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A multi-objective optimization approach for health-care facility location-allocation problems in highly developed cities such as Hong Kong

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ABSTRACT

Public health-care facilities are essential to all communities, and their location/allocation has long been an important issue in urban planning. Given the steady growth of Hong Kong's population, new health-care facilities will need to be built over the next few years. This research examines the problem of where such health-care facilities should be located to improve the equity of accessibility, raise the total accessibility for the entire population, reduce the population that falls outside the coverage range, and decrease the cost of building new facilities. However, because urban areas such as Hong Kong are complex socio-ecological systems, the aforementioned conflicting objectives make it impossible to find one 'best' solution that meets all of the objectives. Therefore, this research uses a genetic algorithm based multi-objective optimization (MOO) approach to yield a set of Pareto solutions that can be used to find the most practical tradeoffs between the conflicting objectives. The MOO approach is used to optimize the location of new health-care facilities in Hong Kong for 2020. Because the MOO approach provides a set of diverse plans, planners can compare the value of each objective and the spatial distribution of facilities to analyze or select the solution that best supports their further decisions. Comparing the Pareto solutions with other solutions, it indicates that the MOO approach is a sensible choice for solving multi-objective problems of health-care facility location-allocation in Hong Kong.

1. Introduction

The problem of where to locate health-care facilities has long troubled urban planners due to the increasing demand generated by population growth and an aging population. Facility location decisions, referred to as location-allocation problems, are a critical element in the strategic planning of health-care programs (Saaty, 1980). In managing health-care facility location-allocation problems, various objectives, including accessibility(Hodgart, 1978; Langford & Higgs, 2006; Murawski & Church, 2009), equity of accessibility(Ngui & Apparicio, 2011), cost (Landa-Torres, Manjarres, Salcedo-Sanz, Del Ser, & Gil-Lopez, 2013), participation (Gu, Wang, & McGregor, 2010) and so on, rather than just one objective have been considered.

Numerous researches have paid attentions to improving one single objective, but recently more and more scholars began to take problems of locating health-care facility as a multi-objective (MO) problem that commonly face conflicts. It is to say, when just only one objective is concerned, the other objectives will be ignored. As all objectives are conflicting in the system which is named as multi-objective problems, there is no all-best solution at every objective. For MO problems, an optimization approach that provides only one best solution as the final decision and ignores trade-offs between objectives is inappropriate. Within this context, the Pareto solutions have been proposed to cope with the MO problems in different fields. However, most studies on the MO problem of health-care facility location use a sum weighting approach to combine objectives, which provides a single best solution rather than a set of Pareto solutions from which the planners can select their ideal.

Meanwhile, it is obvious that the conflicts are serious in some highly developed cities with high population density. Cities with high population density and limited health-care resources require not only accessibility in health-care facilities but also equity in accessibility; moreover, the cost of building new health-care facility also should be taken into consideration. And in cities with heterogeneous spatial distribution of population or with isolated island, the number of people who fall outside an acceptable travel distance to at least one facility is important. Therefore, for highly developed cities, it is necessary to consider the problem of locating health-care facilities as a complex MO problem where more than two objectives should be considered. While in most of existing studies, even if health-care facility locating problem has

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been taken as a MO problem, just two objectives are considered, which cannot reflect all requirements of locating health-care facility in highly developed cities. Facing up the multiple objectives in locating health-care facility in high developed cities with heterogeneous spatial distribution of population, this research considers multiple objectives which can fully reflect the requirements of locating health-care facility in a highly developed city, attempts to locate the health-care facilities in highly developed cities, find out the trade-offs between objectives, and provide a set of Pareto solutions rather than just one single solution for planners or government.

This research takes Hong Kong, one of Asia's highly developed cities, as the study area to validate the proposed approach. Four objectives in relation to health-care facility location-allocation problem in Hong Kong are selected: (1) minimize inequity of accessibility, (2) maximize accessibility for the whole population, (3) minimize the number of people who fall outside an acceptable travel distance to at least one facility, and (4) minimize the cost of building new public health-care facilities. And, there is one constraint on the total increase in public health-care facility's capacity in the projected year.

There are tradeoffs between the objectives above. Evidently, accessibility and coverage can be increased by adding more new hospitals, leading to an increased cost. Vice versa, cost can be reduced by adding less hospital, which reduces accessibility and coverage. Also accessibility and coverage contradict equity to some extent. A higher accessibility and coverage can be achieved by planning a large number of hospitals at the area with dense population, which, however, results in inequitable solution. Vice versa, to achieve a high equity, hospitals must be spread broadly over the whole region, which increases travel distance in the densely populated areas. Last, accessibility contradicts coverage when health-care resources are limited. In this research, higher accessibility asks for a minimal total distance traveled by population, while large coverage aims at maximal population under an acceptable traveling distance. Since all objectives are conflicting, health-care facility locating problem in Hong Kong is a MO problem.

The rest of this paper is organized as follows. The second section reviews the approaches of locating health-care facilities, and explains why the multi-objective optimization approach should be used. The third section introduces the background of Hong Kong including its economy, population and the data source used in this research. The fourth section describes the objective evaluation and the optimization method in detail. The last two sections discuss the value of proposed method and its benefit to other cities with health-care facility locating problems.

2. Literature review

In problems of locating health-care facility, various objectives have been considered. At first, access to health-care facilities is thought as a crucial issue and a major concern for government planning (Landa-Torres et al., 2013). And the research focuses on the definitions and the measurements of access to medical care (Aday & Andersen, 1974); then, improving the access to health-care facilities is set as one objective in the planning of health-care facility (Hodgart, 1978; Langford & Higgs, 2006; Murawski & Church, 2009; Gu et al., 2010; Wang, 2012). Later, improving the equity of access to health-care has been concerned (Ngui & Apparicio, 2011) and then prompted research on the reasonable allocation of health-care facilities (Wang, McLafferty, Escamilla, & Luo, 2008). Apart from improving the access and the equity of access, reducing the cost metrics (Bretthauer & Cote, 1998; Landa-Torres et al., 2013), increasing flexibility in service location selection (Saaty, 1980), and the number of people within an acceptable travel distance of at least one facility (Gu et al., 2010; Shariff, Moin, & Omar, 2012) are getting more and more concerned, which have been thought as objectives in solving location-allocation problems. Obviously, various objectives have been considered in solving the problem of locating health-care facilities.

As various objectives have been proposed, scholars have concerned more than one objective in locating health-care facility problem early at 1970s. For example, at 1970s, Dokmeci (1979) set reducing cost and increasing utilization criteria as two objectives to determine the sizes and locations at different facility levels. Later, at 1990s, Bailey and Phillips (1990) were aware of the influence of distance, transport and accessibility on the use of health services in Kingston, Jamaica. Current, Min, and Schilling (1990) proposed four objectives, (1) cost minimization, (2) demand oriented, (3) profit maximization, and (4) environmental concern, to decide the facility location. Recently, Cetin and Sarul (2009) made effort on locating blood banks among hospitals or clinics, where three objectives were involved, minimizing total fixed cost of locating blood banks, minimizing total traveled distance between the blood banks and hospitals, and minimizing inequality. Gu et al. (2010) set two objectives, (1) people should have more flexibility to select service location, and (2) each preventive health care facility needs to have a minimum number of clients in order to retain accreditation, to optimize preventive health care facility locations.

