly over the whole service area) when S=3km

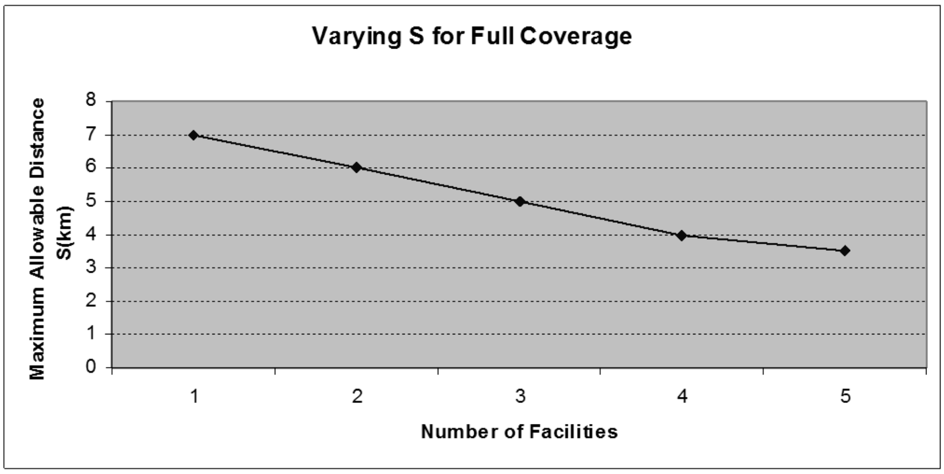

Figure 4.7: Trend in Coverage Percentage (when demand is distributed uniformly over the whole service area) when S varies

Every facility in the area is assigned a different demand volume to serve in proportion to its nominal capacity. For example, facility KB and SD are assigned the demand volume 5114 and 2617 respectively. Tables 4.6 and 4.7 show the new assignment of nodes to its respective facility. The results of using the *p*-median and MCLP for the population distribution are totally the opposite of the existing practice and this may be due to the inclusion of the capacity constraint. It is noted earlier in this study that the facility is assumed to be un-capacitated. The capacitated case will be addressed in the next chapter.

Table 4.6: Comparing the number of demand nodes and volume assignment to each facility (Demand is uniformly distributed within its own service boundary)

Number of facilities	**No model (Existing assignment)**		***p*-median**		**MCLP**	
	Number of nodes assigned	Volume	Number of nodes assigned	Volume	Number of nodes assigned	Volume
SD	20	2617	70	3255	105	10620
SL	32	6157	34	6878	39	10626
KM	26	6485	29	6946	27	6406

Table 4.6 continued

KB	46	5114	23	4910	6	2060
TPG	55	10085	23	8469	2	746
TOTAL	179	30458	179	30458	179	30458

Table 4.7: Comparing the number of demand nodes and volume assignment to each facility (Demand is uniformly distributed within the whole study area)

Number of facilities	**No model (Existing assignment)**		***p*-median**		**MCLP**	
	Number of nodes assigned	Volume	Number of nodes assigned	Volume	Number of nodes assigned	Volume
SD	20	2617	70	6455	105	14060
SL	32	6157	32	7376	39	8546
KM	26	6485	29	6005	27	6006
KB	46	5114	23	5313	6	1386
TPG	55	10085	25	5309	2	460
TOTAL	179	30458	179	30458	179	30458

4.5.2 Location~~al~~ Efficiency Based on Average Traveled Distance

The analysis for the demand volume being distributed uniformly within its own service boundary is carried out based on the 179 and 221 numbers of nodes, respectively. The results are summarised in Table 4.8. It is observed that the average traveled distance decreases from 3.34 km (one facility) to 1.48 km (5 facilities) for the 179 nodes whilst it decreases from 3.40 km to 1.49 km for the 221 nodes. Note that every additional facility improves the average traveled distance between 10 to 31 percent in both cases. Figure 4.8 depicts a decreasing trend of average distance traveled when the demand is distributed uniformly within its own service boundary, for both cases of 179 and 221 nodes.

When the demand is uniformly distributed in the whole study area, the analysis is carried out based on the 179 nodes and 132 nodes as the demand volume is equally divided among all the nodes. It is noted that all the 47 nodes located in the unpopulated regions are assigned a demand volume of 0. Note that this has resulted in an increase in demand volume for each node from 170 to 230. Similarly, as shown in Table 4.9 the average traveled distance decreases with the increase in the number of facilities. It is observed that the average traveled distance decreases from 3.75 km to only 1.89 km when all the five facilities are opened (179 nodes) and the results are even better when the unpopulated regions are excluded from the analysis. This is because the unpopulated areas are located furthest from the facilities. It is noted that every additional facility improves (by reduction) the average traveled distance by 10 to 24 percent. Figure 4.9 depicts the same decreasing trend of average traveled distance when the demand is distributed uniformly within the whole study area.

Table 4.8: Percentage of improvement in average traveled distance with the increase of number of facilities when demand is uniformly distributed within the service boundary

Number of Nodes	Number of Facilities	Total Distance Traveled (in thousands)	Percentage of Improvement	Average Traveled Distance (in km)	Open Facility
179	1	102	-	3.34	KM
	2	70	31.4	2.29	SL, TPG
	3	57	18.6	1.88	SL,KB,TPG
	4	50	12.3	1.64	SL,KM,KB,TPG
	5	45	10.0	1.48	SD,SL,KM,KB,TPG

Table 4.8 continued

221	1	104	-	3.4	KM
	2	70	32.4	2.3	SL,TPG
	3	57	18.0	1.89	SL,KB,TPG
	4	50	12.5	1.65	SL,KM,KB, TPG
	5	45	9.8	1.49	SD,SL,KM,KB,TPG

Table 4.9: Percentage of improvement in average traveled distance with the increase of number of facilities when demand is uniformly distributed within the whole study area

Total number of nodes	Number of Facilities	Total distance traveled (in thousands)	Percentage of Improvem ent	Average Traveled Distance (in km)	Open Facility
179	1	114	-	3.75	KM
	2	87	24.2	2.84	SD,KM
	3	71	17.8	2.34	SL,KM,TPG
	4	64	10.5	2.09	SD,SL,KM, TPG
	5	57	10.2	1.89	SD,SL,KM,KB,TPG
132	1	108	-	3.53	KM
	2	73	32.4	2.41	SL, KB
	3	63	13.7	2.06	SL,KB,TPG
	4	54	14.3	1.77	SD,SL,KB,TPG
	5	47	13.0	1.54	SD,SL,KM,KB,TPG

With the current number of facilities, the average traveled distance for TPG ranges between 1.48 km and 1.89 km compared to the national policy of 3 km.

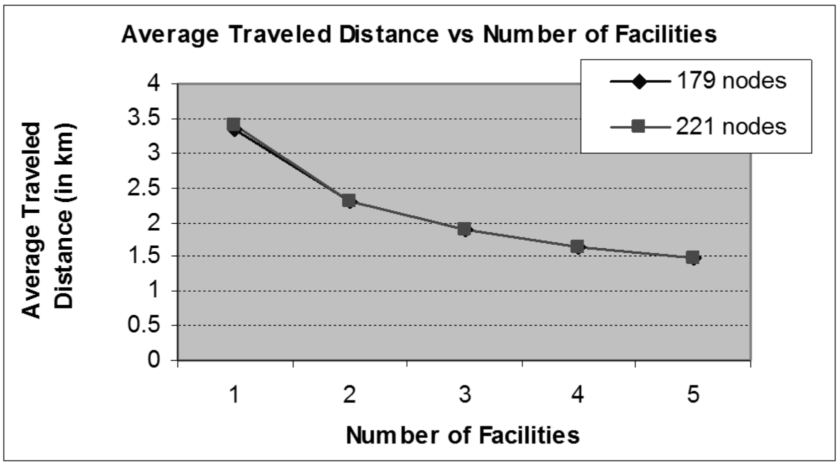

Figure 4.8: Trend in average traveled distance when demand is distributed uniformly within its own service boundary

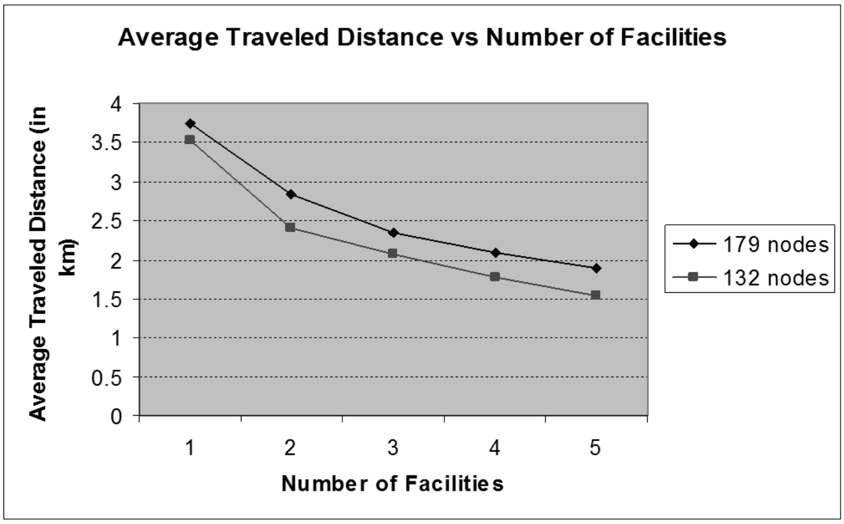

Figure 4.9: Trend in average traveled distance when demand is distributed uniformly over the whole study area

4.6 CONCLUSION

This chapter examined the efficiency of the existing primary health delivery systems in the study area. An assumption of the demand being uniformly distributed was categorised into two: uniformly distributed within its own service boundary and uniformly distributed within the whole study area. The problem was formulated as a standard MCLP and the *p*-median problems and the analysis was carried for the various numbers of nodes, taking into account that some parts of the area of study were unpopulated. The results indicated that the maximum traveled distance for the present number of facilities was less than or equaled to 3 km (within the distance recommended under MOH) of 5 km was sufficient if the unpopulated areas were excluded from the analysis. Full coverage was achieved in all cases. However, 100 percent coverage could not be realised if the unpopulated areas were taken into account.

In addition to that, the density of population is different at different locations within the study area, thus coverage will be different. Therefore the only way to justify the optimal solution is to manage the demand variability by assigning variable workforce (service providers). This is acceptable in this case study, since the services provided at the PHC are generally basic and homogenous in nature. Applying the *p*-median and MCLP into the facility location in this area had also resulted in the reassignment of the demand nodes and its volume; however, it was worth noting that all the analysis was done based on the assumption that all the facilities did not have capacity constraints. This limitation will be addressed in the next chapter.

CHAPTER 5

THE CAPACITATED MAXIMAL COVERING LOCATION PROBLEM (CMCLP) MODEL

5.1 INTRODUCTION

As mentioned earlier in Chapter 3, in the Ninth Malaysia plan 2006—2010, (Economic Planning Unit, 2006), the emphasis continues to be on the provision of client-focused services and community needs in order to fulfill the demand for a better healthcare system. It highlights that the norm is to have one Primary Health Care (PHC) for every 15,000 to 20,000 people and one Community Clinic (CC) for every 5000 in the population. The primary health delivery system is referred to as a 2-tiered system in which the Rural Clinics (RC) will serve 4000 population within the 5 km radius and the Health Clinics (HC) will serve between 15,000 to 20,000 populations (summarised in Figure 5.1 below). In the early days, the norm capacity for the RC was to serve between 1500 and 4000 population. However, this norm could hardly be applicable as the country developed and the population volume increased.

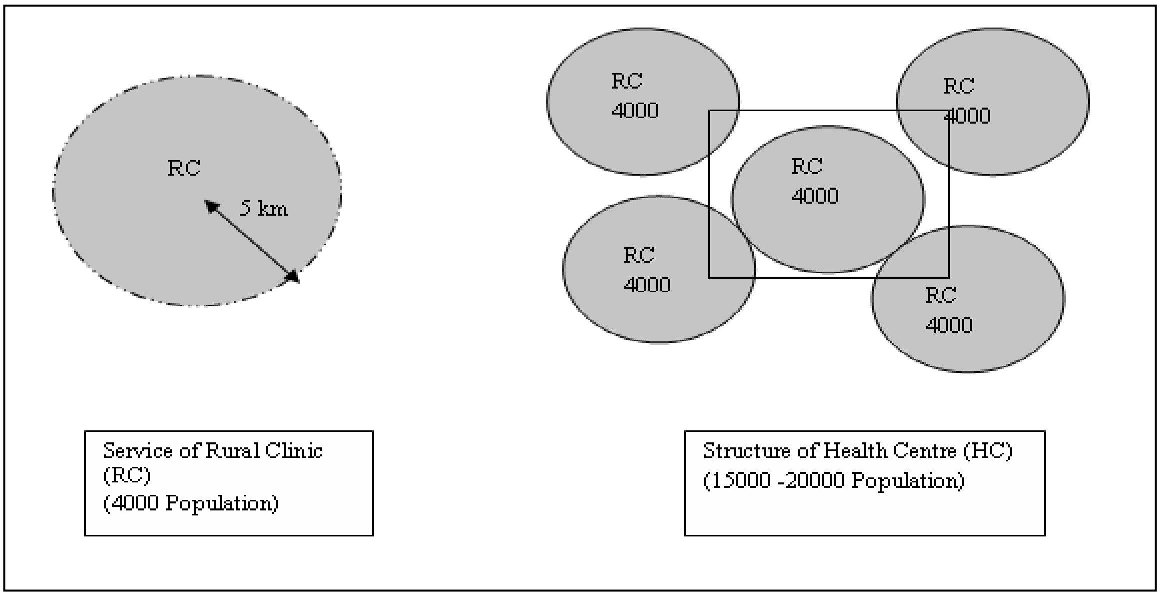

Figure 5.1: 2-tiered System for public health care in Malaysia

In Chapter 4, two assumptions are made: the demand is uniformly distributed and every facility is un-capacitated. Realistically, the un-capacitated assumption is not always valid; as many services, particularly those that are emergency related, often have workloads which push them to the limit of their ability to provide effective services. This chapter discusses the detailed application of capacitated MCLP (CMCLP) and capacitated *p*-median (CPMP) is discussed in Chapter 6.

The limited capacity per facility is added as a constraint to the MCLP. The objective of the model is to maximise the total demand allocated to the open facility and that the availability of the facility to serve the customers or patients is limited by its capacity. In terms of health care unit, the capacity is defined as its ability to serve the customers/patients in terms of the number of patients served within a period of time (Hick et al., 2004). In this study, the period of time is taken as one year.

The chapter is outlined as follows: Section 5.2 gives the formulation of CMCLP and the related previous work on CMCLP. Section 5.3 describes the proposed GA based heuristic to solve CMCLP, followed by the algorithm validation using data from previous literature in Section 5.4. Section 5.5 compares the results obtained using CPLEX 10.2 and the newly proposed GA based heuristic on a relatively small study area. Section 5.6 analyses the application of CMCLP on a larger study area and the last section concludes the study whilst introducing the content of the next chapter.

5.2 CAPACITATED MCLP (CMCLP)

The CMCLP is formulated such that a capacity for each facility is added as a constraint to the MCLP formulation, Z_7 introduced in Section 4.4. While all the constraints (4.2 to 4.6) hold, an additional constraint (5.1) that limits the capacity for each facility is added.

$$\sum_{i \in I} c_{ij} a_i x_{ij} \leq K_j \qquad \forall \quad j \in J \tag{5.1}$$

However, as the constraint (4.2) ensures that each demand point is assigned to some facility while the objective function maximizes the coverage (through c_{ij}) by accounting only for those within the maximum allowable distance, *S*, every demand is assumed to be considered for assignment. However, under this assumption, the capacity is utilized by all *i* who is assigned to a facility *j* in which excluding c_{ij} constraint (5.1) is making more sense. That is, adopting constraint (8) in Pirkul and Schilling paper (1991) by using constraints (4.3) and (4.4). As they also increase the size of the problem, hence a y_j term is added to the right-hand-side of constraint (4.4) and employed simultaneously with constraint (4.3).

Finally, the CMCLP formulation is rewritten as follows:

Maximise $$\bar{Z}_7 = \sum_{i \in I} \sum_{j \in J} c_{ij} a_i x_{ij} \tag{5.2}$$

Subject to

$$\sum_{j \in J} y_j \le p, \qquad \forall \quad j \in J \tag{5.3}$$

$$\sum_{j \in J} x_{ij} = 1, \qquad \forall \quad i \in I \tag{5.4}$$

$$\sum_{i \in I} a_i x_{ij} \le y_j K_j \qquad \forall \quad j \in J \tag{5.5}$$

$$x_{ij}, y_j = \{0,1\} \qquad \forall \quad i \in I, j \in J \tag{5.6}$$

with K_j is the workload capacity for a facility at site j

The formulation uses the more restrictive binary form of the assignment variable x_{ij} (by Chung et al. (1983)) rather than the continuous form used by Current and Storbeck (1988).

5.2.1 Solution Methods from Literature

Chung et al. (1983) were amongst the earliest to solve CMCLP. The authors developed an efficient heuristic which consistently obtained results within 5 percent of the optimal solutions, with less than one-third of the CPU times. The problem was solved through binary assignment variables which were similar to those developed by Church and Re Velle (1974) for the un-capacitated MCLP. The authors presented the computational results for two small problems $(p \le 4, |I| = |J| = 30)$. However, the heuristic was specifically designed for the binary assignment variable formulations of the CMCLP and it was not readily adaptable to the unrestricted problem.

Current and Storbeck (1988) presented an alternative formulation to the CMCLP which had a similar concept but a different objective function. The objective function was to minimise the uncovered volume which calculated the percentage of demand at each demand node that was either assigned to a facility that covered it or which should be counted as uncovered in the objective function. Instead of having the binary constant that indicated the "within" coverage, the covered demand volume was only considered in the assignment to the facility with available capacity. In the formulation, the entire demand at a node did not have to be assigned to the same facility through the variable x_{ij}, and that part of the demand at a node may be covered (that is, assigned to a facility) and the rest of it was not covered. x_{ij} that represented the fraction of demand node i assigned to facility j was not set to equals 0 or 1 as in the $\overline{Z}_7$ formulation. In this formulation also, the number of facilities to open was set to exactly p while in $\overline{Z}_7$, it was at most p .The authors proposed that the CMCLP be reformulated as a generalised assignment problem (GAP) so that various heuristics developed for the GAP may be used to solve CMCLP. Solving the CMCLP as a GAP appeared most promising for the binary assignment variable formulation because of the large number of columns necessary for the unrestricted formulation. However, this may result in a long computational time due to the extensive calculations.

Pirkul and Schilling (1991) who used the formulation $\overline{Z}_7$ introduced in Section 5.2 proposed a heuristic solution procedure, called CAPCOV, which used the Lagrangian problem solution as a starting point in generating feasible solutions for the original problem. The procedure was developed as an integral part of the subgradient optimisation procedure. In this procedure, an attempt was made to generate feasible solution to CMCLP in every iteration of the subgradient optimisation algorithm. The best solution was retained when the subgradient optimisation algorithm was terminated. The method was tested extensively on 2400 randomly generated problems (sets of 200 demand nodes and 30 potential facility sites), as well as on practical problems with 625 demand nodes. The results showed only 30 out of the 2400 problems where the gaps exceeded 5 percent of the lower bounds with the use of computer time within 1 to 135 seconds on an IBM 3081D. In the practical problem with 625 demand nodes, the procedure used an average of 489 seconds of computer time to solve each problem and the average gap was insignificant (0.15 percent of the objective function value) where gap = 100 x (Solution value – Lower bound)/Solution value.

Haghani (1996) extended the models introduced by Pirkul and Schilling (1991) to include the minimum utilisation levels of each facility and developed two solution procedures based on an out-of-kilter network flow problem. The author formulated the CMCLP as follows:

$$\text{Maximise } Z_9 = \sum_{i \in I} \sum_{j \in N_i} x_{ij} \tag{5.7}$$

Subject to constraint (5.3) from $\bar{Z}_7$ that at most p facilities must be located, x_{ij} representing the demand at *i* from *j*, and the following reformulated constraints:

$$-L_j y_j + \sum_{i \in I} x_{ij} \geq 0 \qquad \forall \quad j \in J \tag{5.8}$$

$$U_j y_j - \sum_{i \in I} x_{ij} \geq 0 \qquad \forall \quad j \in J \qquad (5.9)$$

$$\sum_{j \in J} x_{ij} \leq a_i \qquad \forall \quad i \in I \qquad (5.10)$$

$$y_j = 0, 1 \qquad \forall \quad j \in J \qquad (5.11)$$

$$x_{ij} \geq 0 \qquad \forall \quad i \in I,\ j \in J \qquad (5.12)$$

Where

L_j is the minimum level of utilisation (capacity) of a facility located at node j;

U_j is the maximum level of utilisation (capacity) of a facility located at node j

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

In this formulation, the objective function Z_9 is the same as $\overline{Z}_7$ which is to maximise the total covered demand. The formulation includes two constraints which are the constraint set (5.8) and (5.9) to deal with the minimum L_j and maximum U_j levels of the utilisations of the facilities. This meant that a facility was located at node j, and then the demand allocated to it had to be at least as much as L_j. Constraint set (5.3) states that at most p facilities may be located, similar to Pirkul and Schilling (1991). This constraint is an inequality to allow the location of fewer facilities than p facilities when the minimum utilisation constraints are not satisfied. Constraint set (5.10) ensures that the total demand allocated from a demand point i to all sites j could not exceed the total demand at i. Constraint (5.11) imposes the integrality constraint on y_j indicating whether or not a facility at site *j* is open. At the same time, constraint (5.12) allows for partial assignment of demand volume to any available facility.

The first solution introduced by Haghani (1996) was a greedy adding heuristic. At each iteration, the algorithm located a facility and assigned the nearest demand nodes to the facility. The algorithm located the facilities so as to maximise the coverage provided by each additional facility which was sited. Subsequently, the demands were reallocated among the facilities and solved as an out-of-kilter problem. The procedure continued until either no more facilities could be located due to the minimum capacity constraints or all the *p* facilities were located. A dummy facility was added into the set of located facilities, to absorb all of the excess demands which could neither be covered by nor assigned to the located facilities. The second solution was a heuristic based on Lagrangian relaxation. Here, the two capacity constraints (minimum and maximum utilisation) were relaxed. A feasible solution to the original problem would be obtained by having the located facilities and using an out of kilter to allocate the demand. The solution procedure continued until a suitable solution/value was determined for the original problem, in which the solution obtained provided an upper bound of the original problem. Both algorithms were tested on various combinations of coverage distance, minimum and maximum utilisation levels for the located facilities. Both procedures produced comparable solutions when compared to the LINDO in solving a 20 node test problem. However, the greedy adding did not reach the optimal solutions at all time while the Lagrangian based heuristics did not converge nicely in all cases as well.

CMCLP is at least as hard as the standard MCLP which is known to be *NP*-hard (Megiddo et al., 1983). In theory, an exact algorithm could be used to solve the problem with any number of facilities. However, the complexity for such approach will be computationally intractable as the size of the problem increases (Jia et al., 2007). As many solution approaches have been proposed for the various facility locations, (refer section 2.2.3 and section 4.3), the most commonly used to solve CMCLP consist of meta-heuristics. In this study the focus was on the GA based heuristic. Many related location problems have utilised GA and have also reported good results in its solutions. Among the many are: Lai et al. (2010) for the capacitated plant location problem; Mirakhorli (2010) for the capacitated single-assignment hub covering location problem; and Lacomme et al. (2006) for the capacitated arc routing problem that model urban waste collection. In this chapter, the GA based heuristic is used to solve the CMCLP when the capacity of all the facilities within the network is limited.

