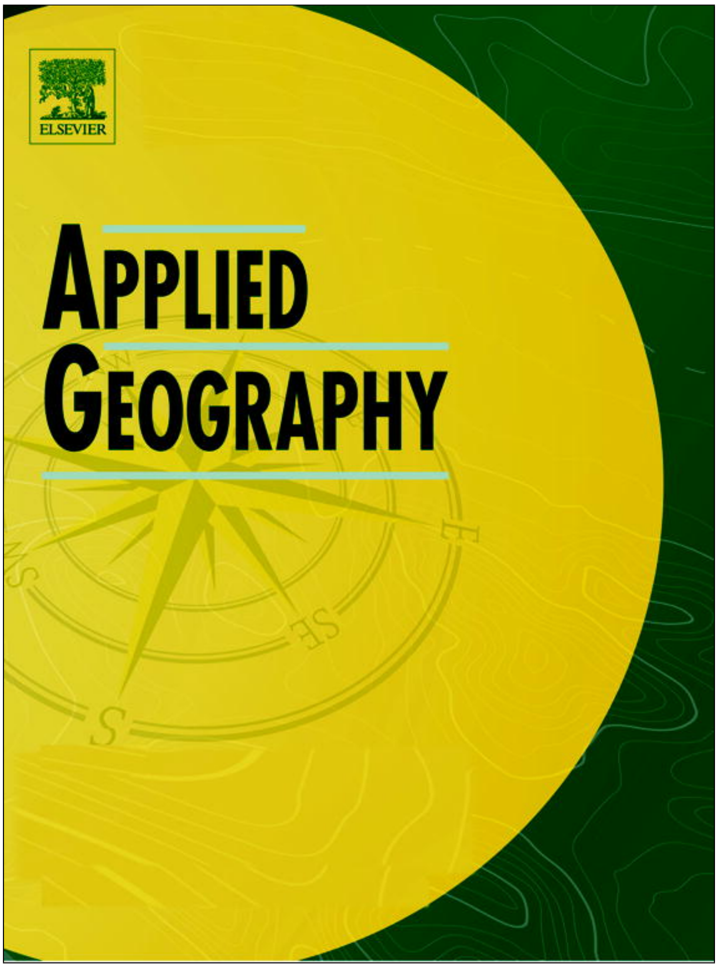
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Optimizing locations for the installation of automated external defibrillators (AEDs) in urban public streets through the use of spatial and temporal weighting schemes

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A B S T R A C T

Objective: Out-of-hospital cardiac arrest (OHCA) occurs when the heart is deprived of oxygen without immediate medical treatment. The use of publicly accessible automated external defibrillators (AEDs) is generally considered to be an effective pre-hospital measure. Although studies have been undertaken to determine the locations of AED installations, the spatial and temporal characteristics of OHCA occurrence have not been considered comprehensively. This study attempts to assess the feasibility of using the 7-Eleven chain of convenience stores as possible locations for the installation of AEDs to capture the spatial and temporal characteristics of OHCA patients.
Methods: The methodological framework was divided into two stages. The first stage involved the development of two weighting schemes, a temporally weighted model (TWM) and a spatially weighted model (SWM), to capture the temporal and spatial variations in selecting AED locations. In the second stage, we proposed a stirring genetic algorithm (SGA) to select the limited subset of 7-Elevens covering the most weighted OHCA occurrences from the first stage.
Results: We considered two modes of conveyance, human running and vehicle transportation, by setting the service range of the 7-Elevens at 100 and 300 m. Among a total of 323 OHCA cases within 100 m of a 7-Eleven, our results showed that there were 177 cases (54.8%) to be covered in the TWM and 150 cases (46.44%) in the SWM. When the service range was increased to 300 m, the total number of OHCA cases increased to 1271, which included 659 cases (51.85%) to be covered in the TWM and 522 cases (41.07%) in the SWM. We also found that, in public streets in urban settings, the TWM selected more 7-Elevens in commercial areas, while the SWM selected more stores in residential areas.
Conclusions: We conclude that each 7-Eleven has a different role for allocating AEDs in an urban setting. The AEDs at 7-Elevens in commercial areas help to compensate for the temporal gap of emergency medical service (EMS) in nighttime occurrences and for a high incidence of OHCA patients. For convenience stores in residential areas, AEDs help to compensate for the spatial gap in areas that are far from fire stations.