Clearly, location-allocation problems of health-care facility have been thought as a kind of MO problem. However, in above research, alternative solutions are calculated by summing the weighted efficiencies in terms of each objective. This approach to solving MO problems has several limitations: (1) the summing weighted approach requires a priori knowledge about the relative importance of the objectives, (2) the summing weighted approach leads to only one solution, (3) trade-offs between objectives cannot be simply evaluated, and (4) the solution may not be attainable unless the search space is convex (Ngatchou, Zarei, & El-Sharkawi, 2005; Yoo & Harman, 2007). Within this context, some scholars have focused on searching for Pareto solutions rather than one best solution in MO problems. The Pareto solution here implies that an improvement in one objective must be achieved at the expense of at least one of the other objectives (Steuer, 1989; Batty, 1998; Miettinen, 1999; Gabriel, Faria, & Moglen, 2006). Pareto solutions are solutions that are superior to the rest of the solutions in the search space when all objectives are considered but are inferior to other solutions in the space in one or more objectives (Srinivas & Deb, 1994). Pareto plans maintain a range of key index values and reflect trade-offs between objectives; thus, planners or decision makers can select from the Pareto plans. Due to the feature of Pareto solutions, more and more scholars search for Pareto solutions rather than one best solution for MO problems.

Even if taking Pareto set as the solutions for MO problems has been popular in various fields, less research searched Pareto solutions for the MO problem of locating health-care facility. Facing up to the MO problem in determining the location of health-care facilities, this research employs the genetic algorithm (GA) based MOO approach to search for the Pareto solutions of health-care facility locations. The GA approach is widely used in solving the MO problems. The GA is a robust and efficient general global optimization algorithm used to search for large, complex, and little-understood search spaces (Garai & Chaudhuri, 2007; Kim & Abraham, 2007). As mentioned above, instead of offering one "best" solution, a number of Pareto optimal solutions are generated by the GA approach. This set of alternative solutions is well suited for practical applications and providing options for planners to choose from. Another alternative plan/solution can be selected from the pool of Pareto optimal solutions if implementing an optimal is difficult or impossible. Given the advantages stated above, the GA approach has been widely used in solving MO problems in field of land use planning (Balling, Taber, Brown, & Day, 1999), surface grinding operations (Saravanan, Asokan, & Sachidanandam, 2002), finance-based construction project scheduling (Fathi & Afshar, 2010), flood control (Qin, Zhou, Lu, Li, & Zhang, 2010), optimal placement and sizing of shunt FACTS controller (Phadke, Fozdar, & Niazi, 2012), and other fields.

3. Background of Hong Kong and data source

Hong Kong is a Special Administrative Region of the People's Republic of China, located in the southernmost part of the country close to Shenzhen. Hong Kong's economy is highly developed, with a GDP per capita of HKD285,146 in 2012 (Census and Statistics Department Hong Kong Special Administrative Region, 2013). The population density in Hong Kong is relatively high at 6620 people per square kilometer (Census and Statistics Department Hong Kong Special Administrative Region, 2013), with a large proportion of elderly residents. Fig. 1 presents the spatial distribution of the population. Hong Kong's topography is mountainous, and thus the population distribution and economic development are both heterogeneous. Efficient facilities are required to provide health-care services to the large and heterogeneously distributed residents.

The data on Hong Kong's population, grouped by street block (SB), were obtained from government webpages. The public health-care facilities in this research refer to clinics/health centers under the Department of Health, the spatial locations of which were retrieved from the Lands Department website (see http://www1.map.gov.hk/gih3/view/index.jsp). There are 174 clinics/health centers in total. The health-care capacity of each facility was retrieved from the 2012 Hospital Authority Statistical Report. The capacity of each public health-care facility comprises six components: bed usage, number of live births, number of operations, presence/absence of a family medicine specialist clinic, presence/absence of a general out-patient clinic, and number of specialist out-patient attendances. As different components require different doctors, nurses, and other resources, each has a different weight that informs the total capacity of the specific health-care facility. The components are weighted as follows: bed usage = 2.5, number of live births = 2.5, number of operations = 1.5, presence/absence of a family medicine specialist clinic = 1, presence/absence of a general out-patient clinic = 1, and number of specialist out-patient attendances = 1.

4. Methods

The location-allocation problem involves locating a given number of facilities, such as clinics or public libraries, so that the population enjoys the best possible geographical access to the service (Hodgart, 1978). In this research, the location-allocation problem for health-care facilities in Hong Kong involves locating a number of new health-care facilities to create an efficient system for all citizens that maximizes accessibility, equity in accessibility, while minimizing the number of people that need to travel beyond the threshold distance and the cost of building the new facilities. The objectives of the MOO approach are to, (1) maximize the accessibility for the entire population, (2) minimize the inequity of accessibility, (3) minimize the uncovered population, and (4) minimize the cost of building new health-care facilities.

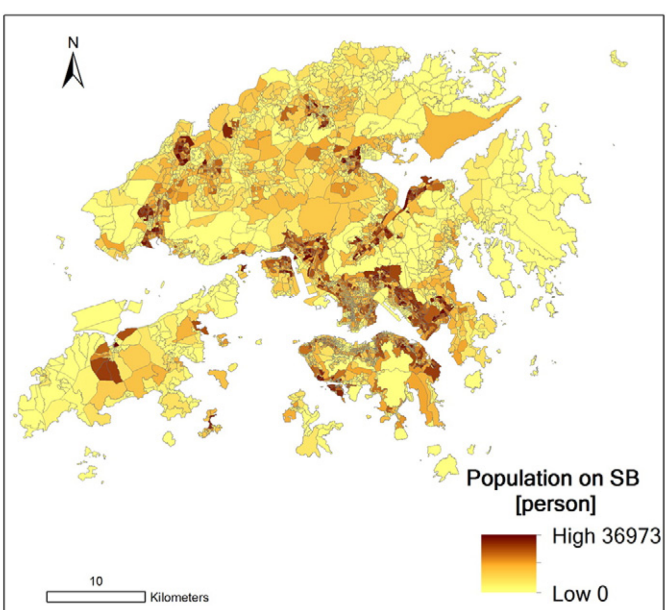

Fig. 1. Spatial distribution of Hong Kong's population.