5.3 GENETIC ALGORITHM BASED HEURISTICS

GA is modeled after the process of evolution. The algorithm first starts with a multiple set of randomly generated solutions also known as chromosomes. By mimicking the random interaction of genes in the natural world, newer and generally better solutions are produced from the older ones. The idea of GA was first proposed by Holland (1975), who presented it as an abstraction of biological evolution (Mitchell, 1998). Holland defined GA as a method of moving from one generation of "chromosome" population to a new generation using the idea of "natural selection" and genetic-inspired operators, such as crossover and mutation. "Natural selection" in this context is the process that preserves the strong chromosomes while eliminating the weak chromosomes. Crossover is the mechanism that combines a pair of parent chromosomes to produce child chromosomes, whilst mutation is the process that introduces randomness to the chromosomes population to preserve diversity and it also acts as a safety net to the information that might have lost during the process of selection and crossover.

The critical issue in GA is to find a suitable form to express the chromosomes and genes, namely coding. There are two major types of coding: binary coding and real coding. The binary coding is when the chromosome consists of an array of binary vectors and the length of the binary vectors depends on the required precision. For the binary implementation, the algorithm must have a conversion mechanism that could convert a bit string (chromosome) to the real value. Many researchers believe that the binary coding is ideal, while the real coding is more applicable and easy in programming (Golub, 1996).

5.3.1 Genetic Algorithm Based Heuristics to Solve Related CMCLP

There has been increased interest in applying GAs to location problems. Some studies have applied GA in solving the un-capacitated model of *p*-median and MCLP as mentioned in Chapter 4. It is noted that the application to solve the *p*-median problem and its related problems (which will be discussed later in Chapter 6) is far more than MCLP and CMCLP.

Recently, Jia et al. (2007) applied GA heuristics to solve the maximal covering problem with multiple facility quantity of coverage and quality of coverage requirements. In the heuristics, two greedy techniques were applied in order to generate good quality solutions and expedite the convergence of the heuristic. The chromosome represented all the selected facilities, in which each gene represented an opened facility site and was distinct (i.e. each facility site can be selected at most once). A non-standard crossover that worked on two phase was proposed. First, two parent chromosomes were combined to form a new illegal offspring and the parents were deleted from the population. The illegal chromosome had to go through a legalisation process using two approaches: the first method selected the genes that were discarded based on a greedy algorithm. Essentially the greedy algorithm checked each individual gene (a facility site ID) in the chromosome and removed the one that contributed the least to the improvement of the objective value in the location problem. The second method selected the p genes to keep in the chromosome based on a small scale GA. This GA selected p facilities from no more than $2p$ candidate facility sites that corresponded to the genes in the illegal chromosomes. The steps of the small scale GA followed the steps of a standard GA.

An invasion operator that generated two new chromosomes randomly was used to operate after each crossover operation. These two new chromosomes were compared to the existing chromosome population with respect to their fitness, and the one with the larger fitness was added into the population. The mutation operator that changed a certain number of genes was mutated to their random genes that were not selected in the selected chromosomes, in order to maintain the diversity. For example, a randomly selected chromosome was [2 **11** **8** 3]. After the mutation, the chromosome could be [2 **7** **4** 3].

The GA in the study was developed together with two other heuristics; a locate-allocate heuristic and a Lagrangian relaxation heuristic to solve the problem of 2054 discrete demand points that selected the numbers of facilities from 10, 20, and 30 up until 200. When the p value was less than 30, the GA heuristic was found to be able to generate better solutions with reasonable computational times compared to the other two.

5.3.2 Genetic Algorithm Based Heuristics for This Study

In this study, a new GA based heuristic is proposed to solve the CMCLP. The details of the GA are as follows:

I. *Data encoding, chromosome representation and fitness evaluation*

The chromosome solution that comprises of two parts is proposed. The first follows the encoding proposed by Jaramillo et al. (2002) where a bit of 1 at the ith bit implying facility i being selected to open, and a bit of 0 at the ith bit implying the facility i is not selected.

$$i = \begin{cases} 1 & \text{if the facility is open} \\ 0 & \text{otherwise} \end{cases}$$

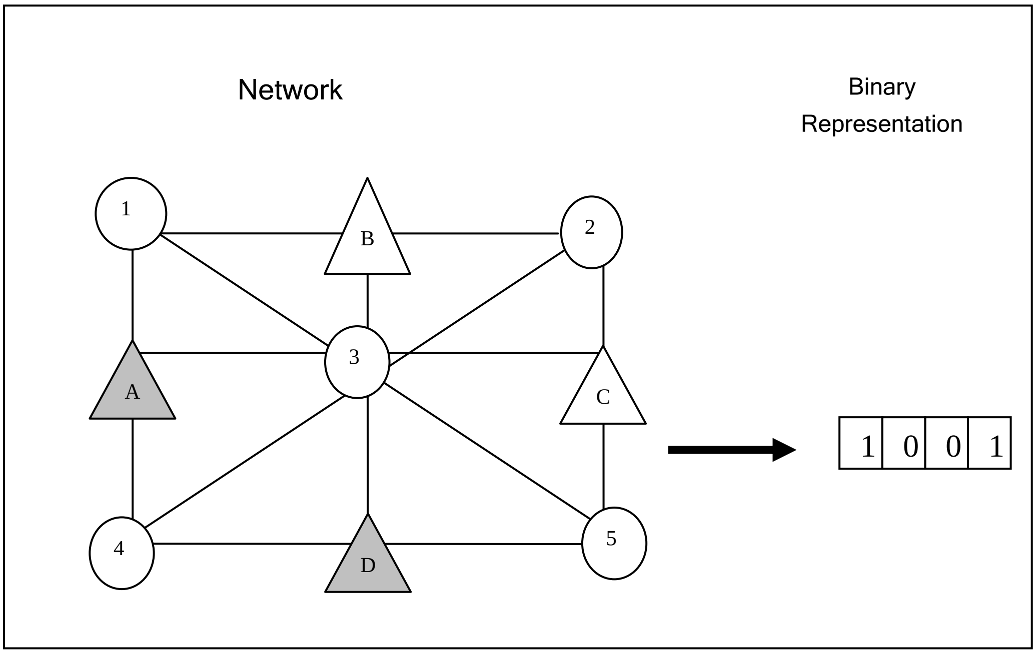

Figure 5.2: An Example of a Chromosome where only two facilities A and D are open. Points 1, 2, 3, 4 and 5 are the demand points.

A solution representation that combines this binary representation and the random permutation of all the nodes that are to be assigned to the open facilities is proposed. The new representation is a vector of length $n+m$ where n and m are the number of facilities and the number of demand points respectively. For example, the following string (0 1 1 0 1 8 11 2 6 4 3 7 9 5 1 10) represents 5 facilities (the first five binary digits) followed by 11 demand nodes (the last eleven integers) as illustrated in Figure 5.3. It is noted that the new representation comprises of a binary vector concatenated with a random permutation of integer vectors. The representation indicates that facilities 2, 3 and 5 in the network are open. In terms of the demand allocation to an available facility, instead of assigning it in the order of 1, 2, 3, 4, and so on, it will be assigned as it appears in the chromosome.

Here, each facility has a maximum capacity of 4 units and each node has a demand represented in the square parentheses. Note that in the conventional assignment based on distance to facility, node 1 would have been assigned instead of node 2. This leaves node 2 with a capacity of 2 units unassigned. Note that the assignment has 3 uncovered nodes due to the limited capacity, with a total demand of 3 units and 1 uncovered node, with a total demand of 2 units due to the maximum allowable distance constraint *S*.

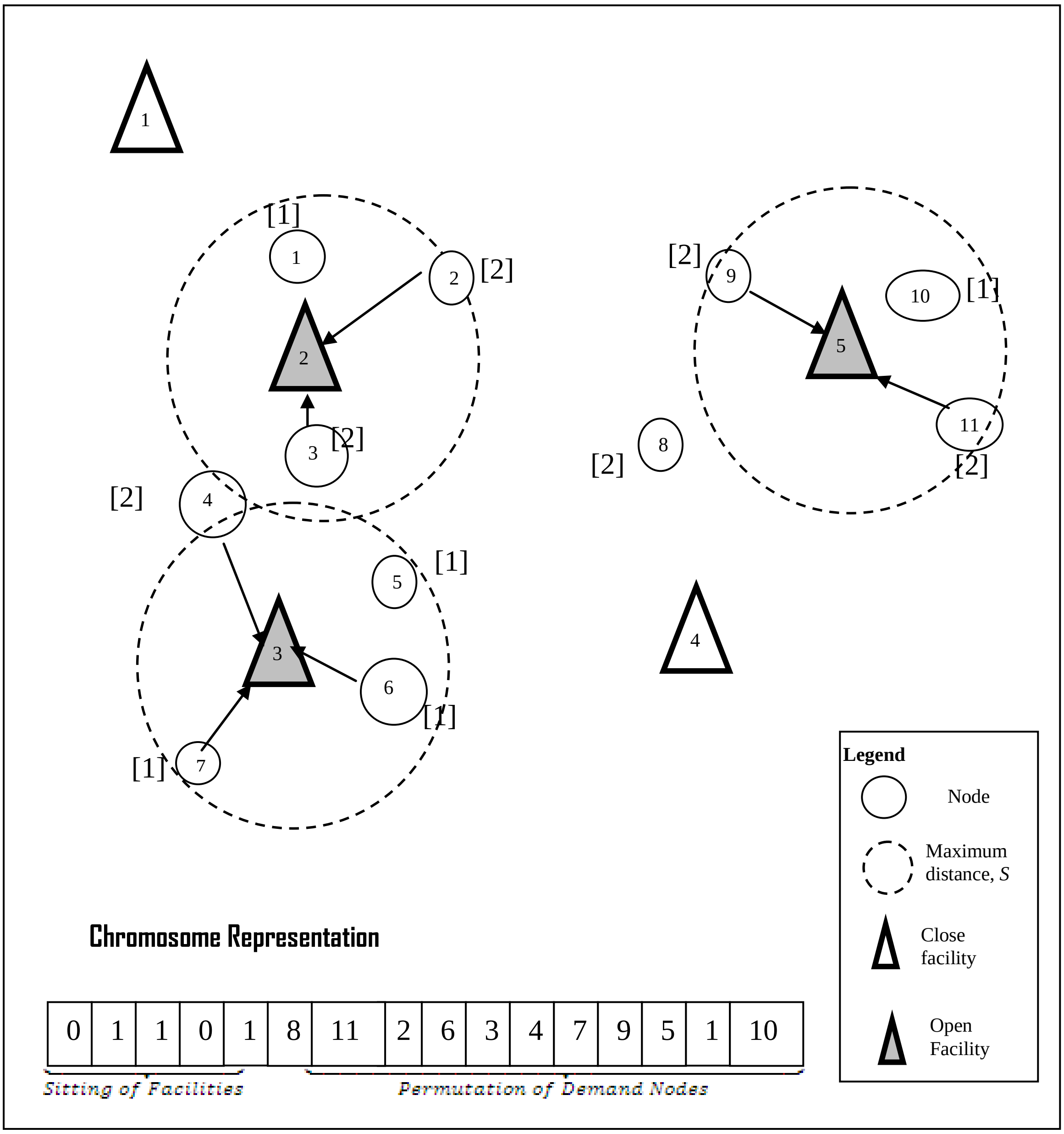

Figure 5.3: An Example of a Chromosome where only facilities 2, 3 and 5 are open. Points 1, 2, 3, 4, 5 … 11 are the demand points.

II. *Genetic operators and offspring generation*

Much of the power of GAs arises from the recombination of genes which explore all the possible search space (Jia et al., 2007). The genetic operator, a crossover operator, has to take into account the different types of representations that are encoded in the chromosome. The parent chromosomes are split into two separate vectors before the process of crossover takes place. The binary vector of the selected chromosome will undergo a uniform crossover whilst an order based crossover proposed by Syswerda (1990) is implemented for the integer permutation vector.

The uniform crossover as depicted in Figure 5.4 uses a mixing ratio between two parents, represented in the mask. It allows for every locus to be a potential crossover point as opposed to a fixed number of crossover points. Unlike, one and two-point crossover, the uniform crossover enables the parent chromosomes to contribute at the gene level rather than the segment level. In the implementation of uniform crossover, a crossover mask of size $m \times 1$, where m is the number of facilities to be sited, is generated randomly. A zero indicates that the gene is inherited from Parent 1 and the positions of ones are inherited from Parent 2. The complementary mask is used to build the second offspring.

The order based crossover given in Figure 5.5, as the name implies stresses on the order of the elements in the chromosome. This is useful as the order of appearance of the demand nodes in the chromosome determines the assignment of the nodes to the open facility. Here, a set of positions is randomly generated, and the order of the nodes in the selected positions of one parent is imposed on the corresponding nodes in the other parent. In the figure, the selected positions are 1, 3, 4 and 8 and the nodes encoded in these positions are 2, 6, 3 and 8. These nodes appear in positions 3, 4, 5 and 7 in the order of 6, 2, 8 and 3. The order in the first parent will be imposed on the second parent resulting in a child with nodes 2, 6, 3 and 8 appearing in positions 3, 4, 5 and 7 as highlighted in the shaded area. The remaining positions will be filled up by those from the second parent.

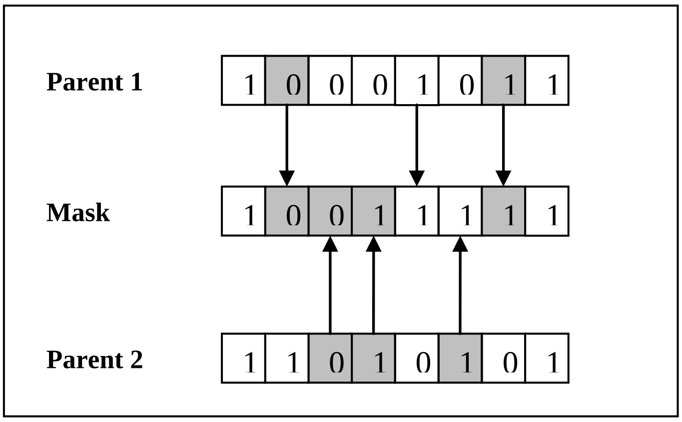

Figure 5.4: An example of uniform crossover operator (OBX) when there are 8 facilities

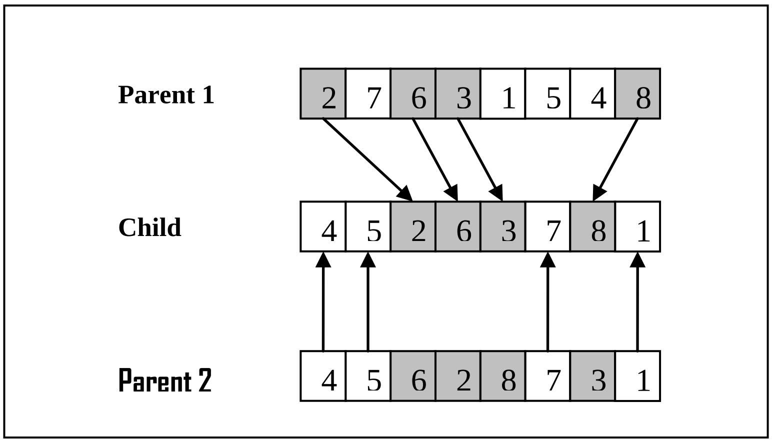

Figure 5.5: An Example of Order Based Crossover Operator (OBX) when there are only 8 demand points

The order based crossover is chosen because the order of assigning the nodes is important in this problem. When the capacity is limited, the order of which the demand volume is assigned is important in order to ensure the best allocation (Ghoseiri and Ghannadpour, 2007).

It is interesting to note that the same procedure is applied to the mutation process. The binary vector will undergo the classical mutation operator of flipping from zero to one and *vice versa*, whilst the integer representation will undergo a simple insertion operator. Figure 5.6 illustrates the insertion mutation.

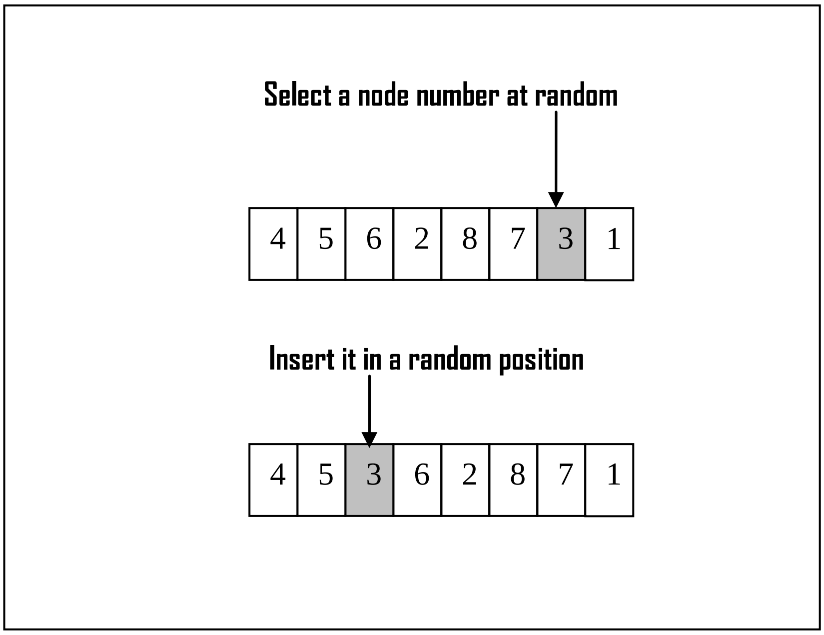

Figure 5.6: An Example of Insertion Mutation when there are only 8 demand points

III. *GA parameters*

The GA parameters such as the population size and crossover rate also influence the efficiency and effectiveness of the heuristic. A small population size will have a risk of under exploring the feasible solution space, while a too large population incurs unnecessary computational cost and time. In this heuristic, the population size N is set to 100, 200, and 300. This is because the feasible solution space is already as big as ${}^{I}C_{p}! \times J!$ given that I is the total number of node and J is the total number of potential sites. To get the initial set of population, the open facilities are chosen randomly based on p (number of facilities to open) and the order of node to be assigned is also randomly from the list of demand nodes (customers).

The crossover rate determines how many chromosomes in each iteration will be involved in the crossover operation. Due to the large feasible solution space, the crossover rate used is fixed to 0.7. In the meantime, the mutation operation is set at 0.01 or 1 percent.

The fitness function is evaluated based on the objective function given in equation (5.2). However, when the constraints are tight, there is a tendency for the capacity constraints to be violated, or some of the demand nodes are not assigned. In view of this, the present objective function was modified to incorporate the penalty term when there exists some demand nodes that are not assigned or when the capacity constraint of the facilities are violated. The modified objective function is given by:

$$\sum_{j \in J} \sum_{i \in I} c_{ij} a_i x_{ij} + \alpha \sum_{j \in J} \sum_{i \in I} c_{ij} \tag{5.13}$$

where α, is the penalty factor for the CMCLP

5.4 BENCHMARKING USING DATA FROM THE LITERATURE

To further validates the GA based algorithm in solving the CMCLP, data from the literature is used by varying the nodes number from small (30 nodes) to large (818 nodes). The 30-node network data are provided by Marianov and Serra (1998) and the other two (324-node and 818-node network) are based on the geographical data base of Sao Jose dos Campos, Brazil (Correa et al., 2008). In order to measure the applicability of the approach, the following parameter values have been calculated for the three sets and summarised in Table 5.1. The number of facilities to be sited, p, is chosen based on the results produced by Correa et al. (2008). Since each demand node is a potential location of the facility, the algorithm is modified by choosing p number of facilities from a set of randomised demand nodes. The total demand volume is calculated to obtain the average demand per facility in order to determine the capacity volume per facility. Every facility is assumed to have the same capacity and the capacity volume per facility is set to be 70 percent above the average demand volume per facility. The 70 percent is chosen to allow for some flexibility in the assignment of nodes to the facilities as some demand nodes can have their demand volume to be more than the average value. For example, in Set III node 814 has a demand volume of 992 compared to the average demand volume per facility is only 583.

The average distance between the demand nodes and the facilities are also calculated in order to determine the maximum allowable distance S. The calculation of parameters needs to be done due to the unavailability of suitable data and the results are not comparable as it solves for a different variant of CMCLP.

Table 5.1: Profile for 3 sets of network

Description	Set I	Set II	Set III
Number Nodes	30	324	818
Number of facilities to site – *p*	5	20	50
Total demand volume	5470	12152	29168
Average demand per facility	1094	608	583
Capacity volume per facility	1900	1000	1000
Average distance (between demand nodes and facilities)	1.52	1.23	2.59

In this section, both MCLP and CMCLP are solved using the commercial optimisation software CPLEX 10.2 and the GA-based heuristics.

Table 5.2 summarises the results for Set I, the 30 node network. Both the CPLEX and GA resulted in 95.2 percent of the total demand volume covered and that only 4 facilities should be open. Both results were also obtained in less than 2 seconds. This was because there were three nodes of total demand volume 260 (or 4.8 percent) which were not within S=1.52. However, it can be seen that for CPLEX, all the demand volume is concentrated in the first assigned facilities which is Facility A having a total of 4640; Facility B with only 370 and so on. For CMCLP, both the CPLEX and GA produced compatible results for Set I and one less than CPLEX, only 4 facilities were opened by GA.

Similarly, the results for Set II, the 324 node network are illustrated in Table 5.3. Note that both the CPLEX and GA resulted in 100 percent coverage for the unconstraint MCLP. CPLEX proposed to open 8 facilities while GA proposed 9 facilities. However, note that CPLEX cumulated the total demand volume only at the earlier assigned facilities as found earlier in the Set I results. For the CMCLP, CPLEX produces an infeasible solution after 9000 seconds (two and half hours) running time.

There are two facilities which violate the capacity constraint of 1000 per facility with a total volume of only 93.8 covered compared to 100 percent by GA. The GA proposed to open only 15 facilities but still managed to achieve total coverage, within an average time of 228 seconds.

The results for Set III consisting of the 818 node network are given in Table 5.4. It is interesting to observe that CPLEX only requires to open 7 facilities compared to 20 by GA and yet Facility A accumulated almost 13000 demand volume. In Set III with even larger number of demand nodes, CPLEX only produced one feasible solution with 52.4 percent of the total demand volume covered. The GA achieved 96.6 percent coverage with 33 open facilities. There was one node with a high volume of 992 (or 3.4 percent) which could not be allocated within the capacity limit of 1000. The average time taken was 1396 seconds.

The results concluded that the GA based heuristics produced feasible solutions that do not violate capacity constraints compared to the CPLEX. The algorithm is extended to solve the MCLP and CMCLP on the location of healthcare facility in the study areas.