Introduction

Out-of-hospital cardiac arrest (OHCA), a medical emergency in which an absence of systole occurs beyond the range of care of a hospital so that the heart is deprived of oxygen with no immediate medical treatment, remains a main cause of cardiovascular sudden death. Studies have shown that the survival rate of an OHCA declines by 5–6% per minute without treatment (Larsen, Eisenberg, Cummins, & Hallstrom, 1993). The survival rate is strongly correlated with shortening the time between the collapse of the OHCA patient and the first defibrillation, with studies showing that an interval of less than 4 min to defibrillation significantly raises the survival rate (Valenzuela, Roe, Cretin, Spaite, & Larsen, 1997). On the other hand, although 80% of OHCA events occur at home and 60% occur in the presence of another person (de Vreede-Swagemakers et al., 1997), the OHCA survival rate depends significantly on the ambulance dispatch

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point (Lyon, Cobbe, Bradley, & Grubb, 2004). Therefore, one of the most important issues in emergency medicine over the past decade has been to improve the provision of emergency medical services to increase the survival rate of OHCA patients (Bång, Biber, Isaksson, Lindqvist, & Herlitz, 1999) because OHCA patients who receive early cardiopulmonary resuscitation (CPR) have a greater chance of survival (Callaham & Madsen, 1996; Maguire, 1998). The survival rate is approximately 23%–29% higher for patients receiving CPR than for those who do not (Eckstein, Stratton, & Chan, 2005; Herlitz et al., 2005; Holmberg, Holmberg, & Herlitz, 2000). A Swedish study showed that bystander CPR has increased the OHCA survival rate from 31% in 1992 to 50% in 2005 (Hollenberg et al., 2008). Moreover, the installation of automated external defibrillators (AEDs) in locations accessible to the public is also considered to be the effective means of reducing the time from collapse to first defibrillation (Becker, Eisenberg, Fahrenbruch, & Cobb, 1998; Folke et al., 2009; Weaver et al., 1988). In Taiwan, early defibrillation programs in Taipei City began in June, 2000 (Ko et al., 2004), with the goal of making AEDs available in public locations such as airports and shopping malls.

The utility of spatial analytical methods has been discussed in research on the spatial patterns of medical services (Murray & Tong, 2009; Zhang, Wong, So, & Lin, 2012). Although studies on the locations of AED installation have been performed over the years (Caffrey, Willoughby, Pepe, & Becker, 2002; Folke et al., 2009; Malcom, Thompson, & Coule, 2004), the spatial and temporal variations of OHCA occurrence and the availability of emergency medical services (EMS) have not been considered comprehensively. Regarding temporal variations, among OHCA patients with similar demographic characteristics, co-morbidity and concomitant pharmacotherapy, cardiac arrest at night may be more dangerous than cardiac arrest during the day because human activity may be generally lower during the night than during the day. Nighttime cardiac arrest may therefore have a smaller probability of being discovered, increasing the delay in treatment. In addition, meteorological factors such as temperature and humidity may cause differences in the frequency of cardiac arrest in a given location (Nichol et al., 2008), and the variance of temporal frequency may appear significant over weeks or months (Brooks et al., 2010). Therefore, the installation of defibrillators is important in areas with a high frequency of cardiac arrests so that bystanders can offer emergency treatment before the ambulance arrives.

Regarding spatial variations, AED installation can compensate for geographical obstacles to timely EMS treatment to raise the survival rate of OHCA patients (Lyon et al., 2004). Therefore, determining locations for defibrillator installation focuses on the efficiency of fixed locations or mobile vehicles for AED devices. Defibrillator devices are installed at fixed locations, such as parks, shopping malls, bus stops, and airports, where they are reported to have served millions of people per year (Caffrey et al., 2002). The main advantage of installing AEDs at fixed locations is that the position of the AED installation can be easily identified during an emergency. However, because of the utilization rate of this equipment, fixed AED locations would be concentrated in high-activity areas, giving rise to a delay in the time from collapse to defibrillation for OHCA patients in low-activity areas. Instead of having a fixed location, some AEDs are mobile, having been installed on vehicles for conventional emergency medical rescue. AEDs installed in police cars may offer another strategy for faster defibrillation (Myerburg et al., 2002). However, these vehicles may be occupied with other duties, thereby delaying the AED treatment of OHCA. Installation at fixed locations therefore remains the most common approach. Furthermore, current AED installation focuses on indoor public areas with high activity, paying less attention to low-density population areas and outdoor locations, where it is unlikely that an OHCA event would be witnessed. These areas still rely on EMS, and the obstacle to eliminating the delay in treatment remains the time required for the ambulance to arrive.

In Taiwan, over 8000 convenience stores are open every day for 24 h, the highest density in the world. The installation of AEDs in convenience stores may be an effective means to compensate for the deficiency of EMS in locations far from city centers and for nighttime OHCA incidents, offering early defibrillation for OHCA patients and thus increasing survival rates. This study attempts to assess the feasibility of using 7-Eleven convenience stores in Taipei City as possible locations for the installation of AEDs. Because of economic considerations, it is financially infeasible to install AEDs at every such convenience store, and it is therefore necessary to determine the appropriate subset of convenience stores that have the largest coverage areas. In addition, identifying this subset of convenience stores should also take into account spatial and temporal variations in the occurrence of OHCA incidents, including onset time, frequency, and the distances between the locations of AED installation and EMS (i.e., fire stations), in evaluating the provision of early defibrillation for OHCA cases. Therefore, the focus of this study is to search for appropriate public locations for installing AEDs by capturing these spatial and temporal characteristics of OHCA patients.