In the MOO approach, a set of population centers is selected to serve as candidate sites for facilities, and multiple objectives are used to select an optimal location from the candidate sites. In this research, 4993 SBs in Hong Kong serve as population centers and candidate sites for facilities. The capacity of one health-care facility is the minimum unit in the MOO approach.

For clarity, the following definitions apply:

D_i is the demand on the i-th SB; specifically, the SB's population acts as demand D.
dis_{ij} is the distance or travel time between the i-th and j-th SBs; specifically, the distance between the barycenters of the i-th and j-th SBs.
ThresD is the threshold travel distance, which indicates the acceptable travel distance to at least one facility.
D_{ik} is the demand on the i-th SB anticipated to use the k-th facility based on relative proximity.
SO_i is the supply capacity of the public health-care facility on the i-th SB before optimization.
$S_i = \Delta S_i + SO_i$ is the total supply capacity of the i-th SB.
ΔS_i is the increased supply capacity of the clinic on the i-th SB, and satisfies the constraint that $\Delta S_i \geq 0$.
m is the number of SBs.
n is the number of health-care facilities.
A_i is the accessibility at demand location i.
OA_i is the accessibility of the i-th SB to the health-care facility before optimization.

In the optimization process, the value of ΔS_i on each SB is optimized. If the ΔS_i is zero, it means that there is no new health-care facility on this candidate site. If the ΔS_i is larger than zero, it means that a new health-care facility with a capacity of ΔS_i will be built on this candidate site. And the total increased capacity of the new located facilities is set by referring to Hong Kong's forecasted population. In summary, the MOO approach attempts to determine the ΔS_i for each SB in space.

4.1. Objective evaluation

4.1.1. Objective 1: maximize accessibility for the whole population

The objective of maximizing accessibility can be written as

$$\text{Maximize} \sum_{i=1}^{m} D_i * (A_i - OA_i) * f_{md}(OA_i) \tag{1}$$

where, f_{md} is the marginal benefit of improving accessibility. A marginal benefit denotes the increase in total benefit when a unit of product is produced or consumed. According to the principle of marginal benefit, the marginal benefit decreases as the produced or consumed product increases (Mansfield & Yohe, 1988); thus, when the original accessibility, OA_i, of the existing health-care facilities is relatively high, there is little benefit in adding a new health-care facility. In contrast, when the original accessibility is relatively low in the i-th SB, adding a new health-care facility can result in a large benefit. Therefore, the relationship between benefit of adding per-unit accessibility and the value of original accessibility can be written as $Unit\,benefit = k * OA_i^{-\alpha} + \varepsilon$, where k and α are positive number. Under the context of this study, the f_{md} can be written as $UnitBenefit = (0.1+\frac{OA_i-\min(OA)}{\max(OA)-\min(OA)})^{-0.5}\Big/5 + 0.2$. Based on f_{md}, the benefit of increasing accessibility in the i-th SB can be calculated.

In Eq. (2), the accessibility, A_i, is written as (Dokmeci, 1979; Wang & Tang, 2013)

$$A_i = \sum_{j=1}^{n} \frac{S_j f(dis_{ij})}{\sum_{k=1}^{m} D_k f(dis_{kj})} \tag{2}$$

where f is a general distance-decay function. The distance-decay function in the measure of accessibility takes various forms. In this research, the popular and widely used gravity-based index is used, which is written as (Wang, Fu, & Shi, 2013; Wang & Tang, 2013)

$$f(dis_{ij}) = dis_{ij}^{-\beta} \tag{3}$$

Wang and Tang (2013) conducted a sensitivity analysis of multiple values within the range [0.6, 1.8] for the travel friction coefficient β, and the optimization was conducted using $\beta = 0.6$; similarly, in Liu, Kang, Gao, Xiao, and Tian (2012) and Kang, Ma, Tong, and Liu (2012)'s study on intra-urban patterns, the coefficient β is set as 1.2 ± 0.15 and then the distance distribution can be fitted well; Rosero-Bixby (2004) took 1.56 as the travel friction coefficient to calculate the spatial access to health care in Costa Rica. Indeed, a larger β value suggests that residents are more discouraged by long travel time in seeking health-care facility, and thus have a higher tendency to settle for facilities in nearby locations(Luo & Wang, 2003). Under the context of Hong Kong, the coefficient β was set as 0.8.

4.1.2. Objective 2: minimize inequity of accessibility

Although unequal access is inevitable as some people will always be closer to services than others (Hodgart, 1978), making access to health-care facilities as equitable as possible for all citizens remains an important objective in planning health-care facilities. Equity of accessibility is usually measured as the deviation from the mean of actual accessibility. In this research, inequity in accessibility is measured as the extent of the deviation from the mean number of people living within an acceptable travel distance of at least one of an SB's facilities. Thus, the objective of minimizing inequity is written as (Wang et al., 2013; Wang & Tang, 2013).

$$\text{Minimize Var}(D_{ij}) \quad (dis_{ij} > \text{ThresD}) \tag{4}$$

where Var is the function used to calculate the variance of matrix. D_{ij} can be measured by following equation.

$$D_{ij} = D_i * \left(\frac{S_j f(dis_{ij})}{\sum_{k=1}^{m} D_k f(dis_{kj})} \Big/ \sum_{j=1}^{n} \frac{S_j f(dis_{ij})}{\sum_{k=1}^{m} D_k f(dis_{kj})} \right) \tag{5}$$

where $\sum_{j=1}^{n} \frac{S_j f(dis_{ij})}{\sum_{k=1}^{m} D_k f(dis_{kj})}$ is the accessibility of the i-th SB provided by all facilities and $\frac{S_j f(dis_{ij})}{\sum_{k=1}^{m} D_k f(dis_{kj})}$ is the accessibility of the i-th SB provided by the j-th facility. According to this equation, the demand on the i-th SB can be assigned to all of the facilities.

The acceptable travel distance of Hong Kong in Eq. (4) is defined as 10 km. Various values have been used as the acceptable distance in different places. For example, some studies conducted in Illinois (U.S.) used a 30-minute drive as the threshold travel distance to a health-care facility (Wang et al., 2008; Gu et al., 2010), based on the standard used by the U.S. Department of Health and Human Services. In a review of the literature on optimization of access to public services, Hodgart (1978) discussed the distance objective and took 3 km as the threshold distance. Ngui and Apparicio (2011) set the threshold distances as 500 m, 1 km, 2 km, and 3 km, respectively, in their simulations. According to the regulations on the gradation and classification of urban land (Ministry of Land and Land Use Management Division China et al., 2001), the service radius of public service facilities in Chinese cities should range from 0.3–3 km. Because the public transportation system is highly developed in Hong Kong, 10 km is selected as the acceptable travel distance for citizens in this research.

4.1.3. Objective 3: minimize the number of people outside the acceptable travel distance to at least one facility

The objective of minimizing the number of people outside the acceptable travel distance to at least one facility can be written as (Noor, Zurovac, Hay, Ochola, & Snow, 2003; Gu et al., 2010).

$$\text{Minimize} \sum D_{ij} \quad (dis_{ij} > \text{ThresD}) \tag{6}$$

where ThresD is the acceptable travel distance for Hong Kong citizens and denotes the threshold distance that residents are willing to travel.