Table 5.2: 30 node network (Set I)

Facilities	**MCLP (S=1.52)**					**CMCLP (S=1.52)**			
	CPLEX		**GA**			**CPLEX**		**GA**	
	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Capacity	Number of nodes	Demand Volume	Number of nodes	Demand Volume
A	21	4640	7	2520	1900	8	1500	0	0
B	4	370	5	400	1900	9	1330	8	1770
C	3	280	5	460	1900	4	360	5	460
D	2	180	10	1830	1900	6	1260	9	1520
E	0	0	0	0	1900	3	1020	5	1460
TOTAL	30	5470	27	5210	9500	30	5470	27	5210
Population Volume Covered		**5210**		**5210**			**5210**		**5210**
Percentage of Coverage		**95.20%**		**95.20%**			**95.20%**		**95.20%**

Table 5.3: 324 node network (Set II)

Facilities	MCLP (S=1.23)				CMCLP (S=1.23)				
	CPLEX		GA			CPLEX		GA	
	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Capacity	Number of nodes	Demand Volume	Number of nodes	Demand Volume
A	168	4619	**0**	0	1000	**60**	**1588**	17	342
B	21	484	0	0	1000	16	486	28	755
C	70	3313	29	1158	1000	13	641	27	983
D	3	87	0	0	1000	13	618	28	1000
E	44	2049	64	1521	1000	16	956	44	1000
F	0	0	17	932	1000	**16**	**1056**	17	943
G	10	771	0	0	1000	20	835	0	0
H	0	0	0	0	1000	13	369	0	0
I	0	0	0	0	1000	21	571	30	998
J	4	223	11	249	1000	13	337	20	501
K	4	606	0	0	1000	10	421	11	994
L	0	0	0	0	1000	15	508	0	0
M	0	0	14	304	1000	13	411	0	0
N	0	0	73	1828	1000	13	337	10	243
O	0	0	33	2943	1000	10	725	12	1000
P	0	0	41	1426	1000	15	538	16	998
Q	0	0	0	0	1000	12	315	30	770
R	0	0	0	0	1000	8	350	20	996
S	0	0	0	0	1000	18	643	14	629
T	0	0	42	1791	1000	9	447	0	0
TOTAL	324	12152	324	12152	20000	324	12152	324	12152
Population Volume Covered		**12152**		**12152**			**11398**		**12152**
Percentage of Coverage		**100.00%**		**100.00%**			**93.80%**		**100.00%**

Table 5.4: 818 node network (Set III)

Facilities	MCLP (S=2.59)				CMCLP (S=2.59)				
	CPLEX		GA			CPLEX		GA	
	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Capacity	Number of nodes	Demand Volume	Number of nodes	Demand Volume
1	296	12427	21	111	1000	13	270	0	0
2	64	1638	0	0	1000	16	375	18	783
3	0	0	0	0	1000	15	239	0	0
4	312	9324	54	4655	1000	18	552	17	996
5	6	95	0	0	1000	12	533	26	999
6	15	276	16	290	1000	**13**	**1097**	26	890
7	0	0	31	606	1000	19	606	21	958
8	0	0	0	0	1000	20	968	15	1000
9	89	4343	0	0	1000	16	888	0	0
10	0	0	0	0	1000	12	378	0	0
11	0	0	0	0	1000	14	255	27	993
12	36	1065	0	0	1000	19	576	38	901
13	0	0	0	0	1000	13	503	12	998
14	0	0	0	0	1000	21	659	14	147

Table 5.4 continued

15	0	0	34	746	1000	**21**	**2056**	35	991
16	0	0	0	0	1000	19	606	15	987
17	0	0	0	0	1000	16	471	23	1000
18	0	0	47	2418	1000	22	498	27	999
19	0	0	27	583	1000	16	792	28	984
20	0	0	0	0	1000	19	574	27	987
21	0	0	0	0	1000	15	743	0	0
22	0	0	0	0	1000	17	625	24	996
23	0	0	18	941	1000	21	417	0	0
24	0	0	0	0	1000	20	612	15	1000
25	0	0	35	509	1000	11	394	36	330
26	0	0	0	0	1000	20	832	0	0
27	0	0	20	631	1000	15	220	0	0
28	0	0	0	0	1000	10	147	32	995
29	0	0	0	0	1000	9	137	5	196
30	0	0	0	0	1000	20	612	16	200
31	0	0	0	0	1000	11	720	30	924
32	0	0	49	1158	1000	19	580	0	0
33	0	0	0	0	1000	15	550	0	0
34	0	0	73	3931	1000	10	244	29	951
35	0	0	94	2143	1000	13	314	0	0
36	0	0	0	0	1000	21	741	14	1000
37	0	0	0	0	1000	**19**	**1011**	0	0
38	0	0	22	239	1000	16	364	8	109
39	0	0	0	0	1000	19	671	0	0
40	0	0	0	0	1000	14	994	29	987
41	0	0	84	3563	1000	23	518	23	987
42	0	0	7	145	1000	12	267	10	891
43	0	0	54	3387	1000	**21**	**1047**	0	0
44	0	0	0	0	1000	**20**	**1026**	0	0
45	0	0	35	1001	1000	17	517	36	1000
46	0	0	0	0	1000	17	395	0	0
47	0	0	55	1016	1000	16	470	47	997
48	0	0	42	1095	1000	11	325	56	1000
49	0	0	0	0	1000	24	619	0	0
50	0	0	0	0	1000	8	160	38	1000
TOTAL	818	29168	818	29168	50000	818	29168	817	28176
Population Volume Covered		**29168**		**29168**			**15283**		**28176**
Percentage of Coverage		**100.00%**		**100.00%**			**52.40%**		**96.60%**

5.5 APPLICATION OF GA ON SMALL STUDY AREA

TPG is a sub-district in the district of Kuala Langat. Details of its health profile are described in Section 3.4.1. As mentioned earlier in Section 5.1, the capacity for each RC in the 2-tiered system is to serve 4000 population. When the population volume increases together with the development of a new design of the RC building, some clinics are assumed to be able to serve more than 4000. For example, KD KM is operating in the new 2-storey building which can accommodate 14000 population~~s~~ per year as perceived by the staff (JM KD Sijangkang, personal communication, 15 October, 2007). KM was previously operating 62 percent above its capacity. In the study area, two clinics are still operating in the old type of buildings and are operating above their capacity. KD SL and KB are to serve 6157 and 5114 mothers and children respectively despite the said capacity to be 4000 only (Refer to Table 3.5). SL and KB are operating above their capacities by 54 percent and 28 percent respectively, whilst the other facilities, SD and TPG are operating below their respective capacities. They are operating within 35 percent and 50 percent of their capacities only.

In this study, the information was gathered from the Staff In Charge (SIC) in the district office of Kuala Langat. The capacity of each facility was said to also depend on the size of the building (JM KD Sijangkang, personal communication, 15 October, 2007), which could also be seen from the potential population to go to the clinic (include~~s~~ children between 0 to 12 years old and women aged between 15 and 44 years old, refer Table 3.5). Pictures of clinics in the study area are enclosed in the Appendix to explain the situation. Based on the size and the design of the facility building, the staff~~s~~ have their own perceptions regarding the maximum capacity. Hence, this set of capacity is named the staff perception (SP). Based on the potential visitor to each facility, it is observed that the minimum volume is around 6000 population. Hence, it is proposed that the minimum capacity of each facility within the area be upgraded to 6000 or an increase by approximately 1.5 of the current nominal capacity value. This increase is also proposed based on the average growth of population value or 1.48. Details of the population growth rate will be discussed in Chapter 7. This set of capacity is named the proposed new policy (PP). For comparison purpose, the set that follows the government policy that each facility has a minimum capacity of 4000 is named the government policy (GP). In this section, the performance of the GA based algorithm in solving the CMCLP will be analysed based on the three sets of policies.

The analysis will use the same setting for the study as in the un-capacitated study in Chapter 4. Similarly, the total population of 30458 is assumed to be uniformly distributed: (1) within its own service boundary, (2) within the whole study area. As also mentioned earlier, in order to confirm the optimality of the solution, because of the huge solution space, the problem in GA converges after 2000 generations.

5.5.1 Locational Analysis Using CMCLP

The analysis is carried out based on the maximisation of the covered percentage of population within some maximum allowable distance, *S*, and simultaneously enforcing the fixed capacity on each facility. Both the 3 and 5 km are used as the values of *S*.

I. The population demand is uniformly distributed *within its own service boundary*

Tables 5.5, 5.6 and 5.7 summarise the results for the CMCLP solved by both the CPLEX 10.2 and GA. It was observed that for the GP set of capacity, 4 facilities were assigned the demand volume more than its nominal capacity by CPLEX when the maximum distance was *S*=3 km. The coverage was also low, at 38.1 percent. The GA produced better results where all the capacities were not violated and the coverage was better at 90.6 percent. It is worth noting that when *S*=5 km, the coverage increased to 91.6 percent for CPLEX with GA achieving 100 percent coverage. Similarly, CPLEX produced results that violated the capacity constraint (shaded) of facility SL.

Table 5.5: Comparison of CPLEX versus GA results for CMCLP based on government policy (GP)

Facilities	**Capacity**	**CMCLP (S=5km)**				**CMCLP (S=3km)**			
		CPLEX		**GA**		**CPLEX**		**GA**	
	(GP set)	Number of nodes	Demand Volume	No of nodes	Demand Volume	Number of nodes	Demand Volume	No of nodes	Demand Volume
SD	4000	61	2870	39	3893	73	**5747**	31	3966
SL	4000	22	**4213**	22	3981	25	**5625**	19	3996
KM	4000	19	3828	37	3956	23	**4867**	31	3952
KB	4000	13	2724	18	3967	27	**6309**	20	3975
TPG	20000	64	16823	62	14661	31	7910	42	11713
TOTAL	36000	179	30458	179	30458	179	30458	143	27602
Population Volume Covered			**27980**		**30458**		**11618**		**27602**
Percentage of Coverage			**91.9**		**100.0**		**38.1**		**90.6**

When $S = 3\text{km}$, the results obtained from CPLEX for the perceived capacity (SP) showed a slight improvement where only 2 facilities (SL and KB) did not satisfy the capacity (shaded) imposed. However, the coverage decreased to 35.4 percent. When $S = 5\text{km}$, CPLEX produced results that achieved only 97.9 percent. On the other hand, GA produced 100 percent coverage for both *S* values

Table 5.6: Comparison of CPLEX versus GA results for CMCLP based on staff perception policy (SP)

Facilities	Capacity	CMCLP (S=5km)				CMCLP (S=3km)			
		CPLEX		GA		CPLEX		GA	
	(SP set)	Number of nodes	Demand Volume	No of nodes	Demand Volume	Number of nodes	Demand Volume	No of nodes	Demand Volume
SD	8000	78	6042	44	4734	73	6051	33	4412
SL	4000	21	3547	20	3994	27	**6315**	19	3873
KM	14000	24	6109	57	8789	21	4906	56	9550
KB	4000	15	3394	19	3970	29	**6323**	18	3965
TPG	20000	41	11366	39	8971	29	6863	31	8058
TOTAL	50000	179	30458	179	30458	179	30458	179	30458
Population Volume Covered			**29817**		**30458**		**10779**		**30458**
Percentage of Coverage			**97.9**		**100.0**		**35.4**		**100.0**

A similar pattern of results was seen when the PP set was imposed on the facility. When $S = 3\text{km}$, CPLEX produced 100 percent of coverage achieved and when $S = 5\text{km}$, CPLEX produced better results of 98.7 percent compared to the SP results of 97.9 percent. GA achieved 100 percent coverage for both S values. Hence, it can be concluded that 6000 is a better value for a minimum number of population to be served by each facility.

Table 5.7: Comparison of CPLEX versus GA results for CMCLP based on proposed policy (PP)

Facilities	Capacity	CMCLP (S=5km)				CMCLP (S=3km)			
		CPLEX		GA		CPLEX		GA	
	PP set	Number of nodes	Demand Volume	No of nodes	Demand Volume	Number of nodes	Demand Volume	No of nodes	Demand Volume
SD	6000	69	3784	42	4409	79	4982	34	4663
SL	6000	25	5094	30	5973	26	5567	29	5911
KM	6000	23	5605	44	5944	25	5599	39	5819
KB	6000	19	5026	26	5663	19	4154	26	5845
TPG	20000	43	10949	36	8469	30	10156	29	8220
TOTAL	44000	179	30458	179	30458	179	30458	179	30458
Population Volume Covered			**30064**		**30458**		**30458**		**30458**
Percentage of Coverage			**98.7**		**100.0**		**100.0**		**100.0**

II. The population demand is uniformly distributed within *the whole study area*

The results for the population demand volume being uniformly distributed within the whole study area are illustrated in Tables 5.8, 5.9 and 5.10, respectively. When the capacity followed the GP, the results using CPLEX 10.2 violated (shaded) the capacity constraints for all the facilities except in TPG. As mentioned earlier CPLEX will always assign all nodes regardless whether the capacity or the maximum coverage constraints are violated as opposed to GA where all constraints are treated as hard constraints. It was observed that almost 25 percent (51) nodes were not been assigned for *S*=3 km and this was reduced to 3 percent (5) nodes when *S*=5 km. However, the coverage produced by GA was higher in both cases.

The GA algorithm produced better results overall compared to CPLEX. The overall percentage of the coverage for this case was also a bit worse compared to when the demand volume was distributed within its own service boundary. This was due to the fact that the density of the demand volume actually differed in different service boundaries.

Table 5.8: Comparison of CPLEX versus GA results for CMCLP based GP set

Facilities	**Capacity**	**CMCLP (S=5km)**				**CMCLP (S=3km)**			
		CPLEX		**GA**		**CPLEX**		**GA**	
	(GP set)	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Number of nodes	Demand Volume
SD	4000	63	**4841**	**30**	3918	71	**6460**	21	3921
SL	4000	17	3691	18	3919	29	**6464**	17	3923
KM	4000	16	3228	36	3923	24	**5305**	31	3927
KB	4000	4	923	17	3927	31	**6694**	17	3927
TPG	20000	79	17775	73	13850	24	5535	42	8081
TOTAL	36000	179	30458	174	29537	179	30458	128	23779
Population Volume Covered			**29308**		**29537**		**9465**		**23779**
Percentage of Coverage			**96.2**		**97.0**		**31.1**		**78.1**

Table 5.9: Comparison of CPLEX versus GA results for CMCLP based on SP

Facilities	Capacity	CMCLP (S=5km)				CMCLP (S=3km)			
		CPLEX		GA		CPLEX		GA	
	SP set	Number of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume
SD	8000	81	**8987**	46	7606	79	**8529**	34	6914
SL	4000	17	3693	18	3920	14	3229	17	3918
KM	14000	38	8080	56	8541	46	10157	56	9697
KB	4000	17	3926	17	3927	15	3003	17	3927
TPG	20000	26	5772	41	6464	25	5540	33	6002
TOTAL	50000	179	30458	178	30458	179	30458	157	30458
Population Volume Covered			**30227**		**30458**		**29996**		**30458**
Percentage of Coverage			**99.2**		**100.0**		**98.5**		**100.0**

Table 5.10: Comparison of CPLEX versus GA results for CMCLP based on PP

Facilities	Capacity	CMCLP (S=5km)				CMCLP (S=3km)			
		CPLEX		GA		CPLEX		GA	
	PP set	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Number of nodes	Demand Volume	Number of nodes	Demand Volume
SD	6000	61	4151	39	5992	80	**8299**	30	5990
SL	6000	15	3460	27	5994	26	5998	26	5996
KM	6000	25	5301	44	5771	26	5538	40	5772
KB	6000	2	462	25	5775	22	5082	25	5775
TPG	20000	76	17084	43	6926	25	5541	36	6695
TOTAL	44000	179	30458	178	30458	179	30458	157	30228
Population Volume Covered			**29535**		**30458**		**28610**		**30228**
Percentage of Coverage			**97.0**		**100.0**		**93.9**		**99.2**

5.6 EXTENSION OF APPLICATION OF GA ON LARGE DATA SET

The algorithm was extended to solve the CMCLP for a larger study area, covering the whole district of Kuala Langat. The health profile of Kuala Langat is described in section 3.4.2. Table 3.6 summarises the target population breakdown for the twenty seven clinics under study in Kuala Langat. It also describes the breakdown of the target service volume for every clinic, showing the number of babies and number of pregnant mothers who are expected to go to clinics. This work is based on the primary and secondary sources of data. The data on population size was collected from the Kuala Langat District Health Office in Banting, which reported the total population to serve as 235300.

Although the population was spread over the area of the study, it is convenient to identify a smaller number of population nodes with the population assumed to be clustered at each. Hence, the existing 27 service regions were subdivided into 809 sub-regions, with their demand nodes located centrally (Yeh and Hong, 1996; Jia et al., 2007).

5.6.1 Locational Analysis for Kuala Langat Using MCLP and CMCLP

The mathematical model given in Section 5.2 is solved analytically using the CPLEX 10.2 for a maximum period of 7200 seconds (2 hours). The GA was run using a population size of 100 for a maximum number of generations of 100. Similarly, a probability of crossover of 0.7 and a mutation rate of 0.1 was implemented for all the GAs. The incremental replacement method was chosen in which the average fitness of the population would improve if the child solution~~s~~ had better fitness values than those of the solutions replaced. This method was chosen over the other method of generational replacement which generated a new population of children and replaced the whole parent population (Beasley and Chu, 1996). Using this method, the best solutions are always in the population and the newly created solutions are immediately available for selection and reproduction. It is noted that when replacing a solution, care must be taken to prevent excessive copies of a solution from entering the population. Allowing too many duplicate solutions to exist in the population may be undesirable because a population could come to consist of identical solutions, thus severely limiting the GA's ability in generating new solutions, which may result in premature convergence (Jaramillo et al., 2002).

The initial results of the GA for the un-capacitated models showed that when $S = 3\text{km}$, 82.6 percent (in bold) of the total demand volume was covered, while 91.8 percent (in bold) coverage was achieved when $S = 5\text{km}$. Four facilities (shaded), KK Telok Datok (facility number 1), KD Morib (facility number 19), KD (facility number 24) and KK Jenjarom (facility number 25) were not assigned any demand. The detailed analyses showed that it was due to more than one facility are available within the coverage distance. As the capacity was not a constraint, only one of the facilities within the coverage distance was logically assigned.

Table 5.11: Results using GA based heuristics for MCLP (un-capacitated model)

Facilities	**Capacity**	**No model (Existing assignment)**	**MCLP *S*=5km**		**MCLP *S*=3km**	
		Demand Volume	Number of nodes assigned	Demand Volume	Number of nodes assigned	Demand Volume
KK Telok Datok	20000	28279	0	0	17	25253
KD Sg Kelambu	4000	1719	40	12882	19	3067
KD Kg Sg Lang	4000	3437	21	6612	18	4327
KD Telok Bunut	4000	5625	30	19694	17	5105
KK Tg Sepat	15000	7408	7	2635	7	2635
KD Tumbuk Darat	4000	1988	27	7463	19	6903
KD Kundang	4000	2733	22	2847	14	2202
KD Batu Laut	4000	3401	24	2830	19	2668
KK Bandar	15000	11660	31	13097	19	10845
KD Sg Buaya	4000	4560	22	18931	17	8959

Table 5.11 Continued

KD Permatang Pasir	4000	3780	18	4806	14	4036
KK Bukit Changgang	15000	13092	34	14140	22	9569
KD Labohan Dagang	4000	6294	51	5171	28	4720
KD Olak Lempit	4000	5791	33	6472	26	3606
KK Kanchong Darat	15000	13862	26	15743	19	13110
KD Kg Endah	4000	2582	23	4126	18	2849
KD Kanchong Tengah	4000	2108	23	1364	17	1364
KD Kelanang	4000	3954	33	3715	26	2921
KD Morib	4000	3848	0	0	9	2720
KK Telok Panglima Garang	20000	25509	19	9843	16	6049
KD Sijangkang Dalam	4000	6616	37	10947	19	7569
KD Sijangkang Luar	4000	13536	8	14173	8	14173
KD Kampung Medan	4000	14323	21	18195	10	10230
KD Kebun Baru	4000	12723	0	0	14	10583
KK Jenjarom	20000	27135	0	0	12	21807
KD Kg Jenjarom	4000	5325	34	15813	17	4027
KD Sri Cheeding	4000	4012	47	4516	28	3032
Total	200000	235300	631	216015	469	194329
Percentage Covered				**91.8%**		**82.6%**

It was noted that due to the large data sets, the GA did not converge to the same value in every run, as observed in many meta-heuristics. The algorithm was run 10 times and the percentage of the total demand volume covered on average 69.7 percent when S=3km, while when S=5km the percentage covered on average 77.8 percent. The standard deviation was 0.6 and 0.3 respectively, which was relatively small. Table 5.12 tabulates the best results found using the GA. The best results for GA was 70.8 percent (in bold) when $S = 3\text{km}$ and 78.3 percent (in bold) when $S = 5\text{km}$ or a decrease in efficiency by 11.8 percent and 13.5 percent respectively.

Further analysis of the uncovered nodes (373 nodes for *S*=3km and 238 nodes for *S*=5km) showed that some of them were located in less populated areas such as tea farms (ladang teh), forest reserves (hutan rizab) and aboriginal villages (perkampungan orang asli), due to the proximity of these locations to the existing health facilities. It is worth noting that these areas are currently served by mobile clinics which visit on a weekly basis from two nearby health clinics, KK Jenjarom (No. 25) and KK TPG (No. 20). There were also some uncovered nodes in highly populated areas, which were unassigned due to the limited capacity. For example, from the current assignment, the total assigned to KK TPG was 25509. However, with the limited capacity of the facility, the algorithm only managed to assign a total of 19837 population~~s~~ to the facility. Similarly, in the neighbouring facilities such as KD KM only 3897 population~~s~~ were assigned to it compared to the current assignment 14323.

Table 5.12: Best Results using GA based heuristics

No	Facilities	Capacity	CMCLP *S*=5km		CMCLP *S*=3km	
			No of nodes assigned	Demand Volume	No of nodes assigned	Demand Volume
1	KK Telok Datok	20000	17	20000	15	19894
2	KD Sg Kelambu	4000	34	3933	19	3067
3	KD Kg Sg Lang	4000	13	3966	17	3403
4	KD Telok Bunut	4000	9	3981	13	3866
5	KK Tg Sepat	15000	13	6133	11	5327
6	KD Tumbuk Darat	4000	21	3965	13	3917
7	KD Kundang	4000	22	2847	14	2202
8	KD Batu Laut	4000	24	2830	19	2668
9	KK Bandar	15000	38	14994	22	12439
10	KD Sg Buaya	4000	6	3975	9	3700
11	KD Permatang Pasir	4000	14	3995	14	3830
12	KK Bukit Changgang	15000	38	14966	23	9744
13	KD Labohan Dagang	4000	43	3991	24	3936
14	KD Olak Lempit	4000	29	3965	27	3781
15	KK Kanchong Darat	15000	25	14980	20	14034
16	KD Kg Endah	4000	19	3011	18	2849
17	KD Kanchong Tengah	4000	25	2534	17	1364
18	KD Kelanang	4000	33	3951	26	2921

Table 5.12 continued

19	KD Morib	4000	9	2720	9	2720
20	KK Telok Panglima Garang	20000	21	19837	27	18401
21	KD Sijangkang Dalam	4000	7	3939	6	3981
22	KD Sijangkang Luar	4000	9	3978	5	3811
23	KD Kampung Medan	4000	6	3897	2	3730
24	KD Kebun Baru	4000	18	3981	9	3846
25	KK Jenjarom	20000	17	19916	16	19997
26	KD Kg Jenjarom	4000	19	3905	12	3954
27	KD Sri Cheeding	4000	42	3986	29	3237
Total		200000	571	184176	436	166619
Total Demand Volume Covered		235300		184176		166619
Percentage Covered				**78.3%**		**70.8%**
Average				**77.8%**		**69.7%**
Standard Deviation				0.32		0.58
Maximum				78.3%		70.8%
Minimum				77.4%		68.8%

5.7 CONCLUSION

In this chapter, the CMCLP was solved using the commercial optimisation software CPLEX 10.2 and it was found that at some point the capacity constraint imposed on the facility prohibited CPLEX to produce good results. A new approach was proposed based on GA to solve the CMCLP. The representation not only incorporated the number of facilities to open but it also encoded the order of assigning the demand nodes. The order based cross over in which the order or position was important was used together with the insertion mutation operator to generate more good random permutations and are shown to be effective. The method was first applied on a set of bench mark data which differed in the size of network. The GA based heuristics produced comparatively better results when compared to that by the CPLEX in terms of objective function values as well as computational times.

The application was then extended to solve the real data sets by analysing the past location decision in both the small and large study areas. The variant used was the uniformity assumption; whether the demand was distributed uniformly at its own service boundary or the whole service area. This had highlighted the effect of density in the allocation of demand to a facility. In addition, the new variant in terms of capacity size was added into the analysis based on: the GP, the size of the building as perceived by the staff (SP), and the new proposed minimum volume for each facility (PP) that highlighted the need for a revision in the planning of the health facility policy. The study is hoped to highlight the health facility planning on the need to revise the policy.

The next chapter will focus on the capacitated *p*-median (CPMP) model and the application of the GA based heuristics approach in solving it. It will also analyse the performance of the CPMP in modeling the health facility location in the study area when compared to the CMCLP.

CHAPTER 6

THE CAPACITATED MODELS - CAPACITATED *P*-MEDIAN (CPMP)

6.1 INTRODUCTION

In Chapter 5, the public health facility was modelled as a capacitated Maximal Covering Location problem (CMCLP) where the objective function was to maximise the total population coverage when the capacity was limited. Aside from the coverage, the travelled distance is also equally important as a measurement to service efficiency. It is always considered in any location allocation model for public health so that the travelled distance between the demand nodes and the facilities is minimised. This is because it is assumed that naturally people will have a higher tendency to go and seek for cure if the facility is near (Weiss et al., 1971; Rahman, 1991). This is related to the vision of the MOH that health is for all (Annual Report MOH 2005, 2006).

The *p*-median problem was discussed in detail in section 4.2 where various algorithms were developed to solve the problem. As highlighted in Chapter 5, the capacitated model was a must extension to the model as in the case of healthcare service especially where offices were fixed to serve users. Capacity for each facility is a constraint that makes the allocation of potential visitors to the facility becomes more difficult which might result in poor service quality. In this chapter, the various algorithms that solve the capacitated *p*-median (CPMP) and use it to model the public healthcare facility location in this study area are explored. The chapter is outlined as follows: Section 6.2 describes the formulation and the previous algorithms developed to solve the problem. Section 6.3 details the GA based heuristic developed in this study and the comparison to other solutions, followed by Section 6.4 that illustrates the application of the model into a small study area. In Section 6.5, the relative performance of the CPMP to CMCLP is tested on different sets of capacities. The conclusion and further research are summarised in section 6.6.

6.2 CAPACITATED *P*-MEDIAN (CPMP)

As mentioned in Chapter 4, the *p*-median formulation Z_8 is adapted from Re Velle and Swain (1970). In order to ensure that the facilities are operating within its capacities, the following constraint is added into the formulation:

$$\sum_{i \in I} a_i x_{ij} \leq K_j y_j \qquad \forall \quad j \in J \tag{6.1}$$

The rest of the constraints (4.3), (4.4), (4.5), (4.6) and (4.8) still hold. Note again that the value of *p* is the total number of facilities to be located.

6.2.1 Literature Review of the Various Solution Methods

A CPMP is a location problem defined as where a set of n customers is to be partitioned into p disjoint clusters, such that the total dissimilarity within each cluster is minimised subjected to the constraints of the maximum cluster capacity (Reese, 2005; Fleszar and Hindi, 2008). Dissimilarity of a cluster is the sum of the dissimilarities between each customer who belongs to the cluster and the median associated with the cluster. The problem can be restated very simply as: given a set of customers with known amounts of demand, a set of candidate locations for facilities, and the distance between each pair of customer-facility, choose p facilities to open that minimise the demand-weighted distance of serving all customers from those p facilities subject to its capacity limit. The CPMP appears also under the names of the capacitated warehouse location problem, the sum of stars clustering problem, the capacitated clustering problem (CCP) and others. If there is no capacity constraint, the CPMP is p-median problem. If the set of medians is fixed, the problem reduces to the generalised assignment problem (GAP). In addition, the CPMP is a special case of the single source capacitated plant location problem (SSCPLP) since the CPMP results from the SSCPLP when fixed charges for medians are assumed to be zero.

In order to solve the CPMP, numerous algorithms, from the exact algorithms, heuristic algorithms to metaheuristic algorithms, have been designed and improved tremendously over the years. There are many relevant solutions being studied and improved for the CPMP under the CCP problems. Several set instances have been created and used for algorithm comparison purposes for the CCP which are also used in the CPMP.

Mulvey and Beck (1984) examined the Lagrangian relaxation of assignment constraints in a 0-1 linear integer programming problem formulation. A primal assignment heuristic is embedded within a sub-gradient method, improved by interchanging medians in clusters. Koskosidis and Powell (1992) improved the results of Mulvey and Beck suggesting various algorithms to find the initial solutions for knapsack problems (Lagrangian sub problems).

Fleszar and Hindi (2008) proposed a variable neighbourhood search (VNS) heuristic for CPMP. The heuristic is characterised by the use of easily computed lower bound to assess whether undertaking computationally expensive calculation of worth of moves, within the neighbourhood search is necessary. The small proportion of moves that needs to be assessed fully is then evaluated by an exact solution of a relatively small sub problem. The algorithm starts with a neighbourhood search to find the initial solution. Then the procedure repeatedly generates a random solution from a neighbourhood of the initial solutions of size *k*, to find a new local minimum starting from the random solution and adopt it if it is better than the current incumbent. For each value of the neighbourhood size *k* the process is repeated *r* times and if the incumbent is not improved in any of these *r* attempts, the neighbourhood size *k* is increased. When the incumbent is improved, the size of neighbourhood is reset to 1. The algorithm is stopped when *k* exceeds the maximum neighbourhood size $k_{\max}$. Computational results are done on five standard sets of benchmark problem instances.

Set A and B comprise of two sets of 10 problem instances of size (50×5) and (100×10) vertices and medians created by Osman and Christofides (1994) and sets C and D are of size (150×15) and (200×20) modified by Baldacci et al. (2002); and the SJC problems, with up to 402 customers which is available from <http://www.lac.inpe.br/~lorena/instancias.html>, 2003. The SJC problem is a real case instance for facility location problems in the San Jose dos campos city, Brazil (Lorena and Senne, 2003). The results show that the heuristic finds all the best known solutions but in a longer *cpu* time for the bigger sets C, D and the SJC problem when compared to two heuristics based on the scatter search, combination by voting (SS-V) and combination by path re-linking (SS-PR) developed by Scheuerer and Wendolsky (2006).

Xiang-Lia and Hui-Linb (2010) proposed an improved scatter search algorithm for the CPMP. The improved scatter search starts by having the initial solutions constructed through demand point's assignment. This is done by dividing median's service areas. Secondly, a local search method based on the contour rectangle is adopted to promote the efficiency of neighbourhood solution search; and finally, path re-linking algorithm is combined to expand the searching scope. The algorithm was tested firstly on the SJC problems and then applied to real life data of 4017 demand points. The real life problem is to choose 29 emergency shelters out of the 100 potential facility sites. Though the results are not significant, it provides an alternative to solve CPMP.

The interest continues when recently Kaveh et al. (2010) proposed a hybrid algorithm called the *k*-means clustering algorithm to solve CPMP. It finds proper solution which is improved by the Fixed Neighbourhood Search (FNS). The performance of the algorithm is compared using data instances of Set A and B. The *k*-means clustering algorithm only achieves two optimal solutions while the FNS achieves all optimal solutions except for two in Set B with minimal deviations.

Several algorithms are proposed to solve the related problem CCP which is comparable to the CPMP. Osman and Christofides (1994) presented an algorithm which is based on a hybrid Simulated Annealing (SA) / Tabu Search (TS) metaheuristic technique to solve CCP. The probabilistic acceptance of solutions of the SA is combined with three TS-derived features: a non-monotonic cooling schedule that occasionally increases the temperature, in order to escape from the local optima but without starting search from scratch; second is a systematic neighbourhood search as opposed to the random search; and lastly the terminating condition, which is not based on the number of iterations, but on the number of temperature resets performed without improving the best solutions. In this study, the authors also defined two sets of 10 problem instances, Set A and Set B, for the CCP which have been used widely in the other related papers for comparison.

Among other studies on CCP are Maniezzo et al. (1998) applied a bionomic algorithm (BA) on CCP; Baldacci et al. (2002) proposed an exact algorithm based on a set partitioning approach for the CCP and the CCP with additional side constraints; Lorena and Senne (2003) presented a Lagrangian/surrogate approach integrated with local search heuristic (LSLSH) for CCP to make primal feasible as a sequence of intermediate dual solutions; Lorena and Senne (2004) in their other study used column generation as it is a powerful tool for solving large-scale linear programming problems; Ahmadi and Osman (2004) proposed a new constructive method, a general framework to improve the performance of greedy constructive heuristics, and a problem space search procedure for CCP; Ahmadi and Osman (2005) again proposed a greedy random adaptive memory search method (GRAMPS) to solve the CCP; Scheuerer and Wendolsky (2006) used a scatter search heuristic approach to the CCP. The heuristic is a population based algorithm that stores solutions in a so called reference set and constructs new solutions by combining existing ones; Diaz and Fernandez (2006) offered a hybrid scatter search and path re-linking method; Osman and Ahmadi (2007) offered guided construction search meta-heuristics (GCSM) to further improve the CCP.

The way to improve the CCP solution continued to be of interests among the researchers, when Rodney et al. (2008) proposed two multilevel refinement algorithms for CCP which filtered solutions from the search space and reduced the level of problem detail to be considered at each level of solution process. Most authors used an iteratively applied two step procedure as the basis for their heuristics, consisting of centre selection and an assignment phase. Despite the abundant methods used, not many have applied GA in solving the CPMP or CCP. GA is also proved to be able to solve difficult combinatorial optimisation problems efficiently, to name a few Wang (2010) on 2D packing problem and Kamrani and Gonzalez (2008) on travelling salesman problem. Hence, this study looks into constructing and applying an alternative GA based heuristic to solve the problem.

Comparison of algorithms based on computational efforts is not easy. This is because the computational effort is not only the speed of the CPU time that indicates the performance cache, main memory, and compliers, as the size of instances also plays a role. Hence, Osman and Ahmadi (2007) also proposed a measurement for the performance of a machine in terms of Mflop/s which stands for millions of floating points operations per second.

6.2.2 Genetic Algorithm Based Heuristic to Solve CPMP

Though several authors have applied GA to solve the *p*-median problem (Estivil-Castro and Velazquez, 1999; Bozkaya et al., 2002; Jaramillo et al., 2002; Alp et al., 2003), only a few studies have used GA on a CPMP (Lorena and Furtado, 2001; Correa et al., 2004; Resurreccion, 2006; Ghoseiri and Ghannadpour, 2007). Due to its robustness, as mentioned in Chapter 5, this study focuses on the use of GA heuristics to solve the problem.

Lorena and Furtado (2001) proposed a constructive GA (CGA) approach for the CPMP which works differently from the classical concept of GA mechanism. The classical concept of the GA mechanism is said to use a ‘building blocks” hypothesis (scheme formation and conservation) in which the schemata are evaluated indirectly. In CGA, the schemata are evaluated directly with a dynamic population size. The good schemata and structures receive ranks at the creation time and the recombination preserves good schemata. The algorithm is tested on the two 10 instances, Set A and Set B instances (Osman and Christofides, 1994) and compared to OC (1994) TS implementation. The results showed that CGA did not improve the best solution in 7 of 20 problems and 5 of them were in Set B that comprise of larger instances. This meant that the approach was not good enough for a larger problem.

Correa et al. (2004) implemented a GA to solve the CPMP. They used the same encoding scheme as Alp et al. (2003) but a different crossover operator was proposed. In their crossover operator, the genes that are common in both parents are preserved, and the uncommon genes are swapped at a random position. They also introduced a heuristic "hyper mutation" operator, which substituted facilities in a solution with facilities not in the solution, and the substitution that most improved the solution was performed. The "hyper mutation" operator is applied to 10 percent of randomly selected chromosomes in the initial population, and after that it is applied with a fixed probability of (e.g. 0.5 percent) to the subsequent populations. They compared the performance of their GA to the TS and concluded that with the "hyper mutation" operator, the GA outperformed TS.

Ghoseiri and Ghannadpour (2007) proposed replacement of the traditional assignment method with the assignment through urgencies to assign the demand points to the p selected facilities. The urgency is a way to define a precedence relationship between the demand points; the urgency to be assigned could also be viewed as a priority. The demand points with the highest urgency are assigned first. The behaviour of the two assignment techniques, the classical assignment and assignment through urgencies are tested using Set A test problems. The classical scenario showed superiority in *cpu* time (with the percentage gap between 2.4 to 7.9 percent) but the assignment through urgencies produced higher quality results (with the percentage gap between 2.1 to 3.7 percent only).

These earlier studies however, have assumed no existing facilities to satisfy any fraction of the networks' demands. Resurreccion (2006) modified a p-median problem into CPkMP which incorporated the network's existing number of k facilities in search of new and additional $p-k$ facility locations. The problem was solved by the proposed GA based heuristic that completes a combination of the needed $p-k$ medians. It proposes a child generation procedure that is based on opportunity cost called OC-GA. The lost opportunity of not choosing the closest facility to minimise the travelled distance is called opportunity cost which happens when the closest facility that can satisfy the demand of a node is removed from the list of candidate locations and the demand is reassigned to another facility farther from the node. The OC-GA is a constructive heuristic algorithm that not necessarily improves the solution; however, the performance tested against the previous algorithms with an assumption that there is no existing facility or $k=0$ shows comparable results with Ghoseiri and Ghannadpour's (2007) classical constructive GA and 4.48 percent deviation from Lagrangian optimal solution (Lorena and Furtado (2001)).

6.3 IMPLEMENTATION OF OUR GA BASED HEURISTIC

6.3.1 Chromosome Representation

The same GA based heuristics solution proposed in Chapter 5 is utilised to solve the CPMP. There are some differences in tackling the solution for CMCLP and CPMP as the objective functions contradict each other. In addition, almost all the studies from the literature make an assumption that every node location is a potential facility site, $I=J$ where I the total number of demand nodes and J the total number of potential facility sites take the same values. The number of facility to open also has been determined and the optimal values to the problem that are published represent the total nodes together with the number of facility to open.

As mentioned earlier, the chromosome representation is the combination of binary representation of the number of facility being selected to open and a random permutation of integer vectors of node assignment. Here, the chromosome is represented as $2m$ bits since every demand nodes is a potential facility site. A straight forward utilisation of the objective function of equation (6.1) produces trivial results since the minimum distance travelled is a minimum if the facility open is only 1. To ensure that the number of facilities open is still p and ensuring that all demand volumes are assigned to the facilities, the penalty is added into the objective function Z_8.

The chromosome selection has been restructured to ensure that the number of facility open remains to be p. A pre-processing stage is introduced where a chromosome of length m is generated randomly and the first p facility is selected to be opened. This ensures that the GA does not produce trivial solutions. The new objective function is given as follows:

Minimise $$\bar{Z}_8 = \alpha \sum_{i \in I} \bar{c}_i + \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \qquad (6.2)$$

where

$$\alpha = \text{total number of nodes } (I) \times \text{maximum demand value } D_{\max}$$
$$\text{or any arbitrarily large value}$$

$$\bar{c}_i = \begin{cases} 1, & \text{if node } i \text{ is not assigned to any facility} \\ 0, & \text{otherwise} \end{cases}$$

The model will be referred to as modified CPMP or mCPMP.

6.3.2 Computational Results

The mCPMP was solved using the GA based heuristic and compared to other heuristics using three sets of instances (Set A, Set B and the SJC problems). For Set A, the performance of the algorithm was compared to Ghoseiri and Ghannadpour (2007) and CGA (Lorena and Furtado, 2001) for a comparable GA performance. The problems were run for 100 generations and the 500 initial populations were similar to that of Ghoseiri's. All the problems were some minimal deviations away from the optimal value but problems 4 and 8 (in bold) produced better results than those of Ghoseiri's. All the problems were run again for 100 generations and an initial population of 1000. Three problems, problems 4, 8 and 10 (in bold) produced better results than those of Ghoseiri's and problem 8 produced even better results than CGA. The performance of the algorithm could be said to be dependent on the number of initial solutions. The algorithm also improved as the capacity constraint became tighter. Table 6.1 details the performance of each problem set in comparison to the other two algorithms.

For Set B, the algorithm was compared to CGA (Lorena and Furtado, 2001) and *k*-means clustering algorithm (Kaveh et al., 2010). All the problems were run for 100 generations and 500 initial populations and re-run for better performance (100 generations and 1000 initial populations.

Table 6.1: Comparison of GA based heuristic, Ghoseiri's and CGA on Set A

No	Optimal Value	Ghoseiri (Scenario 2)		Lorena + Furtado (CGA)		GA						
		Value	%of gap	Value	%of gap	Best value	% of gap	Avg value	% of gap	Std dev	1000 IP Best	% of gap
1	713	728	2.10	713	0.00	741	3.93	744	4.35	6.31	741	3.93
2	740	758	2.43	740	0.00	778	5.14	784	5.97	4.10	761	2.84
3	751	768	2.26	751	0.00	828	10.25	828	10.31	0.70	802	6.79
4	651	669	2.76	651	0.00	662	1.69	667	**2.46**	7.06	662	**1.69**
5	664	687	3.46	664	0.00	713	7.38	729	9.82	13.15	707	6.48
6	778	796	2.31	778	0.00	835	7.33	837	7.56	5.69	835	7.33
7	787	811	3.05	787	0.00	825	4.83	838	6.51	7.27	819	4.07
8	820	842	2.68	826	0.73	825	0.61	836	**1.95**	7.96	825	**0.61**
9	715	732	2.38	715	0.00	745	4.20	752	5.10	5.19	736	2.94
10	829	860	3.74	834	0.60	857	3.38	866	4.48	8.65	854	**3.02**

Using the SJC data, the GA based heuristic was also compared to the Lagrangian/surrogate local search heuristic (LSLSH approach) of Lorena and Senne (2003) and the best known optimal value for the problems. For these instances, the calculation was with three digits after the decimal points, but the results were presented after being rounded to the nearest integer two digits after the decimal point. The GA based heuristic was run 10 times to get the minimum and the average values. Details of the comparison are tabulated in Table 6.3. The results showed that GA does not produce compatible results as the gap was huge for all problems ranging from 11.2 percent to 29.1 percent for the minimum values and from 12.7 percent to 32.3 percent on the average values. However, the trend of an increase of gap in the solution values were the same as both the optimal value and the LSLSH, as depicted in Figure 6.1.

Table 6.2: Comparison of GA based heuristic, CGA and *k*-means on Set B

	Total Vol	Opt Value	% of cov	CGA Value	CGA %of gap	*K*-means Value	*K*-means %of gap	GA Best value	GA % of gap	GA Average value	GA % of gap	GA Std dev	GA 1000 run best	GA % of gap
1	1017	1006	0.99	1014	0.80	1025	1.89	1115	10.83	1171	16.40	19.5	1135	12.82
2	1017	966	0.95	969	0.31	984	1.86	1026	6.21	1046	8.28	14.7	1034	7.04
3	1033	1026	0.99	1026	0.00	1046	1.95	1184	15.40	1187	15.69	3.1	1122	9.36
4	1056	982	0.93	987	0.51	996	1.43	1012	3.05	1037	5.60	18.7	1008	**2.65**
5	1050	1091	1.04	1091	0.00	1100	0.82	1225	12.28	1255	15.03	24.0	1248	14.39
6	1060	954	0.90	955	0.10	957	0.31	1006	5.45	1026	7.55	20.0	1002	5.03
7	1073	1034	0.96	1034	0.00	1090	5.42	1122	8.51	1161	12.28	21.6	1142	10.44
8	1071	1043	0.97	1045	0.19	1063	1.92	1103	5.75	1128	8.15	37.2	1103	5.75
9	1085	1031	0.95	1032	0.10	1039	0.78	1119	8.54	1136	10.18	14.9	1117	8.34
10	1124	1005	0.89	1039	3.38	1048	4.28	1125	11.94	1155	14.93	20.2	1128	12.24

Table 6.3: Comparison of GA based heuristic and LSLSH on the SJC instances

Size	OPT	LSLSH Value	LSLSH %of gap	GA Min value	GA % of gap	GA Average value	GA % of gap	GA Standard deviation
100 x 10	17288.99	17288.99	0.00%	19222.20	11.18%	19483.47	12.69%	175.96
200 x 15	33270.94	33295.38	0.07%	37595.80	13.00%	37816.59	13.66%	1176.67
300 x 25	45335.17	45364.30	0.06%	56645.90	24.95%	58197.40	28.37%	1042.71
300 x 30	40635.90	40635.90	0.00%	50394.70	24.02%	52079.98	28.16%	1064.00
402 x 30	61925.52	62000.23	0.12%	79989.10	29.17%	81948.69	32.33%	929.79
402 x 40	52476.08	52641.79	0.32%	67492.50	28.62%	68220.83	30.00%	728.64
Average	**41822.10**	**41871.10**	**0.12%**	**51890.03**	**21.82%**	**52957.83**	**24.20%**	**852.96**

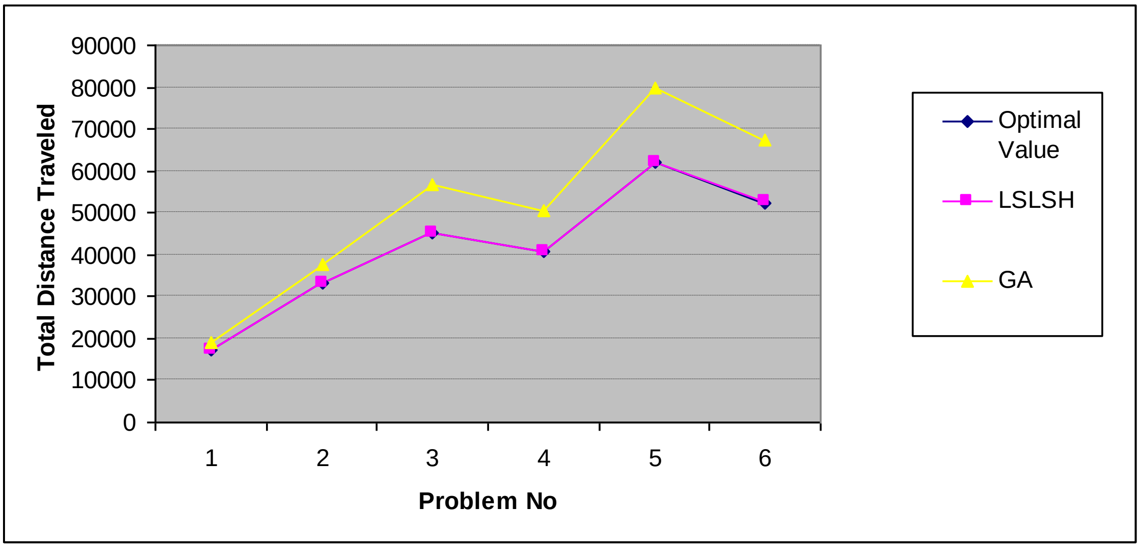

Figure 6.1: Trend of GA based heuristic and LSLSH on the SJC instances

6.4 LOCATIONAL ANALYSIS USING MCPMP

The GA was applied on 179 nodes problem using three set of capacities introduced in Section 5.5. The mCPMP was solved using CPLEX 10.2 for comparison. The analysis on these three sets of capacities is based on two cases, Case I and II, introduced in Section 4.5.

Table 6.4 summarises the results of the mCPMP for the GP set of capacities. All facilities with the exception of TPG operated at 99 percent of their capacities, in Case I. TPG was operating at 97 percent of its capacity (refer Section 5.5). The average distance travelled increased to 1.78 km or a 20 percent decrease in the system efficiency when compared to the un-capacitated results of 1.48 km (refer to Section 4.5.2). It is interesting to note that similar result of the un-capacitated *p*-median was obtained in Case II where SD was assigned 27 percent more than its capacity. It is noted that the nodes assigned to SD carry higher demand volumes as compared to Case I. In addition, the only available facility TPG was too far to be selected. It can also be seen that with the limited capacity the average distance travelled increased to 2.17 km from 1.89 km (un-capacitated *p*-median) or a 15 percent decrease in system efficiency. It can be seen that CPLEX produced a solution that violated the capacity constraint for SD (in bold and shaded).

GA produced comparable results when compared to CPLEX in cases where the capacity constraints were not violated. GA obtained slightly superior solutions in cases where the capacity constraints were violated by CPLEX. It is observed that the great advantage of using GA is in its efficiency where the computer processing unit (CPU) time for all the problems was an average of 3 seconds. On the other hand CPLEX required considerably larger CPU time with a maximum of more than 3 hours. Similar situations have been observed by Yang (2006). Although an optimal solution may be provided, the author expressed concern on the computational time. The author experimented the computational time for the dispatching problem and concluded that the computational time was not simply related to the number of variables or constraints but also to the structure of the problem.