4.1.4. Objective 4: minimize the cost of building a new public health-care facility

The cost of building new public health-care facility is typically considered to be linearly related to the capacity or the type of facility (Landa-Torres et al., 2013). The objective of minimizing the cost of building a new public health-care facility can be written as follows (Dokmeci, 1979):

$$\text{Minimize cost} = \sum_{j=1}^{m} fc(\Delta S_i) \tag{7}$$

where fc is the cost evaluating function based on the number of new capacity, ΔS_i. Traditionally, the linear relationship between capacity and average cost per unit of capacity is used. It is generally considered that adding one health-care capacity increases the unit cost by one. However, in the real world there are economies of scale that provide enterprises with cost advantages due to the size, output, or scale of their operations. The cost per unit of output decreases with increasing scale, as the fixed costs are spread out over more units of output (Duffy, 2009). The fixed costs of building a new health-care facility include building equipment and labor, while the variable costs include pharmaceuticals and supplies. The variable costs are reduced if a facility does not provide a service, whereas the fixed costs are not reduced in the short term when a health-care facility reduces a service (Roberts et al., 1999). The economies of scale in building health-care facilities have been widely proven (Smith-Daniels, Schweikhart, & Smith-Daniels, 1988) and thus need to be considered. In this research, the function fc, which denotes the relationship between a specific hospital's capacity and average cost, is determined by considering economies of scale.

The classic economies of scale function in terms of output versus average cost are represented in Fig. 2 (Mansfield & Yohe, 1988). In the first stage, before the optimal output (OOP) is reached, the average cost decreases; hence, this is defined as the economy of scale stage. When the output exceeds the OOP, the average cost increases; hence, this is defined as the diseconomy of scale stage. In this research, output refers to the capacity of a hospital in the Hong Kong health-care system. The scale of health-care facilities in Hong Kong is limited due to the scarcity of land; therefore, given the high population density, it would be impossible to generate excess capacity to reach the diseconomy of scale stage. Thus, it is assumed that there are no diseconomies of scale in Hong Kong. Specifically, the average cost after the OOP is set as the minimum average cost, with the OOP defined as the mean capacity of existing health-care facilities (3.2209×10^5); the minimum average cost is set as 0.2; and the maximum average cost is set as 1.

4.1.5. Constraint: total increase in new public health-care facility

The optimization is carried out for the projected year, 2020. New health-care facilities should be built to meet the increasing

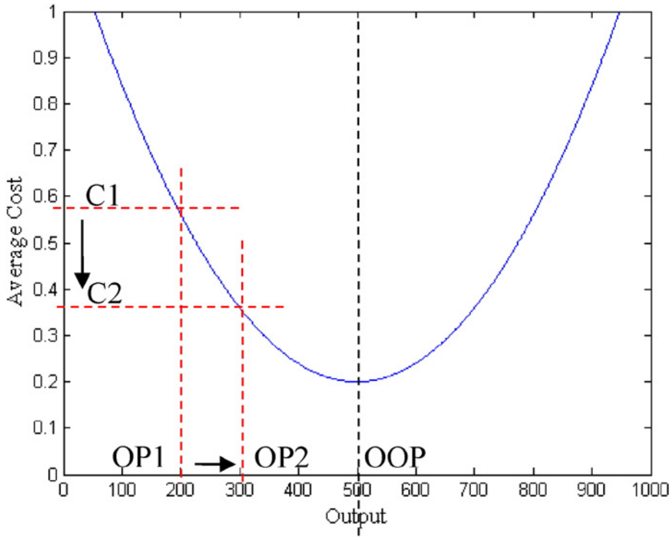

Fig. 2. Relationship between the average cost and output of economies of scale.

population/demand. However, the scarcity of land in Hong Kong means that capacity should not increase faster than the population increases. The population growth pattern (1981–2012) and trend line are presented in Fig. 3.

The population growth trend (linear regression, $R^2 = 0.9687$) indicates that the population growth rate from 2012 to 2020 is 0.083067 (see Fig. 3). Within this context, the constraint on the total capacity is set so that the increased health-care capacity should not exceed 1.083067 times the health-care capacity in 2012. The constraint is written as follows:

$$\sum_{i=1}^{m} \Delta S_i \le \alpha \sum_{i=1}^{m} S_i \tag{8}$$

4.2. Optimization methods

4.2.1. Genetic algorithm

The genetic algorithm is selected to conduct the multi-objective optimization. The smallest unit in a GA is a gene, which denotes a specific SB within the study area. A series of genes creates a chromosome, which is also considered as one solution. In the GA used in this research, the value assigned to a gene represents the specific value assigned to each SB to denote its new health-care capacity, ΔS_i. Given that the existing capacity, SO_i, of each SB is known, the results for the optimal ΔS_i reveal the total capacity, S_i, for the i-th SB (see Fig. 4). In the GA, a number of

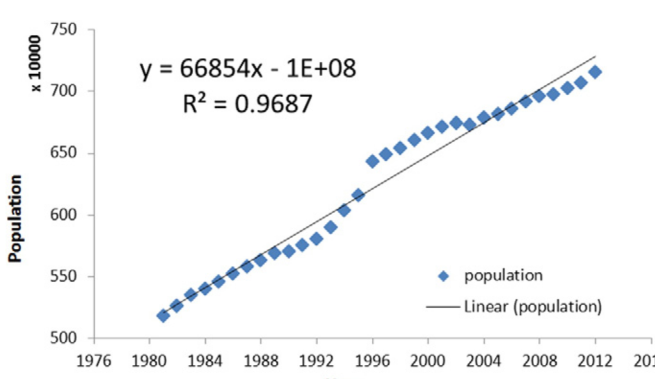

Fig. 3. Hong Kong population from 1981 to 2012 and its trend line.

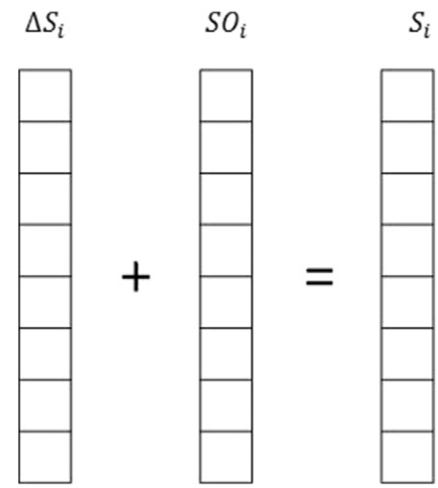

Fig. 4. Relationships between ΔS_i, SO_i and S_i.

chromosomes comprises one generation, which is represented as a set of solutions achieved by the GA.

Typically, the GA starts by randomly generating 100 solutions to create the first generation. Then, the solutions in the first generation that satisfy the constraints are ordered according to their fitness. The second set of 100 solutions is obtained via the processes of selection, crossover, mutation, and elitism in the first generation:

(1) Selection: Ten plans with high fitness are selected as potential father and mother from the pool of feasible plans; then two plans are assigned as the father and mother randomly from potential father and mother plans. By the process of selection ten plans first, it prevents local optimization to some extent.

(2) Crossover: Parental genes of the father and mother are exchanged via a crossover to generate children.

(3) Mutation: To avoid the local optimum, a mutation process is conducted by applying a mutation probability of 0.05 to all of the child plans. Thus, for each gene, there is a 0.05 probability of a random change to another land use value. These processes continue until 100 plans are generated.

(4) Elitism: To maintain the good quality of the previous generation, about 10% of the plans with the highest fitness are maintained in the next generation.

The same processes are used to generate subsequent generations until the improvement in the average fitness of each generation is smaller than a certain threshold, or the number of iterations reaches a relatively large number.

4.2.2. Fitness evaluation

Fitness is an indicator of the quality of a solution in one generation. Thus, the higher the fitness value, the better the plan (Balling, 2003; Balling, Powell, & Saito, 2004; Lowry & Balling, 2009). There are numerous ways to compute fitness including ranking, normalized sum objective approach, and weighted average of normalized objective approach, altering objective function (Hajela & Lin, 1992; Konak, Coit, & Smith, 2006). Normalized sum objective approach and weighed average of normalized objective approach are straightforward implementation, while not all Pareto-optimal solutions can be investigated by the approach when the true Pareto front is non-convex (Zitzler, Deb, & Thiele, 2000; Konak et al., 2006). The main advantage of the altering objective approach is easy to computationally implement, while the major drawback is that the population tends to converge to solutions which are superior in one objective, but poor at others (Konak et al., 2006). The maximin function is a simple, elegant fitness function that can be used in multi-objective evolutionary optimization (Balling, 2003) and direct GA towards final generations that are both close to the universal Pareto front and diverse (Balling & Wilson, 2001). Therefore, the

Table 1
Objective values of TO and configuration of existing health-care facility.

Four objectives	Inequity of accessibility	Total accessibility	Population out of coverage	Cost
Existing configuration	3.5915	2.9633	3.4413	1.7237
Mean solution of TO	2.8566	2.8852	2.9242	1.7050
Minimum inequity solution in TO	2.6209	2.7300	2.9418	1.5392
Maximum total accessibility solution in TO	4.4959	2.9633	4.1761	1.6994
Minimum population out of coverage solution in TO	3.5443	2.7963	2.3287	1.5828
Minimum cost solution in TO	2.6248	2.7264	2.9349	1.5368

maximin fitness function proposed by Balling (2002) is used to measure the goodness of plans in one generation. First, all of the objectives are translated into the min(Z) format by Eq. (9), and then Ob_{ki} is taken as the value of the k-th objective in the i-th plan.

$$Z = -Z \tag{9}$$

Now, consider two plans in one generation, the i-th plan and the j-th plan. The i-th plan is dominated by the j-th plan if

$$Ob_{1i} > Ob_{1j}, Ob_{2i} > Ob_{2j}, \ldots, Ob_{ki} > Ob_{kj} \tag{10}$$

and this equation is equivalent to the following equation:

$$\min(Ob_{1i} - Ob_{1j}, Ob_{2i} - Ob_{2j}, \ldots, Ob_{ki} - Ob_{kj}) > 0 \tag{11}$$

Thus, the i-th plan is dominated if

$$\max_{i \neq j}\left(\min(Ob_{1i} - Ob_{1j}, Ob_{2i} - Ob_{2j}, \ldots, Ob_{ki} - Ob_{kj})\right) > 0 \tag{12}$$

and the fitness of the i-th plan is

$$f_i = \left[1 - \max_{j \neq i}\left(\min\left(\frac{Ob_{1i} - Ob_{1j}}{Ob_{1-\max} - Ob_{1-\min}}, \ldots, \frac{Ob_{ki} - Ob_{kj}}{Ob_{k-\max} - Ob_{k-\min}}\right)\right)\right]^{p} \tag{13}$$

In the above equations, the scaling factors $Ob_{k-\max}$ and $Ob_{k-\min}$ are the maximum and minimum values of the k-th objective in one generation. In Eq. (13), the fitness of Pareto-optimal plans is between 1 and 2^p, whereas the fitness of dominated plans is between 0 and 1. If the exponent p is larger than 1, the fitness of Pareto-optimal plans increases and that of dominated plans decreases. Balling used a high p value, which made the GA quite aggressive in pursuing Pareto-optimal solutions (Balling et al., 1999). In this research, p is set as 1.

5. Results and discussion

Before carrying out the optimization for the projected year, a test optimization (TO) is conducted under the assumption that there are no public health-care facility in Hong Kong, and the capacity constraint is set so that the optimal capacity does not exceed the total capacity in 2012. The results of the TO are presented in Table 1. A comparison of the objective value of the existing configuration with the mean solution of the TO indicates that the existing configuration of health-care facilities provides the overall population with relatively high accessibility. However, for the other three objectives—minimizing the inequity of accessibility, minimizing the number of people that fall outside the acceptable travel distance, and minimizing the cost of building new facilities—the existing configuration is not as good as the mean solution provided by the TO. This suggests that the existing configuration focuses on the total accessibility and ignores or fails to make a tradeoff between the other objectives. Because the objectives are conflicting, the improvement of one has to come at the cost of the other three.

The solutions provided by the TO, with the best solution for each separate objective, are reported in Table 1. The minimum inequity in accessibility provided by the alternative plans generated by the TO is