Table 6.4: Comparison of CPLEX 10.2 and GA results for mCPMP (based on GP)

Facilities	**Capacity**	**CASE I(*own service boundary*)**				**Case II(*whole study area*)**			
		CPLEX		**GA**		**CPLEX**		**GA**	
	Based on Govt Policy (GP)	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume
SD	4000	73	3960	39	3898	64	**5072**	26	3917
SL	4000	21	3976	22	3976	17	3916	17	3918
KM	4000	17	3950	31	3890	17	3234	28	3927
KB	4000	21	3980	24	3980	17	3927	17	3927
TPG	20000	47	14592	63	14714	64	14309	91	14769
TOTAL	36000	179	30458	179	30458	179	30458	179	30458
Total Distance Travelled			**54227**		**55061**		**66110**		**66971**
Average Travelled Distance (in km)			**1.78**		**1.81**		**2.17**		**2.19**

SP and PP sets of capacities are also examined and the results are tabulated in Tables 6.5 and 6.6. The results were comparable for Case I but GA produced slightly better results by 2.5 percent (1.58 to 1.62). Interestingly, a similar pattern was seen in the PP results. Again, it can be seen that CPLEX produced solutions that violated the capacity constraint for SD (shaded and bold) in Case II. As the PP is based on the minimum volume of the demand at each service area, the capacity per facility is enough to service almost all demand points within the service area or almost all demand points within the service area are assigned to the facility within its boundary. The use of PP set of capacity results in the best average travelled distance in all of the three sets as depicted in Figure 6.2. This also means that the proposed capacity volume per facility was sufficient for the study area.

Table 6.5: Comparison of CPLEX and GA results for mCPMP (based on SP)

Facilities	**Capacity**	**Case I (*own service boundary*)**				**Case II (*whole study area*)**			
		CPLEX		**GA**		**CPLEX**		**GA**	
	Based on Staff Perception (PS)	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume
SD	8000	76	4459	43	4459	76	7838	45	7145
SL	4000	20	3963	21	3963	17	3917	18	3917
KM	14000	40	9224	57	8846	42	9005	61	9698
KB	4000	19	3970	20	3975	17	3927	17	3927
TPG	20000	24	8842	38	9215	27	5771	38	5771
TOTAL	50000	179	30458	179	30458	179	30458	179	30458
Total Distance Traveled			**46832**		**46843**		**49354**		**48030**
Average Traveled Distance (in km)			**1.54**		**1.54**		**1.62**		**1.58**

Table 6.6: Comparison of CPLEX and GA results for mCPMP (based on PP)

Facilities	Capacity	Case I (*own service boundary*)				Case II (*whole study area*)			
		CPLEX		GA		CPLEX		GA	
	Based on Proposed Policy(PP)	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume	No of nodes	Demand Volume
SD	6000	73	3888	41	4080	73	**7146**	40	5992
SL	6000	30	5996	31	5996	26	5993	27	5993
KM	6000	24	5881	43	5938	25	5080	42	5773
KB	6000	26	5477	26	5477	25	5775	27	5775
TPG	20000	26	9216	38	8967	30	6464	43	6925
TOTAL	44000	179	30458	179	30458	179	30458	179	30458
Total Distance Traveled			**45556**		**45583**		**47954**		**46991**
Average Traveled Distance (in km)			**1.49**		**1.50**		**1.57**		**1.54**

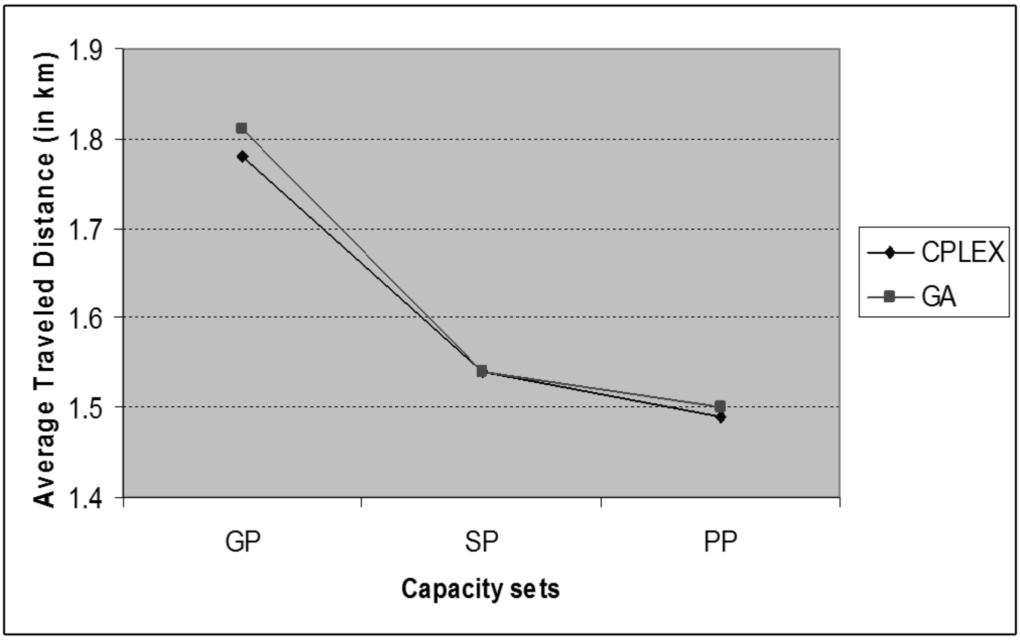

Figure 6.2: Trend of CPLEX and GA results for CPMP (based on the three capacity sets, GP, SP and PP) when demand is distributed uniformly within its own service boundary

6.5 RELATIVE PERFORMANCE TO CMCLP

The Malaysian health policy plan states the need to ensure full coverage for the total population which is the objective of MCLP to maximise the total population covered within some allowable distance, with fixed number of facilities. However, the objective of mCPMP can have a relative performance in ensuring that the maximum demand volume is assigned. It shows that by minimising the number of nodes uncovered and the travelled distance, it will result in higher population volume to be assigned.

In this section, the GA based heuristic is used to solve mCPMP and compared relatively to the performance of CMCLP. Two data are used, first is on the small network of 20 nodes (Haghani, 1996), and the second on a larger network of 809 nodes.

6.5.1 Initial Study on Data from Literature (20 nodes network)

The data of 20 nodes network from Haghani (1996) were used to measure the performance of the proposed mCPMP model. Based on the paper (Haghani, 1996), the number of facility to open was fixed to be 6 and there were four coverage distance values of *S* being tested which were 100, 125, 150 and 175. The capacity of the facility was also fixed to be at 140 for with a total capacity of 840 or 24.6 percent above the total demand of 674.

Using the mCPMP, the total volume assigned was maximised to 75.1 percent with the average travelled distance to be at 77.8. Additionally, only one node with demand volume 168 is unassigned. This is because it is bigger than the maximum capacity of the facility. The CMCLP results showed that the maximum value that could be assigned was only 408 or 60. 5 percent coverage when *S* was at the highest value of 175.

Table 6.7: Results of 20 nodes network

Model	Average travelled distance	No of facility to open	Volume assigned	Coverage percentage	Unassigned node
mCPMP	77.8	6	506	75.10	1
	Coverage distance, S	**No of facility to open**	**Volume assigned**	**Coverage percentage**	**Unassigned node**
CMCLP	100	6	370	54.90	11
	125	5	382	56.70	10
	150	5	382	56.70	10
	175	5	408	60.50	9

6.5.2 Case Study of Larger Data sets (809 nodes network)

In this case study, the mCPMP was solved by GA based heuristics on the larger study area, the 809 nodes of the district of Kuala Langat. The area is currently served by 27 facilities (refer to section 3.4.2 for detail profile).

Initially, the objective function of *p*-median Z_8 (4.7) was solved by GA and the results showed that with the current locations and all the 27 facilities were open, an 84.7 percent demand volume was assigned with the average travelled distance of 5.37 km. The balanced demand was unassigned.

Table 6.8 summarises the best results when the mCPMP, $\overline{Z}_8$ (equation 6.3) was used. The results showed that when all 27 facilities were open, 51 nodes or 6.3 percent of the nodes were unassigned due to the limited capacity. Consequently, 84.2 percent of the total population were assigned to the average travelled distance of 4.97 km or 1.97 km above the lower target level of 3 km and at par with the higher target level of 5km.

In contrast, for CMCLP when $S = 5\text{km}$, the best result was only 78.3 percent coverage with 238 nodes being unassigned (refer Table 5.12 and Table 6.8 for details). Table 6.8 also shows the number of nodes assigned to the facility between the MCLP and mCPMP. It shows that 7 facilities (shaded) had very large gaps of more than 900 nodes. Two facilities, 15 and 16 clearly complemented each other while the rest were simply restricted by the maximum allowable distance $S = 5\text{km}$.

Table 6.8: Comparison between CMCLP versus mCPMP for Kuala Langat

			CMCLP *S*=5km		**mCPMP**				
		Capacity	**Nodes assg**	**Vol assg**	**Nodes assg**	**Vol assg**	**% usage**	**Diff nod**	**Diff vol**
1	KK Telok Datok	20000	17	20000	22	19947	99.7	5	-53
2	KD Sg Kelambu	4000	34	3933	44	3951	98.8	10	18
3	KD Kg Sg Lang	4000	13	3966	17	3989	99.7	4	23
4	KD Telok Bunut	4000	9	3981	14	3972	99.3	5	-9
5	KK Tg Sepat	15000	13	6133	21	14964	99.8	8	8831
6	KD Tumbuk Darat	4000	21	3965	25	3973	99.3	4	8
7	KD Kundang	4000	22	2847	30	3960	99	8	1113
8	KD Batu Laut	4000	24	2830	26	3932	98.3	2	1102
9	KK Bandar	15000	38	14994	71	14966	99.8	33	-28
10	KD Sg Buaya	4000	6	3975	12	3990	99.8	6	15
11	KD Permatang Pasir	4000	14	3995	17	3964	99.1	3	-31
12	KKBukit Changgang	15000	38	14966	44	14961	99.7	6	-5
13	KD Labohan Dagang	4000	43	3991	57	3947	98.7	14	-44

Table 6.8 continued

14	KD Olak Lempit	4000	29	3965	30	3924	98.1	1	-41
15	KK Kanchong Darat	15000	25	14980	29	14074	93.8	4	**-906**
16	KD Kg Endah	4000	19	3011	21	3998	100	2	**987**
17	KD Kanchong Tengah	4000	25	2534	25	3925	98.1	0	1391
18	KD Kelanang	4000	33	3951	32	3922	98.1	-1	-29
19	KD Morib	4000	9	2720	18	3948	98.7	9	1228
20	KK Telok Panglima Garang	20000	21	19837	47	19992	100	26	155
21	KD Sijangkang Dalam	4000	7	3939	18	3948	98.7	11	9
22	KD Sijangkang Luar	4000	9	3978	7	3979	99.5	-2	1
23	KD Kampung Medan	4000	6	3897	6	3925	98.1	0	28
24	KD Kebun Baru	4000	18	3981	20	3994	99.9	2	13
25	KK Jenjarom	20000	17	19916	19	19997	100	2	81
26	KD Kg Jenjarom	4000	19	3905	21	3992	99.8	2	87
27	KD Sri Cheeding	4000	42	3986	65	3986	99.7	23	0
Total		200000	571	184176	758	198120	99.1	187	13944
Total Demand Volume Covered		235300		184176		198120			
Percentage Covered				78.3%		84.2%			
Total Distance Travelled						984970			
Average Travelled Distance (in km)						**4.97**			

6.6 CONCLUSIONS AND FURTHER RESEARCH

In this chapter, the average travelled distance was considered as a measure to service efficiency in locating the facility and a capacity of a facility was added as a constraint called capacitated *p*-median (CPMP). The GA based heuristic introduced in Chapter 5 was used to solve the CPMP. For comparison with the earlier solution method in the literature, the chromosome selection was restructured to be of length $(2m)$ where m was the total number of nodes since each demand node was a potential facility site. However, the objective function equation needed to be modified and become a mCPMP, so that the same chromosome representation could be used for comparison with the earlier methods from the literature. The objective function was modified to include the minimisation of the total number nodes uncovered.

The past location decision was analysed using the three set of capacities, GP, SP and PP. The PP set of capacity showed better results compared to the other two due to its basis that considered the density of the population within the service area. Church and Re Velle (1976) gave a historical perspective of the development of the two models and identified the theoretical links between them that MCLP was a *p*-median problem with maximum distance constraints. Yet, the input data needed to be pre-edited in order to make use of *p*-median solution to solve MCLP.

The performance of mCPMP was compared relatively to CMCLP using two sets of data, from the literature and on a large set of data. As expected, the mCPMP produced a higher demand volume being assigned with less average travelled distance compared to the maximum allowable distance value S. As the MOH policy stated the need for full coverage within the two maximum allowable distances (3 and 5 km), the mCPMP presented the optimal location allocation decision that could improve the coverage by 5.9 percent (84.2 versus 78.3) from the other model, CMCLP.

The analysis was necessary as no such study has been conducted on the Malaysian health delivery system to date. The case studies are hoped to be able to conjecture and provide the initial method to study the entire system. The study also enables the planner to make use of the model in case of limited capacity available in the system as most real life cases present. The study is further extended to combine the two measurements in a multi objective model which will be discussed in Chapter 7. Although the two have been closely related in producing the results, the optimal way of considering the two should be analysed. Chapter 7 will also input the extended model on the effect of time changes into the allocation of demand to the facilities. As the study also focuses on the study area, the other areas of a totally different profile should also be looked at and compared, in order to generalise the best model for the national planning policy.

CHAPTER 7

EXTENDED MODELS

7.1 INTRODUCTION

The location of the facilities providing public health service is very crucial in ensuring that the chosen location network serves the purpose of minimising social cost or equivalently maximising the benefits of the people. Similarly, the demand allocation to these facilities has a direct impact on the whole system's efficiency. This location-allocation model plays a significant role in health service planning, as it provides a framework for investigating accessibility problems, comparing the quality (in terms of efficiency) of previous location decisions, and providing alternative solutions to change and improve the existing system (Rahman and Smith, 1999). The problems have been formulated and solved as mathematical optimisation problems using different approaches due to the utilisation of different objective functions. The earlier chapters discussed the applications of the basic models and the analysis of the past location decisions. This chapter will look at the various modifications that can be made to improve the models.

Numerous extensions of the maximum covering location problem (MCLP) have been developed to address the facility location problem. However, in modelling the location of the public health service facility, a single criterion such as maximising the percentage of population covered within some maximum allowable distance to access a service facility is insufficient to address the interests of the decision maker. Other factors such as customer service and market demand as well as quantitative factors such as travelled distance and operating costs need to be appropriately weighted and addressed in the model.

A dynamic model is introduced where the time factor is included as a constraint. The dynamic model allows one to examine the effect of future growth in the current decision. In the field of the dynamic location, traditional assumptions of fixed demands and locations are challenged by considering continuously or periodically changing demand volumes or locations. Both the multi-objective and dynamic models will be solved using a genetic algorithm (GA) based heuristics introduced in Chapter 5.

In this chapter, the extensions of the location model are studied as in the multi objective and dynamic models. Section 7.2 discusses the multi-objective model followed by the dynamic model application in section 7.3. Section 7.4 summarises the findings from the study and highlights the future research potentials in both areas.

7.2 MULTI-OBJECTIVE MODEL

Many models that designed different procedures for the problem of selecting a facility site have been developed in the literature. It is an established fact that a number of different criteria are important in making location decisions regarding public facilities. Ross and Soland (1980) utilised a discrete model and considered objectives such as the average travel time, maximum travel time, the number of facilities, the total system cost and the utilisation of facilities. However, the paper considered only one criterion at a time, except through the use of constraints, and no consideration was given to tradeoffs among several criteria. Re Velle et al. (1977) discussed the multi-attribute aspects of the fire station location and cited coverage of fires, area, population, property value, property value hazard as the criteria to be maximised. Human endeavours generally have many objectives. These include profit or cost, quality of products or services, performance, safety, time (refer to items like target dates) and quantity. The choice of the criterion is fundamental to the design and manipulation of the model. The different objectives determine the value system by which the endeavour is conducted. Unfortunately, very few models in the literature have dealt with a multi-objective approach to solve a service facility location problem. In the context of locating the service facilities, decisions are inherently strategic and long term in nature (Daskin, 1995). As such, there are many possible conflicting or competing objectives that need to be addressed.

Multi-objective analysis has several advantages over single objective analysis. For example, for comparable quantity of measurements, it allows the various criteria to be evaluated in their natural units of measurements (e.g. variable cost per unit of demand). This eliminates the necessity of transforming the various objectives to a common unit of measurement such as dollars. In addition, such techniques present the decision maker with a set of non-inferior or non-dominated solutions. Another major advantage is that they provide a methodology to analyse the impact of strategic policy decisions. Such decisions frequently entail a reordering of the priorities on a firm's objectives (Winn and Keller, 2001).

In general, in multi-objective models, the objectives are in conflict. There is no one solution that exists that is optimal for all of the objectives. In such problems, the notion of optimality is replaced by that of non-dominance and non-inferiority. A non-inferior solution is one in which an improvement in any one objective will result in the degradation of at least one of the other objective's value. Therefore, multi-objective models are used to generate various non-inferior solutions to the problem rather than to identify a single optimal solution. Jayaraman (1999) proposed a multi-objective model which is a mixed integer (zero-one) problem. It is noted that in general the zero-one variables would not be very large; hence, most problem instances can be solved using the standard branch-and-bound techniques. The model was applied on a 30-nodes data from the literature and a sensitivity analysis on the number of facility to open and the coverage of demand was carried out. The results showed that the model could be useful to evaluate tradeoffs among the different objectives defined: (1) fixed investment cost, (2) variable operating cost, and (3) service attribute in terms of average response distance (or time). However, all the three items for consideration were similar in terms of optimisation direction of being minimised.

Pirkul and Schilling (1991) extended the CMCLP model where the objective was to maximise the coverage of population within some maximum allowable distance and to also simultaneously consider the service level of the uncovered demand. The authors presented two formulations. The first one was to consider only the covered demand being assigned to the capacitated-constrained facility. The second formulation was an extension of the first by including the assignment of the uncovered demands to its nearest facility. The two objectives were of contradicting direction where the first one was to maximise whilst the second one was to minimise. The authors proposed a greedy heuristic which was used to find good initial solutions for the Lagrangian relaxation procedure. It was found that the seeded Lagrangian relaxation yielded better results when compared to the un-seeded version. In their earlier paper, the authors (Pirkul and Schilling, 1988) wrote on the sitting of emergency service facilities with workload capacities and with backup services and later on the MCLP with capacities on total workload (1991). However, both of the papers (Pirkul and Schilling, 1988 and 1991) did not take into account the minimum utilisation that was required for each facility to open.

Haghani (1996) extended the model in Pirkul and Schilling (1991) to include the minimum utilisation levels of each facility. In Haghani's study, he developed two solution procedures based on an out-of-kilter network flow problem. The first one used a greedy adding heuristic and the second procedure formulated the CMCLP as a Lagrangian problem. Both were tested using various combinations of coverage distances and minimum and maximum utilisation levels for the located facilities. The results showed that the two heuristics provided good overall solutions on a 20 nodes network data, despite some combinations lack good convergence.

Recently, Hosseini and Ameli (2011) presented a bi-objective model for emergency services location-allocation problem on a tree network considering the maximum distance constraint. The first objective function called *centdian* was a weighted mean of a minisum, (which instead of minimising the average travelled distance, it considered the combination of the centre and the median values) and a minimax criterion and the second one was a maximal covering criterion (which minimised the penalty function considered for the customers who were unable to reach a facility within a predefined maximum distance). The penalty function was in terms of the distances between the demand nodes and their corresponding allocated emergency services. If an emergency service is too far from the demand node, it might not be able to provide service to the demand as it takes too much time to get there. For the solution of the bi-objective optimisation problem, the problem is split in two sub problems: the selection of the best set of locations, and a demand assignment problem to evaluate each selection of locations. The authors proposed a heuristic algorithm to characterise the efficient location point set on the network and some numerical examples were presented to illustrate the effectiveness of the proposed algorithm. The algorithm was solved by getting the Pareto optimal solutions using generation technique called e-constraint method. In the *e*-constraint method, one objective function is optimised and the other objectives are considered as constraints. The problem is tested on very small network of locating 2 new facilities in a tree network with 6 demand nodes.

GA based heuristic described in Chapter 5 is extended to solve a bi-objective model that maximise the percentage of population covered while simultaneously minimising the distance travelled by the uncovered population for a health service facility location problem. In this section the study is organised as follows: Section 7.2.1 details the mathematical formulation for the bi-objective model, followed by the literature on previous solutions and details of the GA based solution approach in Section 7.2.2. Section 7.2.3 illustrates the comparison of the GA based solution and the results of using Lagrange heuristics, followed by Section 7.2.4 on the case study of the real data. Section 7.2.5 describes some analysis on the choice of weights and section 7.2.6 states the conclusion and directions for future researches.

7.2.1 The Mathematical Formulation of Multi-objective Model

The formulation presented in this study involves two measurements for the service facility location problems. They include maximisation of the percentage of total population covered and minimisation of the total travelled distance for the uncovered nodes. All the notations introduced in the previous chapters will carry the same meaning in this chapter.

The single objective CMCLP is expressed as (5.1) with the rest of the constraints (5.2 to 5.5) for CMCLP in Section 5.2 which follows and is referred to as objective A. The second objective of minimising the total travelled distance of the *uncovered* nodes is formulated as (6.1) with the rest of the constraints (6.2 to 6.8) in Section 6.2 which follows and is referred to as objective B. Objective function A (through the use of the binary constant c_{ij}) maximises the population assigned to a facility within the coverage distance *S*, such that c_{ij} is equal to 1 if $d_{ij} \leq S$ and $N_i = \{j \mid d_{ij} \leq S\}$, whilst objective function B attempts to simultaneously minimise the distance of the uncovered nodes.

Appending (6.1) in (5.1), the full new multi-objective function can be expressed as follows:

Maximise $$Z_{10} = \underbrace{\alpha \sum_{i \in I} \sum_{j \in N_i} c_{ij} a_i x_{ij}}_{A} - \underbrace{\beta \sum_{i \in I} \sum_{j \notin N_i} a_i d_{ij} x_{ij}}_{B} \tag{7.1}$$

where α and β are the weights that can be varied to trade-off between maximising the coverage and improving the service to the uncovered nodes. As mentioned earlier, proper choice of α and β can always ensure that coverage maximisation becomes the primary objective.

In the earlier model, it is assumed that the demand at each node does not exceed the capacity of the facilities and the demand is assumed to be allocated to at most one facility only. However, the constraint (5.3) is modified as follows if one or more demand points exceeds the capacity constraint.

$$\sum_{j \in J} x_{ij} \leq 1 \qquad \forall \quad i \in I \tag{7.2}$$

The constraint (7.2) is to indicate that the demand at a node can be split into different available facilities in ensuring that the whole demand within the population is assigned to a facility in addition to the capacity and the distance constraints imposed. This is especially true if the demand points exceed the capacity of one or more facilities. Hence,

$$x_{ij} = [0,1] \qquad \forall \quad i \in I, j \in J \tag{7.3}$$

7.2.2 The Solution Method

In any multi-objective model with conflicting objectives as in this case, there exists no one solution that is optimal for both the objectives. Here, the notion of optimality is often replaced by that of non-dominance or non-inferiority. There are several methods for generating non-inferior solutions to multi-objective problems: the weighting method, the constraint method, the Non-Inferior Set Estimation (NISE) method and the multi-objective simplex algorithm (Cohon, 1978). The weighting method generates non-inferior solutions by varying the weight values in the objective functions whilst the constraint method identifies non-inferior solutions by optimising one of the original objectives subjected to the constraints on the values for the other objectives. Various non-inferior solutions are generated by varying the bounds on the other objectives. NISE, a variation of the weighting method, operates by finding a number of non-inferior extreme points and evaluating the properties of the line segments between them. It guarantees good coverage of the non-inferior set in manner that allows the accuracy of the approximation to be controlled. The multi-objective simplex algorithm is used to generate exact representation of the non-inferior set. This is done by moving from one non-inferior extreme point to the adjacent extreme points until all are determined.