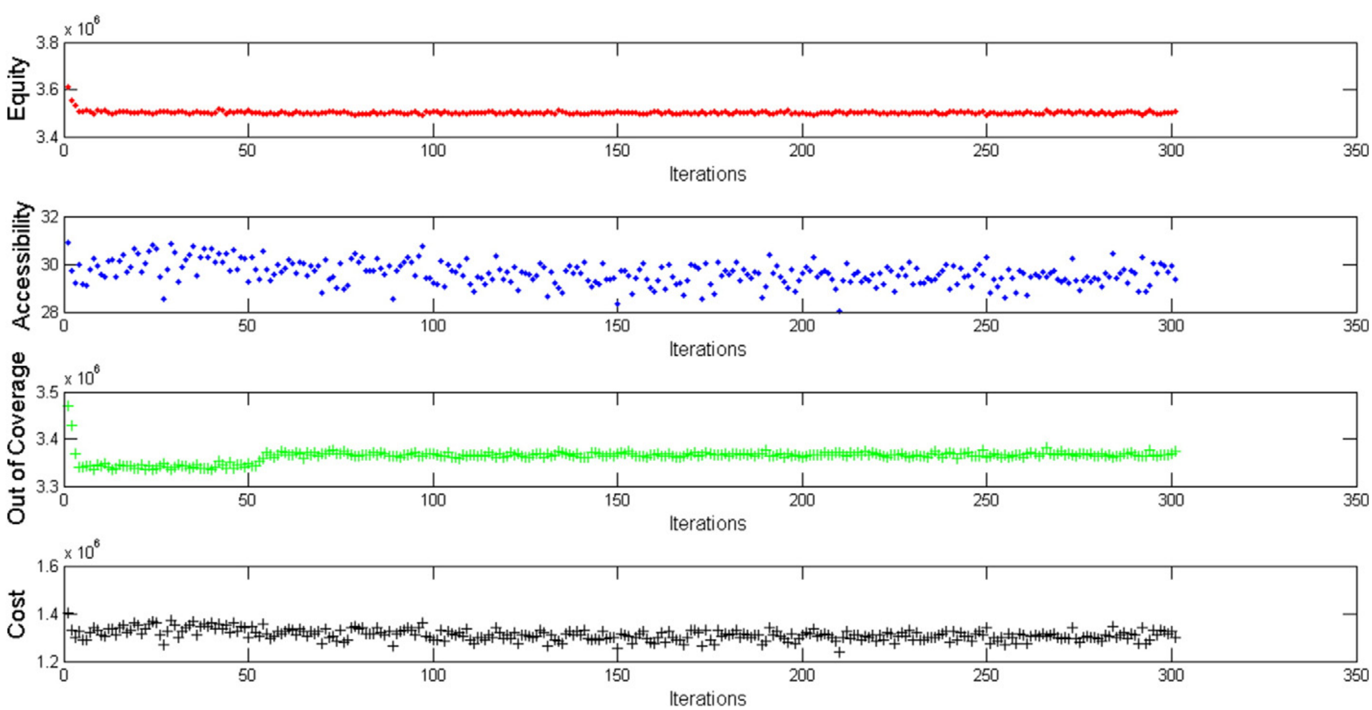

Fig. 5. Variations in the objective value from the first to the last generation for different objectives.

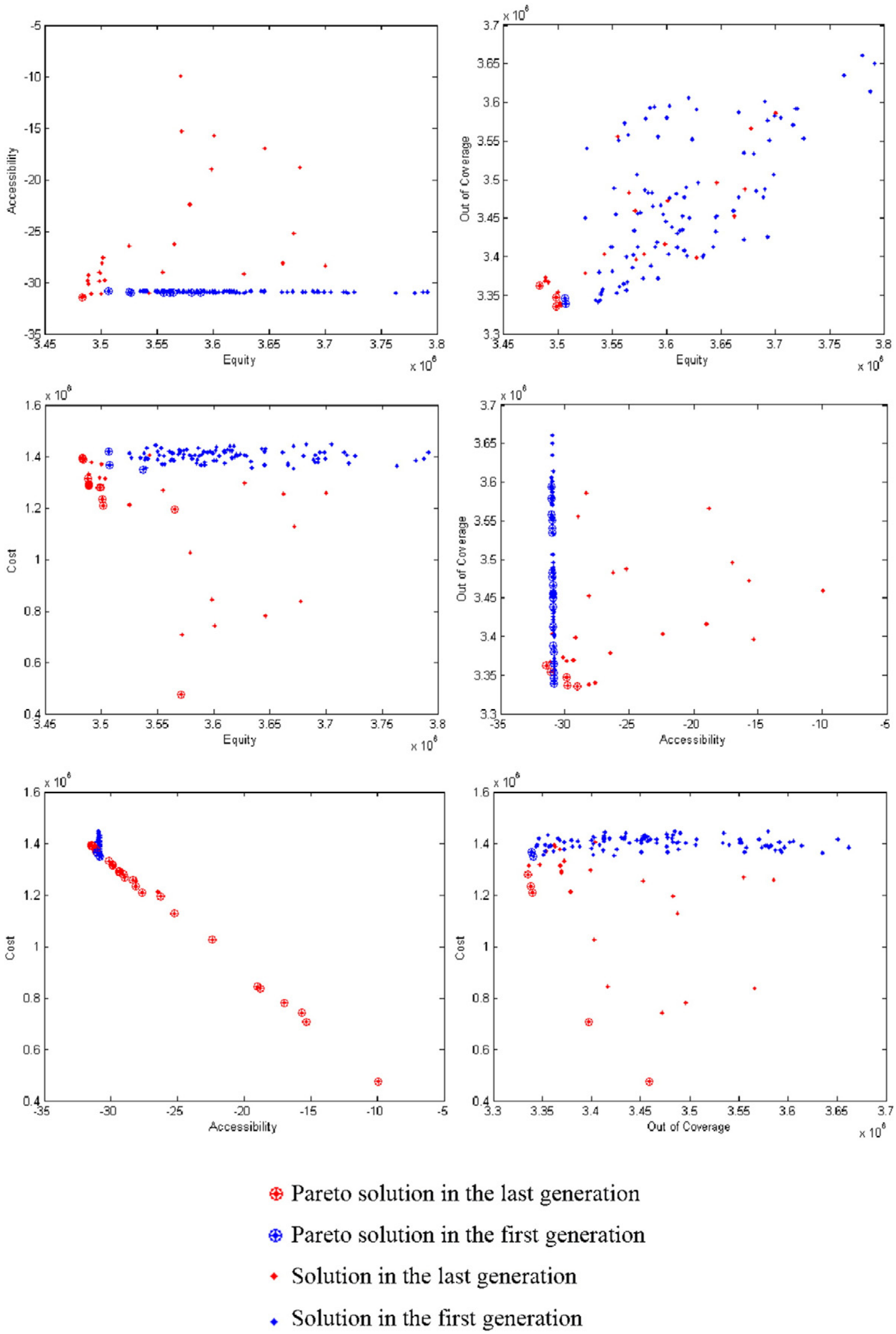

Fig. 6. Pareto solutions between each pair of objectives.

Table 2
Comparison of existing and optimal facility configurations.

Four objectives	Inequity of accessibility	Total accessibility	Population out of coverage	Cost
Existing configuration	3.5915	2.9633	3.4413	–
Mean solution of optimal configuration	3.1768	5.8485	3.1866	1.7050
Minimum inequity solution of optimal configuration	3.0425	5.6932	3.2018	1.5392
Maximum total accessibility solution of optimal configuration	3.3969	5.9263	2.9030	1.6787
Minimum population out of coverage solution of optimal configuration	3.3726	5.7595	2.8954	1.5828
Minimum cost solution of optimal configuration	3.0574	5.6896	3.1990	1.5368

2.6209×10^6, compared with 3.5915×10^6 in the existing configuration. The minimum value of the uncovered population is 2.3287×10^6 in the alternative plans, whereas it is 3.4413×10^6 in the existing configuration. The minimum value of the cost of building new health-care facilities in the alternative plans is 1.5368×10^7, and 1.7237×10^7 in the existing configuration. In terms of maximizing total accessibility, the objective value in the solutions provided by the TO is 2.9633×10^7, which is the same as the total accessibility in the existing configuration. In summary, the TO provides a set of solutions rather than one best solution. Most importantly, some of the Pareto solutions in the TO improve the existing configuration, which validates the use of the MOO approach in solving the health-care facility location-allocation problems of Hong Kong.

After testing the approach by carrying out the TO, the GA based MOO approach is used to determine the locations of Hong Kong's new public health-care facilities in 2020. As there are 100 alternative plans in each generation and each plan has four objectives, for ease of comparison, the average value of each objective for the 100 plans in each generation from the first iteration to the last iteration is represented (see Fig. 5). The variation lines generally indicate that the minimizing objectives are minimized and the maximizing objectives are maximized from the first to the last generation; that is, the MOO approach is successful.

The Pareto solutions are analyzed to clarify the results provided by the MOO approach. In Fig. 6, two specific objectives are represented on the x and y axes, respectively. All of the solutions in the first and last generation are noted first, followed by the Pareto solutions in the first and last generation. Given that only one objective is a maximizing objective and the other three are minimizing objectives, the maximizing objective is transformed into a minimizing objective to make it simpler to compare all four objectives simultaneously. In Fig. 6, the red points (solutions in the last generation) are closer to the origin than the blue points (solutions in the first generation). This suggests that the objectives are improved by the MOO approach from the first to the last generation. Furthermore, more Pareto solutions are obtained in the last generation than in the first, which validates the practice of searching for Pareto solutions through the MOO approach.

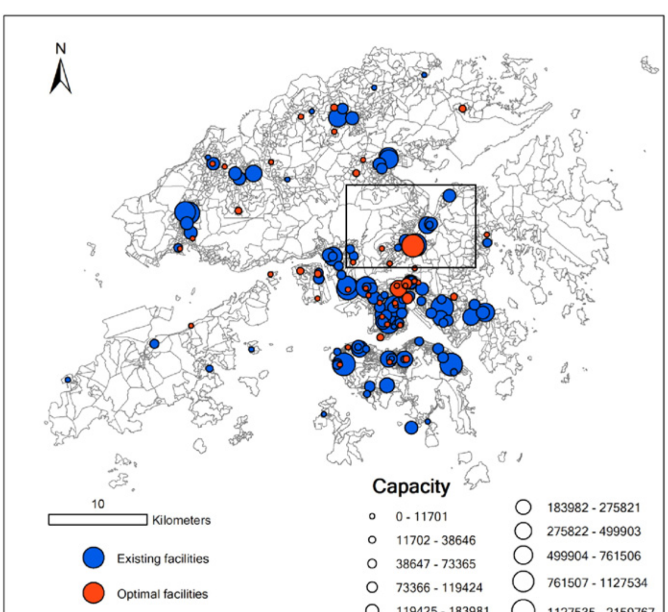

Fig. 7. Existing and optimal configurations of public health-care facilities.

The objective value of the existing configuration and several special solutions provided by the MOO approach are listed and compared in Table 2. Five of the solutions provided by the MOO approach are selected and presented. The first selected solution is the mean solution of 100 plans in the last generation. The second solution is the one that has the minimum inequity of accessibility value in the last generation. The third solution has the maximum total accessibility value in the last generation. The fourth solution has the maximum non-covered population value in the last generation. The fifth solution has the minimum cost in the last generation. The mean solution of 100 plans in the last generation maintains better values for three objectives than the existing configuration; the exception is the minimizing cost objective. The inequity of accessibility is reduced from 3.5915×10^6 to 3.1768×10^6; the total accessibility is increased from 2.9633×10^7 to 5.8485×10^7; and the population out of coverage is reduced from 3.4413×10^6 to 3.1866×10^6. However, the cost of the mean solution is 1.7050×10^6. Obviously, the mean solution of the optimal configuration improves the three other objectives, but at the price of increasing the cost of building new public health-care facility. In addition to the mean solution, the other four special plans with maximum or minimum solutions for one specific objective are also listed in Table 2. The minimum inequity is 3.0425×10^6, the maximum total accessibility is 5.9263×10^7, the minimum population out of coverage is 2.8954×10^6, and the minimum cost is 1.5368×10^7. Obviously, the best outcome for each objective is achieved in different solutions, suggesting that all of these objectives are conflicting, and no solution can obtain the best value for all of the objectives. Even if the best solution for one objective can be obtained, it must come at the cost of diminishing at least one other objective. Thus, there is no best solution, but rather a set of Pareto solutions from which planners can make their selection.

The spatial distribution of optimal health-care facilities in one Pareto solution is represented in Fig. 7, and Fig. 8 presents the population under different levels of accessibility, before and after optimization. AccessOr and AccessOp in Fig. 8 denote the population under the accessibility of the existing and optimal configurations, respectively. More of the population suffers from poor accessibility in the existing configuration, while in the optimal configuration, more people experience better accessibility. This suggests that the optimal solution promotes accessibility, and that this promotion occurs among most of population rather than just a small proportion.

The new health-care facilities tend to be located in more heavily populated areas that lie outside the acceptable travel distance to at least one health-care facility (see Fig. 9). An area of interest in Fig. 7 is amplified in Fig. 10. The figure shows that the health-care facility with the largest capacity is located in the area with the largest number of