The weighting method is employed in this study in which the first objective for the model is prioritised. The method is a good approach when the values of the assigned weight can be controlled and provide significant attribute to the solution technique (Cohon, 1978; Jayaraman, 1999). In Haghani's (1996) paper, the choice of weights was always to ensure that the coverage maximisation became the primary objective and in fact the threshold value of α can be determined for this purpose. The value of α is selected such that:

$$\alpha > A(d_{\max} - d_{\min}) \tag{7.4}$$

where $A = \sum_{i \in I} a_i$ is the total demand and $d_{\max}$ and $d_{\min}$ are the maximum and the minimum distances between any pair of demand nodes and facilities in the network respectively.

For the analysis in this section, the GA is referred to as mGA for the ease of reading.

7.2.3 Computational Results

The performance of the mGA was evaluated on a set of benchmark problems taken from Haghani (1996). It is to be noted that there has been no recent benchmark problems with the same parameter values available to date for comparison. The network consisted of 20 nodes and all the nodes in the network were considered to be candidates for the facility location as well as demand nodes. It is also noted that Haghani (1996) specified the minimum and maximum utilisation levels for each data set and formulated the CMLCP as a Lagrangian problem. As the algorithm was designed for maximum capacity, a comparison was made with the data sets that had zero minimum utilisation. For each coverage distance, three separate model runs were conducted which corresponded to the different combinations of maximum utilisation levels. The coverage distances and the maximum utilisation levels were tabulated in the first three columns of Table 7.1. The total demand for the network was 674 units. As some of the demand nodes may have exceeded the demand of the selected open facility, a split demand was allowed for by including constraints (7.2) and (7.3). The algorithms were run on a personal computer with 1.86 GHz processor and 2.49GB RAM.

These results were also compared to the GA representation proposed by Jaramillo et al. (2002) that encoded the number of facility to be opened. Table 7.1 tabulates the results for the Jaramillo representation (J_GA), the Lagrangian heuristics, Hyper LINDO (both taken from Haghani (1996)) and GA (mGA).

The first comparison was made between the mGA and the Lagrange method proposed by Haghani (third last column). The results were comparable with the lower bounds except on 4 sets of data. It is noted that the results given in the lower bound may not constitute a feasible solution because of the relaxation. The second last column provided a comparison with the solutions from LINDO. The results matched 11 out of the 12 data sets with the exception of one (*S*=150 and *Max Utilisation* =200). Better solutions obtained when compared to the optimal solutions from LINDO were given in bold letters. The last column compared the mGA with that of Jaramillo et al. (2002). The mGA performed better on 5 data sets (shaded), especially on those with higher tightness (with lower maximum allowable distance and smaller maximum utilisation).

It is interesting to observe from Table 7.2 that mGA also provided alternative best locations for some of the data sets (S=150, *Max Utilisation* = 160 and when S=175 and *Max Utilisation* =200).

Table 7.1: Comparison of the Typical Results among mGA, J_GA, Lagrangian Relaxation Heuristics (Haghani) and LINDO (based on objective function values)

S*	Utilisation Max	Min	mGA Result	J_GA Result	Lagrangian Solution LB	UB	LINDO Optimal solution	% gap between mGA & LB Lagrange	% gap between mGA & LINDO	% J_GA gap to mGA
100	120	0	302950230	302940249	302950410	379694769	302950400	0.00	0.00	-0.00329
	160	0	**329973812**	**329973812**	**329973812**	399915738	329973800	0.00	0.00	0.00000
	200	0	**334781428**	**334781428**	327578952	404400073	334781400	2.15	0.00	0.00000
125	120**	0	320349882	320346966	320346257	378367959	320349900	0.00	0.00	-0.00091
	160	0	347376253	347376253	347373845	399894589	347376300	0.00	0.00	0.00000
	200**	0	**352184001**	**352184001**	**352184001**	404401200	352184000	0.00	0.00	0.00000
150	120	0	346164655	346164165	337168101	378178381	346168200	2.60	0.00	-0.00014
	160	0	**370183343**	**370183343**	**370183343**	400303650	370183300	0.00	0.00	0.00000
	200**	0	377391822	374990387	380993147	404400024	390594500	-0.95	-3.50	-0.64040
175	120**	0	380990395	376186319	380990395	404400720	380990500	0.00	0.00	-1.27705
	160	0	**390594424**	**390594424**	383992910	404400024	**390594400**	1.69	0.00	0.00000
	200	0	**404400000**	**404400000**	**404400000**	404404200	**404400000**	0.00	0.00	0.00000

Note: 1. * is the maximal allowable distance for coverage
2. ** denotes the best results out of 10 runs while the remaining produce the same solutions for all the 10 runs

Table 7.2: Comparison of the Typical Results among mGA, J_GA, Lagrangian Relaxation Heuristics and LINDO (based on facility locations)

	Utilisation		mGA	J_GA	Lagrangian (Haghani)	LINDO
S*	Max	Min	**Locations**	**Locations**	**Locations**	**Locations**
100	120	0	2,3,5,10,13,15	2,3,5,10,13,15	2,3,5,10,13,15	2,3,5,10,13,15
	160	0	2,3,5,10,13,15	2,3,5,10,13,15	2,3,5,10,13,15	2,3,5,10,13,15
	200	0	2,3,5,10,13,15	2,3,5,10,13,15	2,3,5,10,13,16	2,3,5,10,13,15
125	120**	0	2,3,5,6,13,19	2,3,5,6,7, 13	2,3,5,6,13,15	2,3,5,6,13,19
	160	0	2,3,5,6,13,19	2,3,5,6,13, 19	2,3,5,6,13,15	2,3,5,6,13,19
	200**	0	2,3,5,6,13,15	2,3,5,6,13, 15	2,3,5,6,13,15	2,3,5,6,13,15
150	120	0	3,4,5,10,13,19	3, 4, 5,10 ,13,19	3,5,9,11,13,19	3,5,9,10,13,19
	160	0	3,4,5,10,13,19	2,4,5,10 ,13,19	2,4,5,10,13,19	3,4,5,10,13,19
	200**	0	3,5,10,13,16,20	3, 4,5,10, 13,19	3,5,10,12,13,19	3,5,10,12,13,19
175	120**	0	1,2,7,9,12,13	1, 2,10,12, 13,19	1,2,7,9,12,13	1,5,7,9,12,13
	160	0	2,4,8,12,13,19	2,3,10,12, 13,19	3,5,8,12,14,18	2,4,8,12,13,19
	200	0	2,4,10,12,18,19	2,4,8,13, 18,19	2,7,9,12,14,18	2,6,9,13,18,19

Note: 1. S* is the maximal allowable distance for coverage
2. ** denotes the best result out of 10 runs while the remaining produce the same solutions for all the 10 runs

7.2.4 Analysis of Weight

A simple analysis on varying the weight values (α and β) was done on the facility location data for a study area of the Kuala Langat district. The value of weight, α was taken to be 9,270,820 such that $\alpha = 235300 \times (39.4 - 0.0)$, the total demand volume was equals to 235300, the maximum demand value was 39.4 and the minimum demand value was 0. Four weight values were determined, using Haghani's (1996) equation (equation 7.4), two values were above 9,270,820 {10,000,000 and 9,300, 000} and two values were below 9,270,820 {9,000,000 and 600,000}. As the values of weight increased from the lowest value 600,000 to 10,000,000, the total distance travelled by the uncovered nodes also increased. This actually reflected the emphasis on maximising the total volume covered assigned. Figure 7.1 depicts the trend of the objective function values for the two objectives, in relation to each other.

Table 7.3: Sample Results of a Weighted Bi-objective Model when S=5km

W	Total volume covered	Percentage covered	Total distance travelled (in km)	Close facility	Time (in sec)
9300000	215148	91.4%	276225	4,8,17,22,**24**,27,28,30,32	514.5
10000000	215495	91.6%	333899	3,6,8,17,**24**,26,27,28,32	495.5
1	172000	73.1%	0	-	535.9
9000000	215917	91.8%	412239	2,3,6,7,19,21,26,32,36	499.0
600000	214427	91.1%	301536	2,4,7,14,19,21,23,**24**,34	543.8

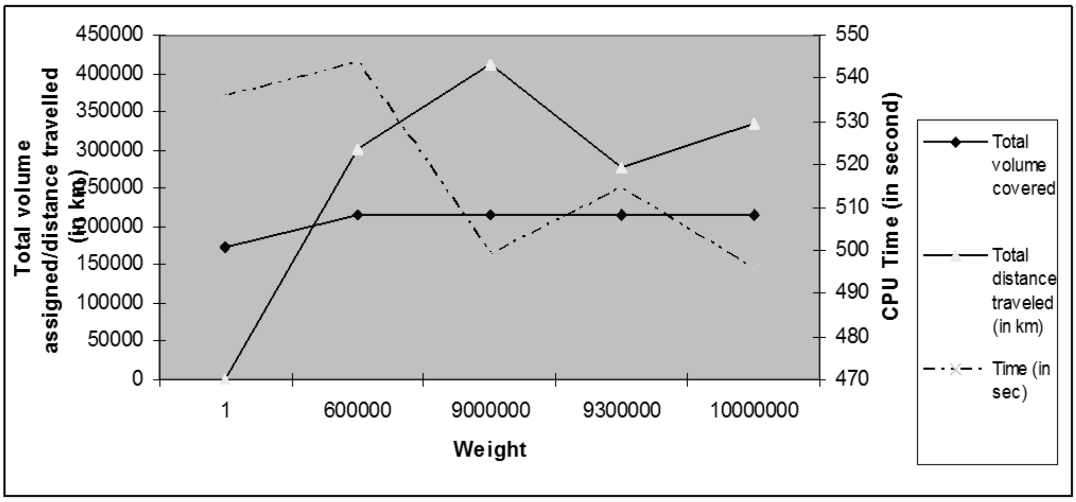

Figure 7.1: Trend of Objective Function Values for a bi-objective model (when S=5km)

Note that the two objective functions used different measurements units; thus the proper values of weights must be carefully selected so that one objective did not dominate the other. In order for both objectives to be fairly weighted, the normalisation of the objective values could be done. Two methods are usually well known for rescaling data. *Normalisation* scales all the numeric variables in the range [0,1]. One possible formula is given as $x_{new} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$. Another method is a standardisation on data set which will transform the data to have zero mean and unit variance, using the equation $x_{new} = \frac{x - \mu}{\sigma}$. However, these techniques have their drawbacks and cannot be applied to these data as normalising them will certainly scale the data to a very small interval.

In this study, an alternative measurement of weight was used, the inverse distance weight (IDW) which allowed the control over the degree of prioritisation of the objectives. To calculate the weight values, the following fact was noted. If it was at its lowest level, the distance travelled by the uncovered was considered to be weighted more, so that it would lead to higher coverage. The number of facilities open was fixed as 27 with the assignment of demand volume was left to the facilities to be randomised; and both the total demand covered and the total distance travelled for the uncovered nodes were calculated. The programme was run for both the *S* values, 3 and 5 km for 100 and 1000 times. The weight value was calculated by taking the summation of the inverse value of the total distance travelled by the uncovered customers (Bartier and Keller, 1996). When *S* equalled to 3 km, the 100 iteration gave weight values to be 2.144×10^{-6}, and for 1000 iterations, the value decreased to 1.56×10^{-6}. When *S* equalled to 5 km, both 100 and 1000 iterations gave the same value of 2.21×10^{-6}. The weight from 1000 iterations was applied to test on the 809 nodes network again. This was because based to the limited experiments the weight value stabilised after 1000 iterations for both the *S* values.

The weight α, assigned to the first objective or the maximum coverage was 0.999998, while the weight β, assigned to the second objective was 0.000002. The two values were tested on the data and as suggested by the analysis of the weight above, the results were basically the same. Further sensitivity analysis on the weight values were done by varying the values of α and β. The results showed that as long as α was greater than β, the first objective will reach its maximum. Figure 7.2 depicts these results.

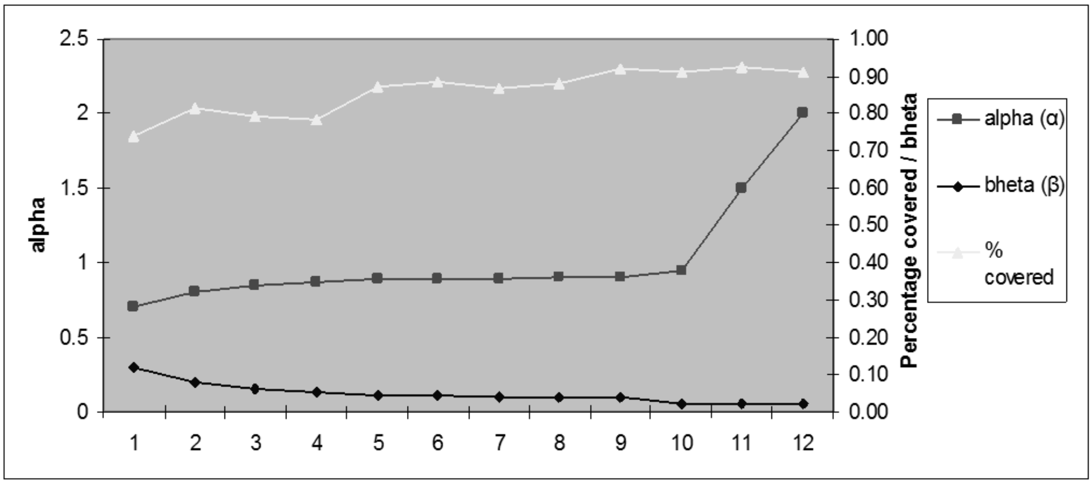

Figure 7.2: Trend of Parameter Values for a bi-objective model (when *S*=5km)

7.2.5 Conclusion and Direction for Future Research

This section presented a multi objective model for locating the healthcare facility. The model was formulated such that it maximised the total volume assigned within some maximum allowable distance while at the same time minimised the total travelled distance from the uncovered (not within the allowable distance) demands to the located facilities. A GA based heuristics was used to solve the model and compared to the previous solution. The choice of weights ensured that the maximisation of coverage became a priority. The mGA was found to be able to produce superior results in almost all of the test problems taken from the literature.

7.3 DYNAMIC MODEL

One of the key successes in modelling a location model is when the model can be replicated and used in the planning of the real world application. The model must be able to accommodate the necessities of the real world situation and be robust to the changes. As the future is hard to predict the future conditions under which the facilities will operate, thus it is important that the model is dynamic and will account for future uncertainty explicitly and that it identifies solutions that are robust with respect to this uncertainty (Current et al., 2002).

7.3.1 Introduction to Dynamic Modelling

As mentioned in the earlier chapters, the *p*-median problem is one of the most widely used location models. The model solves the problem when several facilities p are to be located in an area to satisfy demand. However, let's say the interest is in finding the best location for *p* new facilities when some existing facilities are already located in the area so that the addition will ensure that the whole demand population is covered. The dynamic *p*-median problem is applicable to all situations modelled by the standard *p*-median problem whenever demand changes overtime in a predictable way. The construction of hospitals, schools, public parking lots, stores, restaurants and other facilities in a growing area is typical for such applications when the objective is to minimise the total transportation cost over the time horizon.

The dynamic facility location problem was first introduced in 1973 by Wesolowsky. The author extended the status single facility location problem to a model that permitted location changes within a planning horizon of *r* periods. The developed algorithm optimised the sequence of locations in order to meet changes in costs, volumes and locations of destinations. Wesolowsky and Truscott (1975) considered the problem when the weights varied that is their effects were not continuous. Using dynamic programming, the procedure decided whether or not to locate the facility in a predetermined location at the end of each period. In Drezner and Wesolowsky (1991) the issue of finding the best locations for several facilities was investigated. The facilities could be relocated at a specified number of times during the planning horizon. The best times to relocate the facilities and their best locations were found.

Drezner (1995a) presented a so-called progressive *p*-median model to determine the location of each facility (as each facility is located at a pre-specified time) such that the total cost (distance) is minimised. Wey (2003) applied a model of progressive *p*-median on the parking facility location problem with time dependent demand. In the study, the parking demand predicted in the model changed over a given time horizon. The parking facilities were built one at given times. Once a new facility is built, some of the drivers (customers) will use its services and some of them will patronise an existing facility. At any given time, drivers patronise the closest parking facility under enough facility. The problem is then to find the best parking facility location for the new facilities. The demand for parking facility is found using a regression model in the form of a function of time. The problem is solved using a standard mathematical programming code AMPL (A Modelling Language for Mathematical Programming).

Any practical problem that is modelled by *p*-median formulation can be modelled by the progressive *p*-median if some of the facilities already exist in the area. Current et al. (1998) suggested the problem where several facilities needed to be located immediately and several additional facilities would be located during the time horizon. The question of the best location for the limited number of facilities to be located was investigated in this research.

In the conditional *p*-median problem, *p* new facilities needed to be added in an area where some facilities had already existed. Berman and Simchi-Levi (1990) suggested to solve the conditional *p*-median and *p*-centre problems on a network by an algorithm that required one-time solution of an unconditional (*p*+1) median or (*p*+1) centre problem. Drezner (1995b) solved the problem of finding for the best location for *p* new facilities when some existing facilities were already located in the area. The demand can be satisfied either by a new or by an existing one, whichever is closer as the objective is to minimise the distance. Berman and Drezner (2008) proposed a new formulation on the conditional *p*-median and *p*-centre and solved both problems by defining a modified shortest distance matrix. The procedure was solved using CPLEX.

Combining the progressive and the conditional ideas, in this study of locating the public healthcare facility problem, the coverage of the population was considered to be the objective. As the population or demand volume in the study area increased over the time horizon, the problem was to locate an existing facility with the potential to be upgraded and or to locate an additional new facility within a pre-specified time such that the coverage is maximised. The problem will be referred to as the dynamic conditional CMCLP. The same assumptions in the previous studies on conditional and progressive *p*-median were adopted in this model formulation. It is assumed that the demand at each demand point may be time dependent with a given functional relationship over the time-horizon. Several facilities needed to be located over the time horizon.

The time when each individual facility was constructed was given for each new facility. No relocation of facilities was allowed. This was a reasonable assumption when the relocation cost for health facilities was relatively high.

7.3.2 Dynamic Conditional Mathematical Formulation

The formulation of the dynamic CMCLP firstly, employed the idea of the conditional *p*-median (for un-capacitated facility). The conditional location problem was to locate *p* new facilities to serve a set of demand points given that *q* facilities were already located. When *q*=0, the problem was unconditional. In the conditional *p*-median problem, once the new *p* locations were determined, a demand can be served either by one of the new facilities or whichever was the closest facility to the demand. Hence, this model will locate the *p* new facilities to serve the demand points given that *q* facilities already exist such that the percentage of the demand volume covered within the maximum allowable distance *S* was maximised.

Suppose that there is a set $Q(|Q|=q)$ of existing facilities. Let $y=(y_1,....y_q)$ and $\hat{y}=(\hat{y}_1,.......\hat{y}_p)$ be the vectors of size *q* and *p* respectively, where y_j is the location of existing facility j and $\hat{y}_j$ is the location of the new facility j . The followings are defined as:

I is the total number of demand nodes

J is the total number of facility sites

T is the total planning horizon such that facility j is to be located at time t_j for $j=1,2\ldots p,$ and $0\le t_1\le t_2\le ....\le t_p\le T$

d_{ijt} is distance from demand node i to facility site j in period t

S is the maximum allowable distance

a_{it} is the demand volume at node i in period t

p is the total number of new facilities

q is the total number of existing facilities

K_j is the capacity of facility site j

$N_i = \{j \mid d_{ijt} \le S\}$ and $d(y_{jt}, i)$ represent the distance between the demand node i to an existing facility at j in period t, while $d(\hat{y}_{jt}, i)$ represents the distance between demand node i to a new facility at j in period t.

$$x_{ijt} = \begin{cases} 1, & \text{if demand node } i \text{ is assigned to an existing or new facility at} \\ & \text{site } j \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

$$y_{jt} = \begin{cases} 1, & \text{when an existing facility sited at } j \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

$$\hat{y}_{jt} = \begin{cases} 1, & \text{if a new facility sited at } j \text{ in period } t \\ 0, & \text{otherwise} \end{cases}$$

The objective function is

$$\text{Maximize} \quad Z_{11} = \alpha \sum_{i \in I} \sum_{j \in N_i} a_{it} x_{ijt} - \beta \sum_{i \in I} \sum_{j \notin N_i} a_{it} \min\{d(y_{jt}, i), d(\hat{y}_{jt}, i)\} \tag{7.5}$$

Subject to:

$$\sum_{j \in J} x_{ijt} = 1 \qquad \forall i \in I; \forall t \in T \tag{7.6}$$

$$y_{jt} = 1 \qquad \forall t \in T \text{, for all existing facilities} \tag{7.7}$$

$$y_{j,t+k} \ge y_{jt} \qquad t = 1..T-1; k = 1,...(T-t), \forall j \in J \tag{7.8}$$

$$\sum_{t \in T} \sum_{j \in J} y_{jt} = q \tag{7.9}$$

$$\hat{y}_{jt} = 1 \qquad \forall t > t_p \tag{7.10}$$

$$\sum_{t\in T}\sum_{j\in J}\hat{y}_{jt} \le p \tag{7.11}$$

$$\sum_{i\in I} a_{it} x_{ijt} \le (y_{jt} + \hat{y}_{jt}) K_j \qquad \forall j \in J; \forall t \in T \tag{7.12}$$

$$x_{ijt} \in \{0,1\} \qquad \forall i \in I, j \in J, t \in T \tag{7.13}$$

$$y_{jt}, \hat{y}_{jt} \in \{0,1\} \qquad \forall j \in J, t \in T \tag{7.14}$$

The objective function (7.5) is to maximise the assignment of the total demand volume within the coverage distance *S* subject to available capacities, by both new and existing facilities, whilst simultaneously minimises the total travelled distance by the uncovered volume. Constraint (7.6) states that each demand node is assigned to only one facility, either the new or the existing facility in period *t*. Constraints (7.7) and (7.10) also state that each demand must be assigned to open facility, existing or new. Constraint (7.8) restricts that the existing facility will remain open, over the planning horizon *T*. Constraint (7.9) states that the total number of existing facilities equals to *q* over the planning horizon period *T*, whilst Constraint (7.11) states that the total number of new facilities to be located is to be no more than *p*. Constraint (7.12) enforces the capacity on the opened facilities with the assumption that the capacity is constant throughout the planning horizon period *T*. Constraints (7.13) and (7.14) are standard integrality constraints.

In this model it is considered that the maximum capacity of a facility $K_j, \forall j = 1, 2, ... J$, remains constant during the planning horizon. It is also possible to consider that this maximum capacity can change over the planning horizon. In this case, capacities $\hat{K}_j$ should be considered.

7.3.3 A Case Study on District of Kuala Langat

In this section, the formulation given in Section 7.3.2 will be employed to improve the performance of delivering the healthcare services in this study area, the District of Kuala Langat. Based on the analysis given in Section 5.6.1, the existing capacities were viewed to not being able to cater for the growing demand volume. Table 7.4 shows that some of the facilities were currently either operating way above or below (given in bold) their capacity limit.

The model will assist to determine the best location with the right capacity for the new facility or to upgrade the existing facility that will ensure the full coverage for the growing demand volume. It is assumed that new facilities are added to the area in given future points in time. The planning horizon is set to be segregated into a 5-year period for the duration of 15 years, following the government guideline which carries out the review in every five years.

The existing facilities provide the services for 7 regions. The growth rates for these regions $a_i, i = 1,.....7$ are changing in time. The function (given as equation 7.15) of the growth demand rates in time is an exponentially growing demand (adapted from Department of Statistics Malaysia, 2009) as shown in subsection 7.3.4.

Table 7.4: Healthcare Profile of Kuala Langat Showing the Percentage of Capacity Usage (in 2007)

Facilities	Facility Number	Total Population	Capacity	% Usage
KK Telok Datok	**1**	**28279**	**20000**	**141.4**
KD Sg Kelambu	2	1719	4000	43.0
KD Kg Sg Lang	3	3437	4000	85.9
KD Telok Bunut	**4**	**5625**	**4000**	**140.6**
KK Tg Sepat	5	7408	15000	49.4
KD Tumbuk Darat	6	1988	4000	49.7
KD Kundang	7	2733	4000	68.3
KD Batu Laut	8	3401	4000	85.0
KK Bandar	9	11660	15000	77.7
KD Sg Buaya	**10**	**4560**	**4000**	**114.0**
KD Permatang Pasir	11	3780	4000	94.5
KKBukit Changgang	12	13092	15000	87.3
KD Labohan Dagang	**13**	**6294**	**4000**	**157.4**
KD Olak Lempit	**14**	**5791**	**4000**	**144.8**
KK Kanchong Darat	15	13862	15000	92.4
KD Kg Endah	16	2582	4000	64.6
KD Kanchong Tengah	17	2108	4000	52.7
KD Kelanang	18	3954	4000	98.9
KD Morib	19	3848	4000	96.2
KK Telok Panglima Garang	**20**	**25509**	**20000**	**127.5**
KD Sijangkang Dalam	**21**	**6616**	**4000**	**165.4**
KD Sijangkang Luar	**22**	**13536**	**4000**	**338.4**
KD Kampung Medan	**23**	**14323**	**4000**	**358.1**
KD Kebun Baru	**24**	**12723**	**4000**	**318.1**
KK Jenjarom	**25**	**27135**	**20000**	**135.7**
KD Kg Jenjarom	**26**	**5325**	**4000**	**133.1**
KD Sri Cheeding	**27**	**4012**	**4000**	**100.3**
Total		**235300**	**200000**	**117.7**

7.3.3.1 Analysis on Existing Facilities

GA is used to analyse the existing performance of the public health service delivery of the 809 nodes network, in the Kuala Langat district. It is noted that due to the large data sets, GA did not converge to the same value in every run, as observed in many meta-heuristics. The algorithm was run for 10 times and the percentage of the total demand volume covered was on the average of 69.7 percent when *S* was 3km, while when *S* was 5km the percentage covered was on the average of 77.8 percent. The standard deviation was 0.6 and 0.3 respectively, which was relatively small.

Further analysis of the uncovered nodes (373 nodes for *S* was 3km and 238 nodes for *S* was 5km) showed that some of them were located in less populated areas such as tea farms (ladang teh), forest reserves (hutan rizab) and aboriginal villages (perkampungan orang asli), due to the close distance of these locations to the existing health facilities. It is worth noting that these areas were currently served by mobile clinics which visited on a weekly basis from two nearby health clinics, KK Jenjarom (No. 25) and KK TPG (No. 20). There were also some uncovered nodes in highly populated areas, which were unassigned due to the limited capacity.

7.3.4 Analysis on Projected Volume

The analysis on the existing facilities in Section 5.2 which was also mentioned in Section 7.3.3.1 showed that the best coverage that could be achieved was only 78.3 percent when the maximum allowable distance *S* equals to 5 km. This was very low compared to the targeted full coverage set by MOH. The study was extended to identify the best locations and the best capacities that may improve the percentage of coverage in the next 10 to 15 years. This is achieved through the projected population growth model currently adopted by the Department of Statistics Malaysia (2009) which is responsible for carrying out the population census in Malaysia. The population volume for 2010 and beyond is projected based on the 2007 population data obtained from Housing Census Malaysia. The main model used is the Exponential Growth Rate Model which gives the population volume in year $t+n$ as:

$$P_{t+n} = P_t e^{rn} \text{ (when } P_t > 0) \qquad (7.15)$$

where

P_t is population for year t

r is the growth rate where $r = [\ln(X_{2000} / X_{1991})]/9$, for the growth in 9 years between year 1991 and 2000

X_{2000} is the population or total households in year 2000

n is number of years

The population growth rate for each district council administration area (Mukim) under the district of Kuala Langat is summarized in Table 7.5 (Department of Statistics Malaysia 2009).

Table 7.5: Population Growth Rate based on District Council Administration Area

Service areas	Population Volume	Area (hectares)	Population Density (person/hectares)	Growth Rate
Mukim Bandar	12371	3876	3.2	0.92
Mukim Jugra	8786	18495	0.5	1.39
Mukim Tanjung Dua belas	96540	33612	2.9	1.39
Mukim Batu	24692	12143	2	1.05
Mukim Morib	5214	2470	2.1	1.24
Mukim Kelanang	20078	7108	2.8	1.04
Mukim Telok Panglima Garang	76462	8071	9.5	2.58

It is noted that the total population volume for 2008 and 2009 was based on the real data provided by the Housing Census Malaysia while for the subsequent years starting from 2010 to 2020 it was projected data based on the model given. The coverage percentage based on the existing facilities was evaluated for all the years and the trend is highlighted in the Figures 7.3 and 7.4. It was observed that the percentage of coverage decreased the most (at 1.4 percent) from the year 2018 to 2019 for *S* was 3km and from the year 2016 to 2017 for *S* was 5km. This means that in the year 2020 the coverage percentage when *S* was 3km will only be 60.9 percent and 64.7 percent when *S* is 5km. The analysis showed that in order to improve the coverage percentage, there is a need for upgrading of the existing facilities and/or introduction of new locations.

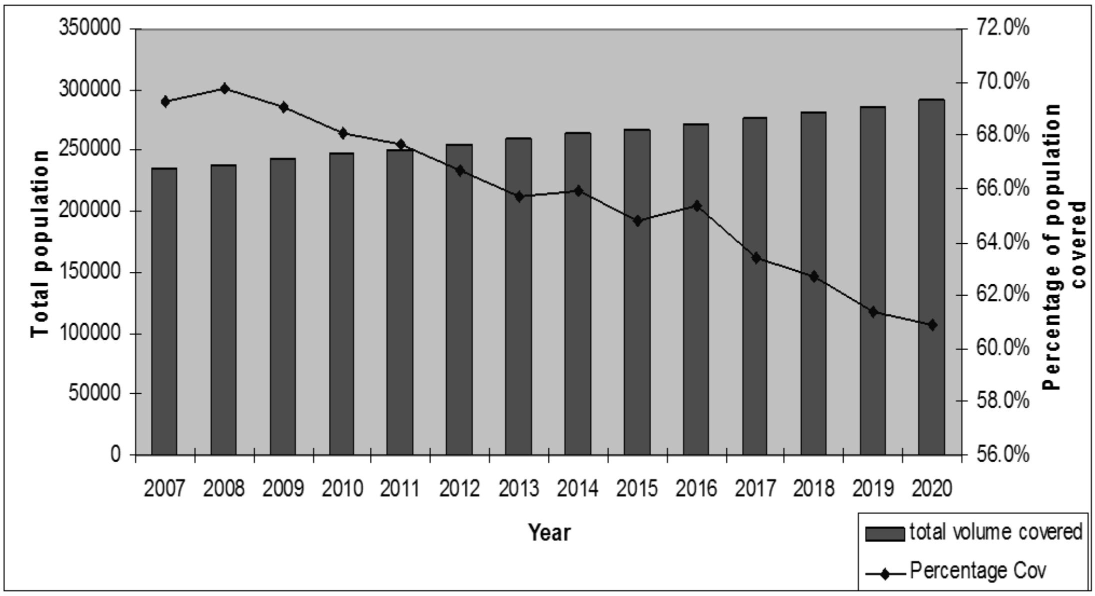

Figure 7.3: Trend in Population Growth and Coverage Percentage (when S=3km)

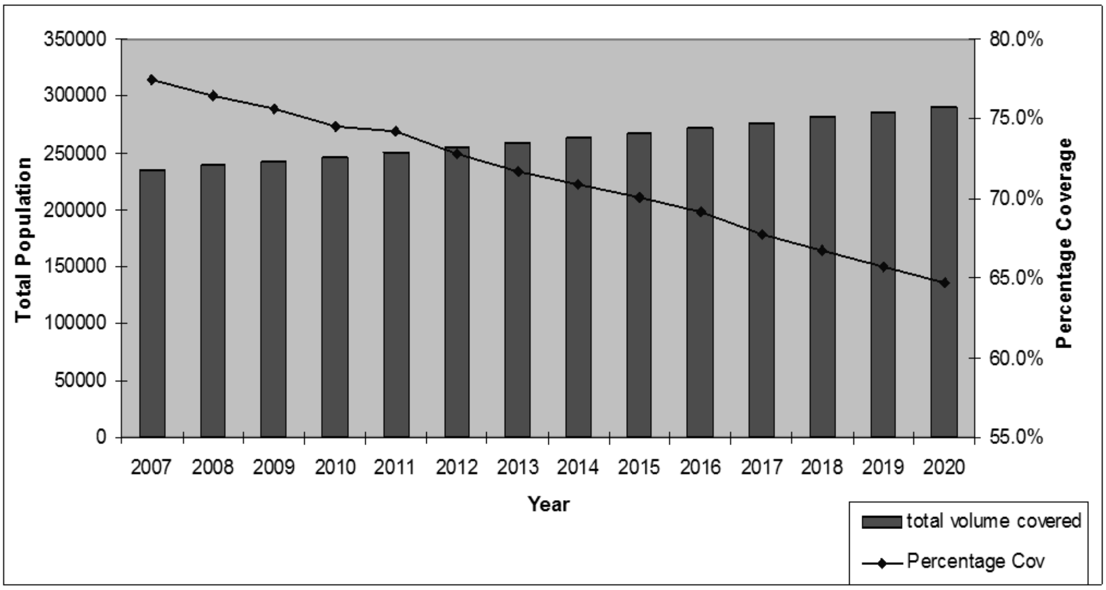

Figure 7.4: Trend in Population Growth and Coverage Percentage (when S=5km)

7.3.4.1 Selection of Upgrading the Existing Facilities and Locating New Facility Sites

In this study two ways of improving the existing coverage were considered: upgrading the existing facilities and the introduction of new facility sites, chosen based on the detail projection of demand volume by nodes. Each projected demand volume by nodes will be totalled to make up the total projected volume by service facility area. This projected demand volume by service facility area will then be compared to the existing capacity of the respective facility. If the projected demand volume is more than 50 percent higher than the capacity, the facility is chosen to be upgraded to the next level. The 50 percent cut off point is chosen because of the potential increase of the capacity volume once upgraded. If it is only above the capacity by 20 percent, the upgrading will end up with too much available capacity which is not encouraged as well. The upgrading will be following some realistic rule. Say, if it is an RC of 4000, it will be upgraded to an HC of minimum capacity 15000 (an increase by 375 percent). If it is an HC of capacity 15000, it will be upgraded to an HC of capacity 20000 (an increase by 33 percent). If it is already an HC of maximum capacity 20000, a new RC of size 4000 will be located (an additional capacity of 20 percent).

The following table, Table 7.6 describes the process of selecting the facilities to be upgraded and the identification of the new potential facility sites. The analysis is segregated into 5-year planning periods.

Table 7.6.1: Total Population Volume Forecast Based on Growth Rate (first 5 years 2007-2012)

	Fac No	Growth Rate per fac	Total Population Volume 2007	2008	2009	2010	2011	2012	*X	Proposed New capacity
KK Telok Datok	1	1.39	28279	28675	29076	29483	29896	30314	**1.5**	20000
KD Sg Kelambu	2	1.39	1719	1743	1767	1792	1817	1842	0.5	4000
KD Kg Sg Lang	3	1.39	3437	3485	3534	3583	3633	3684	0.9	4000
KD Telok Bunut	4	1.39	5625	5704	5784	5865	5947	6030	**1.5**	4000
KK Tg Sepat	5	1.05	7408	7486	7565	7645	7726	7808	0.5	15000
KD Tumbuk Darat	6	1.05	1988	2009	2030	2051	2073	2095	0.5	4000
KD Kundang	7	1.05	2733	2762	2791	2820	2850	2880	0.7	4000
KD Batu Laut	8	1.05	3401	3437	3473	3510	3547	3584	0.9	4000
KK Bandar	9	0.92	11660	11768	11877	11987	12098	12210	0.8	15000
KD Sg Buaya	10	0.92	4560	4602	4645	4688	4731	4775	**1.2**	4000
KD Permatang Pasir	11	0.92	3780	3815	3850	3886	3922	3958	1	4000
KKBukit Changgang	12	1.39	13092	13275	13461	13649	13840	14034	0.9	15000
KD Labohan Dagang	13	1.39	6294	6382	6471	6562	6654	6747	**1.7**	15000
KD Olak Lempit	14	1.39	5791	5872	5954	6037	6122	6208	**1.5**	15000
KK Kanchong Darat	15	1.24	13862	14035	14210	14387	14567	14749	1	15000
KD Kg Endah	16	1.24	2582	2614	2647	2680	2713	2747	0.7	4000
KD Kanchong Tengah	17	1.04	2108	2130	2152	2174	2197	2220	0.6	4000
KD Kelanang	18	1.04	3954	3995	4037	4079	4122	4165	**1**	4000
KD Morib	19	1.24	3848	3896	3945	3994	4044	4094	**1**	4000
KK Telok Panglima Garang	20	2.58	25509	26176	26860	27562	28282	29021	**1.4**	20000
KD Sijangkang Dalam	21	2.58	6616	6789	6966	7148	7335	7527	**1.8**	15000
KD Sijangkang Luar	22	2.58	13536	13890	14253	14626	15008	15400	**3.8**	20000
KD Kampung Medan	23	2.58	14323	14697	15081	15475	15879	16294	**4**	20000
KD Kebun Baru	24	2.58	12723	13056	13397	13747	14106	14475	**3.5**	20000
KK Jenjarom	25	1.39	27135	27515	27900	28291	28687	29089	**1.4**	20000
KD Kg Jenjarom	26	1.39	5325	5400	5476	5553	5631	5710	**1.4**	4000
KD Sri Cheeding	27	1.39	4012	4068	4125	4183	4242	4301	**1.1**	4000
Total		**39.56**	**235300**	**239276**	**243327**	**247457**	**251669**	**255961**		**281000**
Ratio to total demand volume in 2012										1.098

Note: X* is the ratio of population to the capacity of the facility after 5 years

Table 7.6.1 shows that in 5 years time, in 2012, the total population volume would increase by more than 8 percent to 255961. If the current capacity is not increased, the percentage of coverage for the healthcare delivery will decrease tremendously to less than 75 percent (refer to Figure 7.3 for maximum allowable travelled distance *S* equals to 5 km). Hence, based on the analysis in Table 7.6.1, the following facilities (shaded) are proposed to be upgraded:

- KD Labohan Dagang, KD Olak Lempit and KD Sijangkang Dalam to be upgraded from an RC of capacity 4000 to a HC of capacity 15000.
- KD Sijangkang Luar, KD Kampung Medan and KD Kebun Baru to be upgraded from an RC of capacity 4000 to a HC of capacity 20000. This is because the three facilities serve more than 300 percent of its capacity.

From Table 7.6.2, after 10 years, in 2017, the analysis shows that on top of the upgraded capacities in the first 5 years, the following facility (shaded) needs to be upgraded as such:

- KD Telok Bunut to be upgraded from an RC of capacity 4000 to a HC of capacity 15000.

At the same time, the new facilities need to be located around the following sites:

- KK Telok Datok and KK Telok Panglima Garang, a new HC of capacity 15000
- KK Jenjarom and KD Kg Jenjarom, a new RC of capacity 4000.

This is because at the respective locations of facilities, the capacity is already at its maximum.

Table 7.6.2 (cont'd): Total Population Volume Forecast Based on Growth Rate (second 5 years 2013-2017)

Facilities	Fac No	Total Population Volume 2013	2014	2015	2016	2017	Ratio After 10 years	Proposed New Capacity
KK Telok Datok	1	30738	31168	31604	32046	32495	**1.6**	35000
KD Sg Kelambu	2	1868	1894	1921	1948	1975	0.5	4000
KD Kg Sg Lang	3	3736	3788	3841	3895	3950	1.0	4000
KD Telok Bunut	4	6114	6200	6287	6375	6464	**1.6**	15000
KK Tg Sepat	5	7890	7973	8057	8142	8228	0.6	15000
KD Tumbuk Darat	6	2117	2139	2162	2185	2208	0.6	4000
KD Kundang	7	2910	2941	2972	3003	3035	0.8	4000
KD Batu Laut	8	3622	3660	3699	3738	3777	0.9	4000
KK Bandar	9	12323	12437	12552	12668	12785	0.9	15000
KD Sg Buaya	10	4819	4864	4909	4954	5000	**1.3**	4000
KD Permatang Pasir	11	3995	4032	4069	4107	4145	**1.0**	4000
KKBukit Changgang	12	14230	14429	14631	14836	15044	**1.0**	15000
KD Labohan Dagang	13	6841	6937	7034	7132	7232	0.5	15000
KD Olak Lempit	14	6295	6383	6472	6563	6655	0.4	15000
KK Kanchong Darat	15	14933	15119	15308	15499	15692	**1.1**	15000
KD Kg Endah	16	2781	2816	2851	2887	2923	0.7	4000
KD Kanchong Tengah	17	2243	2266	2290	2314	2338	0.6	4000
KD Kelanang	18	4209	4253	4297	4342	4387	**1.1**	4000
KD Morib	19	4145	4197	4249	4302	4356	**1.1**	4000
KK Telok Panglima Garang	20	29779	30557	31356	32176	33017	**1.7**	35000
KD Sijangkang Dalam	21	7724	7926	8133	8346	8564	0.6	15000
KD Sijangkang Luar	22	15802	16215	16639	17074	17520	0.9	20000
KD Kampung Medan	23	16720	17157	17605	18065	18537	0.9	20000
KD Kebun Baru	24	14853	15241	15639	16048	16467	0.8	20000
KK Jenjarom	25	29496	29909	30328	30753	31183	**1.6**	24000
KD Kg Jenjarom	26	5790	5871	5953	6036	6120	**1.5**	8000
KD Sri Cheeding	27	4361	4422	4484	4547	4611	**1.2**	4000
Total		**260334**	**264794**	**269342**	**273981**	**278708**		**330000**
Ratio to the total demand volume (2017)								**1.184**

upgraded	new

Based on the analysis in Table 7.6.3, after 15 years, in 2022, it shows that the upgraded and additional capacities can still accommodate the population growth, at the end of the planning horizon of 15 years that is at the end of 2022.

Table 7.6.3 (cont'): Total Population Volume Forecast Based on Growth Rate (third 5 years 2018-2022)

Facilities	Fac No	Total Population Volume 2018	2019	2020	2021	2022	Ratio After 15 years	Proposed New Capacity	Total Population (2023)	Demand O/flow in 2023
KK Telok Datok	1	32950	33411	33879	34353	34834	**1.00**	35000	35322	1.01
KD Sg Kelambu	2	2003	2031	2059	2088	2117	0.53	4000	2147	0.54
KD Kg Sg Lang	3	4005	4061	4118	4176	4234	**1.06**	4000	4293	1.07
KD Telok Bunut	4	6554	6646	6739	6833	6929	0.46	15000	7026	0.47
KK Tg Sepat	5	8315	8403	8492	8582	8673	0.58	15000	8765	0.58
KD Tumbuk Darat	6	2231	2255	2279	2303	2327	0.58	4000	2352	0.59
KD Kundang	7	3067	3099	3132	3165	3198	0.80	4000	3232	0.81
KD Batu Laut	8	3817	3857	3898	3939	3981	**1.00**	4000	4023	1.01
KK Bandar	9	12903	13022	13142	13263	13386	0.89	15000	13510	0.90
KD Sg Buaya	10	5046	5093	5140	5188	5236	**1.31**	4000	5284	1.32
KD Permatang Pasir	11	4183	4222	4261	4300	4340	**1.09**	4000	4380	1.10
KKBukit Changgang	12	15255	15469	15686	15906	16129	**1.08**	15000	16355	1.09
KD Labohan Dagang	13	7333	7436	7540	7646	7753	0.52	15000	7862	0.52
KD Olak Lempit	14	6748	6842	6938	7035	7133	0.48	15000	7233	0.48
KK Kanchong Darat	15	15888	16086	16287	16490	16696	**1.11**	15000	16904	1.13
KD Kg Endah	16	2959	2996	3033	3071	3109	0.78	4000	3148	0.79
KD Kanchong Tengah	17	2362	2387	2412	2437	2462	0.62	4000	2488	0.62
KD Kelanang	18	4433	4479	4526	4573	4621	**1.16**	4000	4669	1.17
KD Morib	19	4410	4465	4521	4577	4634	**1.16**	4000	4692	1.17
KK Telok Panglima Garang	20	33880	34765	35674	36606	37563	**1.07**	35000	38545	1.10
KD Sijangkang Dalam	21	8788	9018	9254	9496	9744	0.65	15000	9999	0.67
KD Sijangkang Luar	22	17978	18448	18930	19425	19933	**1.00**	20000	20454	1.02
KD Kampung Medan	23	19021	19518	20028	20551	21088	**1.05**	20000	21639	1.08
KD Kebun Baru	24	16897	17339	17792	18257	18734	0.94	20000	19224	0.96
KK Jenjarom	25	31619	32062	32511	32966	33427	**1.39**	24000	33895	1.41
KD Kg Jenjarom	26	6206	6293	6381	6470	6561	0.82	8000	6653	0.83
KD Sri Cheeding	27	4676	4741	4807	4874	4942	**1.24**	4000	5011	1.25
Total		**283527**	**288444**	**293459**	**298570**	**303784**		**330000**	**309105**	
Ratio to the demand volume (2022)									**1.086**	

7.3.5 Results

The data are used to assess the benefits of using the bi-objective dynamic CMCLP model introduced in section 7.3.2 in planning for a better healthcare delivery system in the study area.

The model is solved using the GA introduced earlier in Chapter 5. However, the chromosome is modified such that the binary portion that represents which facility is open will be divided into two parts. The first part will represent the existing facilities that are set to be open and the second part will represent either the upgraded or the new facility. For example, [<u>1</u> <u>1</u> <u>1</u> <u>1</u> <u>1</u> 1 0 1 1 5 6 3 8 2 1 4 7] for 5 existing facilities, 4 potential either upgrading or new facilities, and 8 nodes to be assigned. It shows that 5 existing facilities are set to be open, followed by 3 out of 4 potential upgrades and new facilities. The order of assigning the demand from the node to the facility is given by the last 8 bits of the representation. Note that first five bits can be ignored in the representation since its assessment must have the facilities to remain open through out the planning horizon.

In order to assess the effect of the upgrade and the addition exercise, the GA is written and implemented in MATLAB software. The parameters that are used in this model are empirically set as follows:

- Population size = 100
- Number of iterations = 100
- Probability for mutation = 0.001

- Probability for crossover = 0.7

Three analyses (segregated into three 5 year plans) using the two maximum allowable distance values, *S* equals to 3 and 5 km are done using the bi-objective dynamic model.

A. Upgrading Existing Facilities in the First 5 year Plan

For the first analysis, six existing facilities with demand volumes higher than its capacity are considered for upgrading in 5 years. All six are RCs (facilities no. 13, 14, 21, 22, 23 and 24) with capacities of 4000 to be upgraded to HCs with capacities 15000 or 20000. The total capacity increases to 281000 or 10.0 percent more than the total demand volume of 255961. The average results for *S* equals to 5km show that best total volume covered is 233619 or 91.3 percent, an increase by 11.8 percent from the present coverage scenario. The average travelled distance for the uncovered demand (of 22279) is 13.1 km, an improvement in inefficiency by 94.8 percent from 26.3 km. At the same time, the average result for *S* equals to 3km is 203165 volumes are assigned or 79.4 percent (an increase of 5.9 percent from the existing capacity performance). On the contrary, the average travelled distance for the uncovered demand (of 52648) increases to 8.4 km compared to the earlier value at 7.2 km only. The results also show that the best solution can only be obtained if all the potential upgrades are executed.