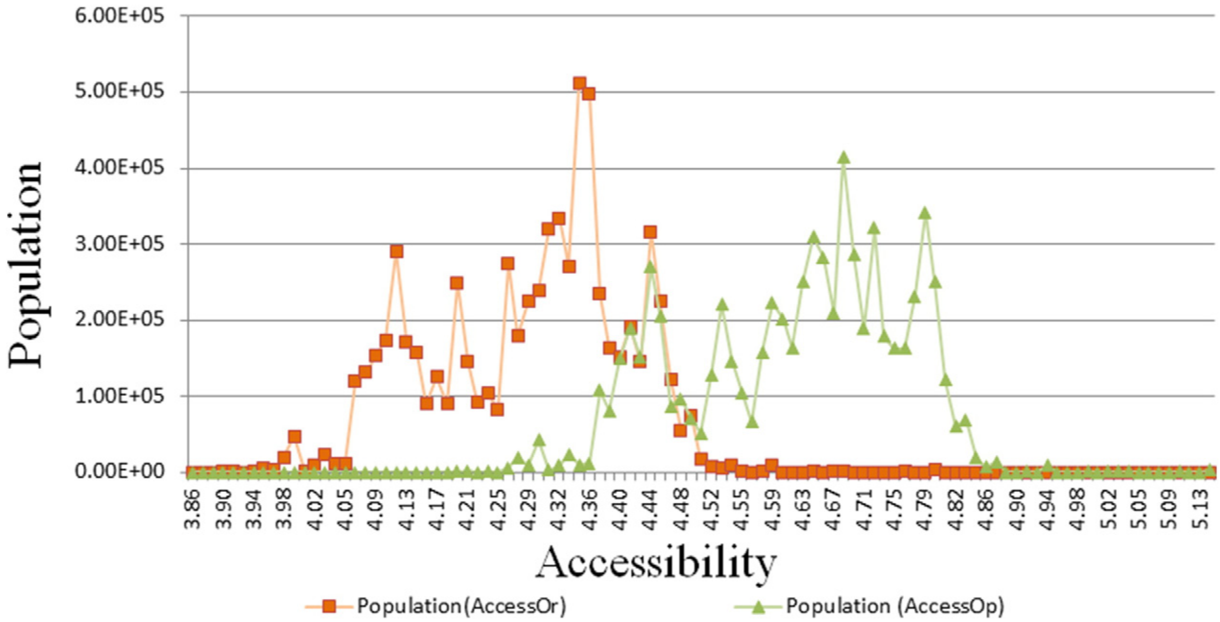

Fig. 8. Population values under various levels of accessibility before and after optimization.

people exceeding the acceptable travel distance. Locating the new health-care facilities in these places simultaneously reduces the number of people exceeding the acceptable travel distance, increases the equity, and improves the total accessibility.

In summary, the research conducts the TO first to validate that the proposed MOO approach is useful in solving the MO problem of health-care facility location-allocation; then, the MOO approach is used to optimize the configuration of health-care facilities in 2020 for Hong Kong. The conflicting between objectives, variations of objective values, Pareto solutions and spatial distribution of one Pareto solutions are carefully analyzed, the results of which indicate that the proposed approach is useful in solving the MO problem in locating health-care facilities in a highly developed city.

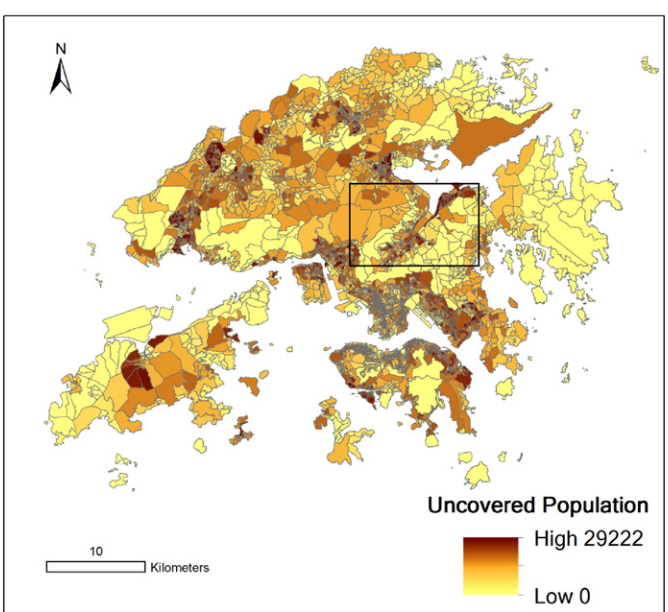

Fig. 9. Spatial distribution of the uncovered population before optimization.

6. Conclusions

Location-allocation models have played a major role in the geographical modeling of health-care facilities (Harper, Shahani, Gallagher, & Bowie, 2005). This research uses a GA-based multi-objective optimization approach to find the optimal tradeoffs between the objectives in locating health-care facilities. Taking the objective of minimizing the cost and maximizing the total accessibility as an example, the former requires a reduction in the number of health-care facilities while the latter requires an increase. Meanwhile, the objectives of minimizing inequity and maximizing total accessibility also conflict to some extent. The former focuses on locating the new health-care facilities in areas with lower accessibility to make the spatial distribution fair for the entire population, while the latter attempts to raise the accessibility in heavily populated areas for more widespread accessibility overall. Given such conflicts, there is no single best plan that achieves all of the objectives. Within this context, the MOO approach attempts a tradeoff among all of the objectives and then generates the Pareto solutions. As presents above, in different Pareto solutions, the tradeoffs between the objectives are different, which means different Pareto solutions maintain different objective values. Planners could then make their selection from the Pareto-solution pool. For example, if the city has easing finances, the planners would like to select the Pareto solution with higher accessibility, equity and coverage, even if this solution leads to larger cost. In verse, in strain finances the selection will be totally different. It is to say, the planners or the government can select different solution from the Pareto-solution pool with in different context.

In this research, four objectives with one constraint are designed for the MO problem of locating health-care facilities in Hong Kong. However, when applying the MOO approach to other case studies, the objectives and the functions used to measure the objectives may vary according to the context of the specific city.

In summary, health-care facility location-allocation problems will continue to be one of the most important planning concerns in the coming decades. Thus, it is important to develop and implement methods of facilitating the planners' decision making process in locating new health-care facilities. The GA-based MOO approach proposed in this research enables a tradeoff to be made between conflicting objectives, and can be used in other cities with different objectives.

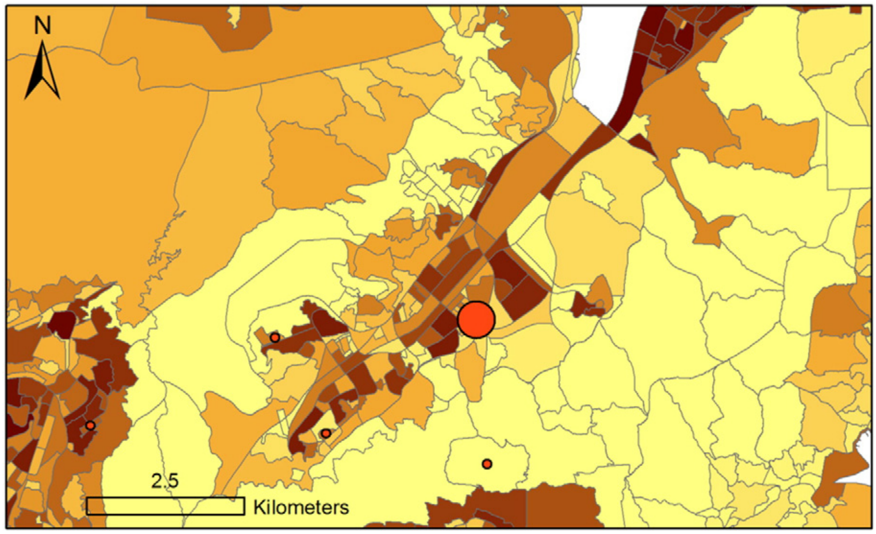

Fig. 10. A hot spot optimal area for health-care facilities and the number of people that would be within an acceptable travel distance of at least one such facility.

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