From the analysis, the best percentage of coverage was only 91.4 percent. Further analysis on the uncovered nodes (total of 116 nodes on average) showed that the nodes consisted of sparsely populated areas located more than 5 km from the nearest existing facility. Table 7.7 details the best results and shows that the upgraded facilities are shaded.

Table 7.7: Details for the Best Results for Upgrading Facilities (first 5 years)

Facilities	Fac No	Projected Demand Volume (2012)	New Capacity	S=3km Nodes	S=3km Volume assign	S=5km Nodes	S=5km Volume assign
KK Telok Datok	1	30314	20000	11	20000	15	20000
KD Sg Kelambu	2	1842	4000	16	4000	32	4000
KD Kg Sg Lang	3	3684	4000	15	4000	15	4000
KD Telok Bunut	4	6030	4000	11	4000	13	4000
KK Tg Sepat	5	7808	15000	11	5647	15	6492
KD Tumbuk Darat	6	2095	4000	13	4000	16	4000
KD Kundang	7	2880	4000	14	2372	23	3243
KD Batu Laut	8	3584	4000	19	2868	24	3055
KK Bandar	9	12210	15000	26	14851	36	14966
KD Sg Buaya	10	4775	4000	11	4000	8	4000
KD Permatang Pasir	11	3958	4000	13	4000	13	4000
KKBukit Changgang	12	14034	15000	22	10275	33	15000
KD Labohan Dagang	13	6747	15000	28	5090	53	5793
KD Olak Lempit	14	6208	15000	26	3914	41	14726
KK Kanchong Darat	15	14749	15000	20	14974	25	15000
KD Kg Endah	16	2747	4000	18	3069	19	3256
KD Kanchong Tengah	17	2220	4000	17	1459	27	2257
KD Kelanang	18	4165	4000	26	3106	30	4000
KD Morib	19	4094	4000	9	2930	12	3857
KK Telok Panglima Garang	20	29021	20000	18	11747	19	13991
KD Sijangkang Dalam	21	7527	15000	19	8652	37	12519
KD Sijangkang Luar	22	15400	20000	8	16166	8	16181
KD Kampung Medan	23	16294	20000	10	11679	11	12859
KD Kebun Baru	24	14475	20000	16	13800	24	14850
KK Jenjarom	25	29089	20000	12	20000	23	20000
KD Kg Jenjarom	26	5710	4000	16	4000	19	4000
KD Sri Cheeding	27	4301	4000	28	3258	40	4000
Total		**255961**	**281000**	**453**	**203857**	**631**	**234045**
Percentage covered (the best)					**79.6%**		**91.4%**
Average (10 runs)					**203165**		**233619**
Percentage covered (average 10 runs)					**79.4%**		**91.3%**
Standard Deviation (10 runs)					**398.8**		**325.8**

Based on the findings above, guidelines in identifying new potential sites are proposed using the following criteria: (i) the facility is outside the coverage of existing facilities (more than 5km), (ii) the potential increase of population volume or high growth rate and/or (iii) the existing healthcare is provided by mobile clinic visits.

B. Adding New Facilities and Upgrading Existing Facilities in the Second 5 year Plan

In the second analysis, two facilities are identified for upgrading and five new locations will be introduced. Facility 4, an RC of capacity 4000 will be upgraded to HC of capacity 15000. The six new locations are identified, one HC of capacity 15000 and five RCs of capacity 4000. This addition increases total capacity by 16.3 percent compared to Analysis A to 327000 or 8.6 percent more than the needing demand volume.

Table 7.8 summarises the details of the new locations. Those are Bukit Komandol, Bukit Cerding, Petaling Tin (all in Mukim Tanjung Duabelas), KT Bumbun and KT Sg Judah (both in Mukim Telok Panglima Garang).

The average results for *S* equals to 5km is when all facilities are open, with the total volume covered is 94.4 percent (an increase of 16.0 percent from the current scenario and an increase of 3.1 percent from the first five year scenario, despite the increase of population volume). The average travelled distance for the uncovered demand (of 15647) is 13.5 km, a slight increase from 13.1 km in the first five year. Despite all the facilities are open, four facilities do not even fill more than half of its capacities. For the upgraded facilities, facilities 13 and 14 only fill up 40 and 28 percent of its capacity respectively. For the new facilities, facilities 29 and 30 only fill up 35 and 39 percent respectively. However, it is viewed from the potential demand growth in the area that the capacity is needed.[4]

Table 7.8: Profile of Potential New Locations

No	Potential Sites	Demand (based on 2007)	Current Serving Facility	% of demand to current serving facility	Capacity
35	KK Tmn Bakti Sg Manggis (New)				15000
36	Bkt Komandol	778	KK Jenjarom	2.87%	4000
37	Bkt Cerding	584	KK Jenjarom	2.15%	4000
38	Kt Bumbun	339	KK TPG	1.33%	4000
39	Kt Sg Judah	150	KK TPG	0.59%	4000
40	Petaling Tin	189	KK Jenjarom	0.70%	4000

The average result for *S* equals to 3km is 87.8 percent demand volume are covered and assigned within the capacity limit. This is also a significant increase of 17.0 percent from the current scenario or 8.4 percent increase from the first five year plan. Consequently, the average travelled distance for the uncovered however also increases from 8.4 km in analysis A to 9.0 km. Table 7.9 details the results for this analysis with the upgraded facility is shaded and the new facilities are shaded diagonally. Figure 7.5 describes the location of the upgraded and new facilities within the network.

[4] The facilities are within the local planning area for the District of Kuala Langat. From Official Portal of District of Kuala Langat, at http://www.mdkl.gov.my , on 9 Sept 2011

Table 7.9: Details for the Best Results for Upgrading and Adding New Facilities (second 5 years)

Facilities	Fac No	Projected Demand Volume (2017)	New Capacity	S=3km Nodes	S=3km Volume assign	S=5km Nodes	S=5km Volume assign
KK Telok Datok	1	32495	20000	13	18113	18	18636
KD Sg Kelambu	2	1975	4000	21	4000	32	4000
KD Kg Sg Lang	3	3950	4000	14	4000	15	4000
KD Telok Bunut	4	6464	15000	18	6546	27	11956
KK Tg Sepat	5	8228	15000	11	5990	14	7067
KD Tumbuk Darat	6	2208	4000	10	4000	17	4000
KD Kundang	7	3035	4000	14	2537	23	3454
KD Batu Laut	8	3777	4000	19	3063	24	3256
KK Bandar	9	12785	15000	24	14188	33	15000
KD Sg Buaya	10	5000	4000	8	4000	7	4000
KD Permatang Pasir	11	4145	4000	13	4000	13	4000
KKBukit Changgang	12	15044	15000	22	11065	29	13801
KD Labohan Dagang	13	7232	15000	28	5465	51	5987
KD Olak Lempit	14	6655	15000	21	3853	23	4191
KK Kanchong Darat	15	15692	15000	19	14904	22	15000
KD Kg Endah	16	2923	4000	18	3284	19	3477
KD Kanchong Tengah	17	2338	4000	17	1549	25	2121
KD Kelanang	18	4387	4000	26	3286	31	4000
KD Morib	19	4356	4000	9	3135	11	3313
KK Telok Panglima Garang	20	33017	20000	18	12556	19	11368
KD Sijangkang Dalam	21	8564	15000	19	9868	38	14455
KD Sijangkang Luar	22	17520	20000	8	18420	8	18431
KD Kampung Medan	23	18537	20000	10	13315	11	14650
KD Kebun Baru	24	16467	20000	16	16416	21	15723
KK Jenjarom	25	31183	20000	10	20000	9	20000
KD Kg Jenjarom	26	6120	4000	17	4000	13	4000
KD Sri Cheeding	27	4611	4000	22	3344	22	3356
KK Taman Bakti	28		15000	13	15000	11	15000
KD Bukit Komandol	29		4000	21	1371	26	1383
KD Bkt Cerding	30		4000	24	1562	27	1574
KD Bumbun	31		4000	17	4000	18	4000
KD Sg Judah	32		4000	18	4000	18	4000
KD Petaling Tin	33		4000	23	3980	26	3992
Total		**278708**	**327000**	**561**	**244810**	**701**	**263191**
Percentage covered (the best)					**87.8%**		**94.4%**
Average (10 runs)					**244600**		**262964**
Percentage covered (average 10 runs)					**87.8%**		**94.4%**
Standard Deviation (10 runs)					**473.6**		**202.4**

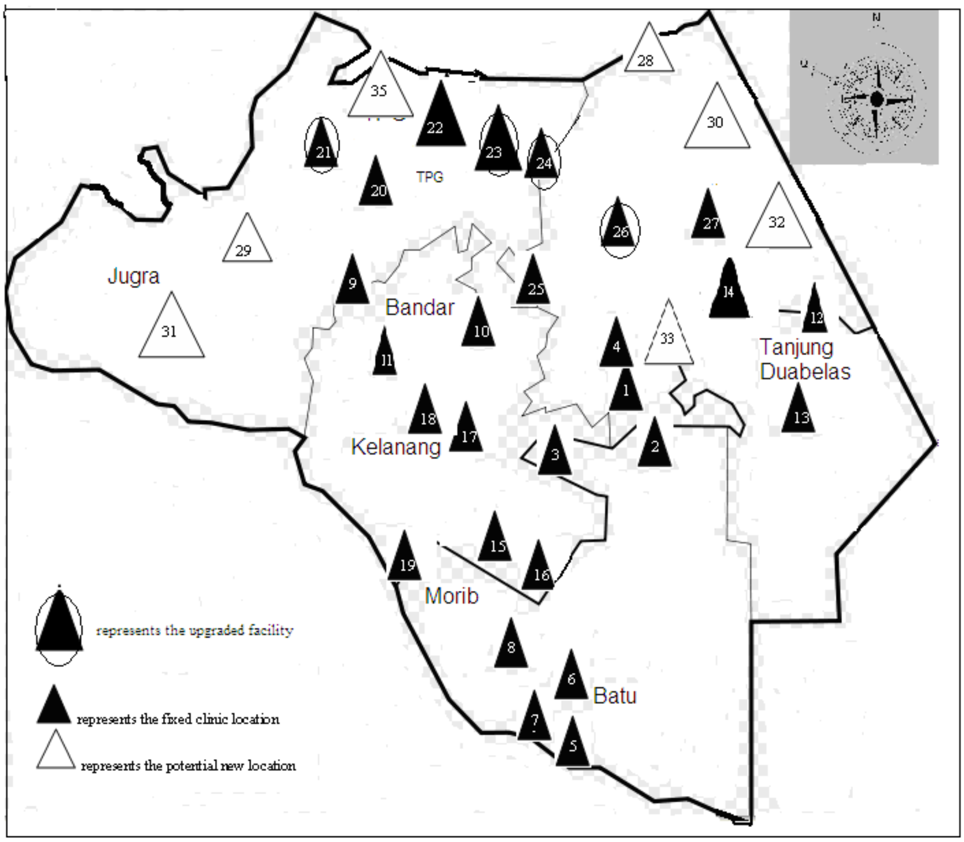

Figure 7.5: District of Kuala Langat indicating the revised facility location

C. Scenario After 15 years (third 5 year plan)

The third analysis analyses the performance of the upgrading and addition of facilities in the third year of the 5 year plan. The total demand volume is projected to have increased to 303784 or 9 percent higher than in the 10th year. The average results for *S* equals to 5km is to open all the facilities, with the total volume covered as 284514 or 93.7 percent with the average travelled distance for the uncovered demand (of 19056.5) is 17.4 km.

For *S* equals to 3km, the average assignment achieved is 262228 or 86.6 percent. The average travelled distance for the uncovered demand of 41175 is also surprisingly higher at 11.0 km compared to the results in Analysis B of 9.0

km. Details of the assignment of demand volume by facilities is summarised in Table 7.10.

It is noted that five facilities were still not performing to their full capacities (highlighted in bold). Aside from the four in which two were from the upgraded and two were new facilities, Facility 5 was one of the existing facilities after the upgrading. This is because the total demand volume (of total 11000) within the area was shared with Facility 6 while some of the volume was assigned to newly upgraded Facility 4. It is also noted that the full coverage was not achieved despite the capacity upgrade and the addition of new facilities. This may be due to some of the nodes were located very far from the potential facility sites.

Sitting a new facility within the coverage distance of these nodes may end up with its operating way below the minimum capacity of 1500 population. The area was the settlement of the aborigines whose main activity was farming and the hilly terrain landscape also prevented development projects of this period.[5] It is noted that the average travelled distance for the uncovered was lower for *S* equals to 3km compared to when *S* equals to 5km. This was expected as the uncovered volume was smaller for *S* equals to 5km compared to *S* equals to 3km and the assignment was easier to make to the nearer facility. It was also conjectured that these uncovered nodes located at the border of the district of Kuala Langat were currently served by facilities located on the other side.

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[5] The facilities are not within the local planning area for the District of Kuala Langat. From Official Portal of District of Kuala Langat, at http://www.mdkl.gov.my , on 9 Sept 2011

Table 7.10: Details for the Best Results for Upgrading and Adding New Facilities (third 5 years)

Facilities	Fac No	Projected Demand Volume (2022)	New Capacity	S=3km Nodes	S=3km Volume assign	S=5km Nodes	S=5km Volume assign
KK Telok Datok	1	34834	20000	12	19999	20	20000
KD Sg Kelambu	2	2117	4000	20	3934	29	4000
KD Kg Sg Lang	3	4234	4000	16	4000	14	4000
KD Telok Bunut	4	6929	15000	20	7413	22	11008
KK Tg Sepat	**5**	**8673**	**15000**	**11**	**6368**	**15**	**7622**
KD Tumbuk Darat	6	2327	4000	10	4000	17	4000
KD Kundang	7	3198	4000	14	2735	23	3732
KD Batu Laut	8	3981	4000	19	3148	24	3514
KK Bandar	9	13386	15000	23	14923	31	15000
KD Sg Buaya	10	5236	4000	9	4000	10	4000
KD Permatang Pasir	11	4340	4000	11	4000	13	4000
KKBukit Changgang	12	16129	15000	22	11904	30	14881
KD Labohan Dagang	**13**	**7753**	**15000**	**28**	**5914**	**52**	**6592**
KD Olak Lempit	**14**	**7133**	**15000**	**22**	**4191**	**24**	**5991**
KK Kanchong Darat	15	16696	15000	18	15000	19	15000
KD Kg Endah	16	3109	4000	18	3527	19	3760
KD Kanchong Tengah	17	2462	4000	19	3546	26	3997
KD Kelanang	18	4621	4000	26	3493	31	4000
KD Morib	19	4634	4000	9	3402	11	3769
KK Telok Panglima Garang	20	37563	20000	18	13454	27	15917
KD Sijangkang Dalam	21	9744	15000	19	11271	34	15000
KD Sijangkang Luar	22	19933	20000	7	20000	9	20000
KD Kampung Medan	23	21088	20000	11	16064	11	17906
KD Kebun Baru	24	18734	20000	17	19298	19	18914
KK Jenjarom	25	33427	20000	7	20000	8	20000
KD Kg Jenjarom	26	6561	4000	17	4000	16	4000
KD Sri Cheeding	27	4942	4000	24	3642	24	3934
KK Taman Bakti	28		15000	11	15000	12	15000
KD Bukit Komandol	**29**		**4000**	**21**	**1534**	**26**	**1575**
KD Bkt Cerding	**30**		**4000**	**24**	**1402**	**27**	**1402**
KD Bumbun	31		4000	15	4000	15	4000
KD Sg Judah	32		4000	15	4000	15	4000
KD Petaling Tin	33		4000	18	4000	24	4000
Total		**303784**	**327000**	**551**	**263162**	**697**	**284514**
Percentage covered (the best)					**86.6%**		**93.7%**
Average (10 runs)					**262228**		**284551**
Percentage covered (average 10 runs)					**86.3%**		**93.7%**
Standard Deviation (10 runs)					**887.5**		**245.3**

7.3.6 Conclusions for Dynamic Modelling

A dynamic CMCLP model when the demand is changing over time and additional new facilities are built to cater for the increased in demand at given times was formulated. The problem was solved by a GA based heuristic. When population in the growing areas was predicted to increase in the coming years, a service system of facilities like the healthcare is to be constructed through upgrading the existing facilities and/or adding the new facilities sequentially at pre-specified times.

The formulation also incorporated the measurement of service to uncover the population through the multi-objective formulation introduced in Section 7.2. An example on the application of the model is described in Section 7.3.3, in which it includes the scenario of the effects of population growth in the next ten years to the health delivery system in the study area. The analysis showed that the total population covered reduced tremendously if nothing was done on the limited capacity of the facility. In this study, the criteria in selecting the potential new location and the potential existing facility that can be upgraded in order to improve the coverage percentage were proposed.

The planning horizon was decided to be in the five year span as per the Malaysian Economic Planning. From the analysis, after every five years the potential new locations and potential upgradeable facilities were identified. In the first five year analysis the upgrading process resulted in an increase of 11.8 percent in the coverage percentage. In the second and the third five year planning horizons, the coverage percentage was maintained high at more than 93 percent.

7.4 CONCLUSIONS

In this chapter, the basic model of location allocation model was extended into a multi-objective model that combined the objectives of the *p*-median and MCLP. The study combined the two models of contradicting objectives and analysed the performance of GA based heuristic in solving the problem. The algorithm was found to be able to produce comparable results to the existing algorithms.

A formulation of conditional CMCLP that incorporated existing and new facilities was formulated, in which once the new *p* locations were determined, a demand could be served either by one of the new facilities or whichever was the closest available facility to the demand.

The chapter also included the scenario of the effect of population growth in the next ten years to the health delivery system in the study area and the analysis showed that the total population covered reduced tremendously if nothing was done on the limited capacity of the facility. Based on the results from the analysis, several criteria in selecting the potential new locations and potential upgradeable facilities were identified and simulated to serve the population. Simulating the potential new location and the potential expansion of the existing facility into the service network showed an increase of about 17 percent in the coverage percentage. It also highlighted the sitting of facilities at the undesirable locations.

This would help the smooth planning by the authority in ensuring that the policy and the guidelines related to the service were followed. The method used can also be applied to other types of service networks like post office, schools, kindergartens and other public related services. As the study also focused on the study area, the other areas of totally different profile should also be looked at and compared, in order to generalise the best model for the national planning policy.

CHAPTER 8

CONTRIBUTIONS OF EACH MODEL TO MALAYSIAN HEALTHCARE DELIVERY SYSTEMS

8.1 INTRODUCTION

This chapter summarizes the proposed solutions that are suitable to model the public healthcare in Malaysia. Chapter 5, 6 and 7 of this study discussed the applications of different models considered as capacitated and dynamic. Thus, it provides alternative solutions rather than a single optimal solution. This chapter will discuss the relative strengths and weaknesses of these alternatives in the context of Malaysia and Malaysian healthcare system. The findings of this comparatives analysis will provide valuable insights for the local health planners.

8.2 STRENGTHS AND ADVANTAGES

8.2.1 Capacitated Maximal Covering Location Problem (CMCLP)

Chapter 5 proposes the use of CMCLP with the objective to maximize the total population covered within 3 and 5 km given that the capacity of current facilities is limited. In Malaysian health system, each facility has its said nominal capacity and the allocation of demand volume and human resources will also be done according to the said capacity. This results in some facility are serving more than its capacity and congested at times, while the other facility is operating below the nominal capacity. The unbalanced spread of the demand assignment to the facility is also due to the location of facilities are in congested area but having the same capacity as those in remote area. The CMCLP helps to optimally locate the facility and also allocate the demand to the available facilities with regard to the objective. In a developing country like Malaysia, the ministry of Health (MOH) will have a limited budget in the size and number of facilities to open, this model will propose the minimum number of facilities possible that are able to cover all population within the stipulated distances.

GA based heuristic is proposed to solve the CMCLP model for Malaysia healthcare delivery system by measuring the effectiveness of existing network and helps the process of finding the optimal network in easier, faster and more efficiently. The CMCLP with GA-based heuristics algorithm also analyze the marginal percentage of the uncovered demand which then will trigger the planner to think about.

8.2.2 Capacitated P-Median Problem (CPMP)

Despite the maximum allowable distance set in the National Health Policy (NHP) of Malaysia, due to the good road system, some population are able to travel farther than that in order to get the service. However, as accessibility to health centers is a serious concern, an inverse relationship between distance traveled to reach health facilities and rate of health service utilization has been noted (Bour, 2002 ; Kinman, 1999). In Malaysia, presence of health facility near the residence increases the odds of health care centre attendance by almost two times (Krishnawamy et al. (2009). Chapter 6 applies CPMP to model the Malaysian healthcare system with the objective of minimizing the average distance need to be traveled by the population in order to get the health care service.

The model also considers the limited number of facility *p* and limited capacity of each facility. The application of the model in Chapter 6 shows that for the existing network in the small study area, Mukim Telok Panglima Garang, the average traveled distance is approximately 5 km or equals to the NHP of maximum allowable traveled distance for Malaysian. The model is also used to analyze the sensitivity of the capacity volume and provides insights on whether there is a need for a revision in the nominal policy of the capacity of healthcare facilities.

8.3 EXTENDED MODELS

Both of the models mentioned above have its own strengths and advantages in modeling the current situation of Malaysian healthcare delivery system. In order to strengthen the two, the extended models that consider both strengths and also the advanced need of the real world system are discussed in Chapter 7.

8.3.1 Multiobjective Model

The multiobjective model proposed in Chapter 7, involves two measurements for service facility location problems the population coverage and the average traveled distance. The model combines the two models introduced earlier, CMCLP and CPMP. This is because in CMCLP, the maximum allowable distance is fixed to certain values and the state of which the uncovered population is serviced is not known. Similarly, CPMP only gives an information of how far on average the population need to travel in order to get the service. Given the fixed number of facility in CPMP, some population population might even need to travel more than the specified distance in CMCLP. Hence the combination of the two objectives will complement each other weaknesses.

8.3.2 Dynamic Model

In some models, assumptions are made in order to simplify the model, yet the actual need of the real world is assumed to be relaxed. For example, in the multi-objective model above, it is assumed that the total population that needs to be serviced is known. In reality, the total population that needs to be diagnosed and treated at first point of health care centre is not known and increasing due to the fact of good medicine and improvement in care for the elderly (Lele et al. 2005). The dynamic model in Chapter 7 proposes the fact that the population is growing and the tendency of increasing the total capacity of service network, either through increasing the number of facility (when needed) or simply improve the efficiency of service at the facility. In Malaysia, the potential growth in the population not necessarily comes from the new born but also from rapid growth of the immigrants and also migration of people to more facilitated areas (Department of Statistics, Malaysia, 2012, Available at: http://www.statistics.gov.my).

The analysis of the model also indicates on where and when actions need to be taken in order to level the service efficiency.

8.4 SUMMARY AND CONCLUSIONS

In Malaysia, the Ministry of Health provides free health services to civil servants, pensioners and the needy. Due to the high governmental subsidies public health care is affordable by the majority of the population. Not least due to the world wide economical crisis, today more and more Malaysians opt for public health care, as private insurance tends to be very expensive. This led to overcrowded hospitals, very long waiting lists and stressed doctors who are not able to pay personal attention to patients. Also, because of higher salaries and more acceptable working conditions, many doctors choose to work in the private sector. This again causes lack of manpower in the public hospitals and health centers and again supports the overflow of these institutions.

Apart from these issues, the Malaysian public health sector is by no means of inferior quality. The doctors are normally more experienced as they treat more patients than private physicians. Public hospitals sometimes even tend to have the better equipment and technologies, as private institutions would have to charge even more for the latest instrumentation. Hence, a proper planning in locating the facility, the resources and the total network capacity is needed and can be done through analyzing proper models proposed in this study.