This problem can be formulated as a location-allocation problem that can be described as how to choose the set of locations for a limited number of AED installations with the largest coverage (Tong, Murray, & Xiao, 2009; Yin & Mu, 2012). It can be considered a set cover problem, which has been proved to be Nondeterministic Polynomial Time Complete (NP-complete) (i.e., it cannot be solved in polynomial time). To reduce the computational complexity, a linear time algorithm for a weighted set-covering problem has been presented to obtain approximation solutions (Bryehuda & Even, 1981; Gonzalez, 1995). Approaches using a combinatorial greedy algorithm have been utilized for the set cover problem in a meta-genomic data analysis with a small number of clusters selected to find studies of microbial communities (Gandhi, 2004; Gori & Folino, 2011). To avoid solutions falling in a local optimum, genetic algorithms (GAs) have been widely used to solve the complex optimization problem (Aickelin, 2002; Vasko, Knolle, & Spiegel, 2005).

GAs are regarded as a heuristic searching approach to solve optimization problems with enormous solution spaces that are difficult to evaluate. In the past decade, GAs have been used in emerging medical fields for set covering problems (Aickelin, 2002; Vasko et al., 2005). For instance, when compared to other searching approaches, GAs provided a higher utility value, which represents efficiency and facility in problem solving and decision making in geographical information systems (GIS) (Li & Yeh, 2005). Response times for ambulance station locations have been evaluated as ambulance allocation problems for EMS considerations (Sasaki, Comber, Suzuki, & Brunsdon, 2010). To maximize coverage, GAs have been applied to locate government and other public facilities, such as fire stations, bike stations, nature reserves, and banks (Garcia-Palomares, Gutierrez, & Latorre, 2012; Tong et al., 2009). However, the convergence of genetic algorithms is highly correlated with the encoding and evolution rule, and stability would occur before solutions move out of the local optimum (Goldberg, 1989; Vasko et al., 2005). Considering the advantages of GAs and their convergence property, we refined a genetic algorithm with stirring chromosomes to solve the maximum cover problem with spatial and temporal variations.

Materials and methods

Data source

The data fall into three categories: OHCA information, 7-Eleven locations, and fire station locations. The OHCA data are from the Emergency Medical Service Registry System of Taipei City Government, and the filter criteria for the OHCA cases include non-trauma cases in 2010, with patients over 18 years of age who were treated by emergency medical services. The registry system was established by the Department of Health, Taipei City Government. The data were compiled by the Fire Department and hospitals in Taipei City. The OHCA data include the time of onset, ranging from January to December 2010; the locations of cardiac arrest; and the response time of the ambulance service. Among a total of 1625 OHCA patients in 2010, 1246 (76.7%) cases occurred at the patient's residence, and 247 (15.2%) occurred in public locations (such as parks, sidewalks and metro). The 7-Eleven and fire station data were collected from the 7-Eleven corporation and the Taipei City Fire Department, respectively. There are a total of 677 7-Eleven convenience stores and 44 fire stations in Taipei City. The geographical distributions of the OHCA patients, 7-Eleven convenience stores, and fire stations are shown in Fig. 1(a)–(c).

Methodological framework

Spatial and temporal variations in OHCA patients and emergency service facilities were considered in evaluating convenience stores to find the optimal locations for installing AEDs on densely populated urban streets. Our methodological framework consists of two stages. The first stage establishes the spatial and temporal weights of OHCA patients by establishing OHCA weights and the defined covering set of each convenience store to form the covering set problem. The second stage proposes a stirring genetic algorithm (SGA) to optimize the covering set problem (Fig. 2).

Early defibrillation within less than 4 min after collapse has the greatest effect on the survival probability for a cardiac arrest patient (Valenzuela et al., 1997). To consider the modes of conveyance of the AED from a convenience store to a patient experiencing OHCA, we created two possible scenarios with service ranges of 100 and 300 m. When the service range is set to 100 m, conveying an AED from a convenience store to an OHCA patient relies on human running. Because we assumed the average human running speed would be 80–100 m per minute, it is possible that an AED can be carried to an OHCA patient within 4 min by running. On the other hand, when the service range is set to 300 m, transporting an AED from a 7-Eleven to an OHCA patient within 4 min can be accomplished using a vehicle (such as a three-wheeled electric scooter or motorcycle) whose average speed is at least 20–24 kilometers per hour. It could be economically feasible for each of the selected convenience stores to have a three-wheeled scooter or motorcycle for emergency events. Assuming this speed and the use of vehicles, it is possible that an AED can be carried to an OHCA patient within 4 min.

Establishing a temporally weighted model (TWM) and a spatially weighted model (SWM)

To capture the temporal and spatial variations for selecting AED locations, we developed two weighting schemes in our models. The temporal variations considered in this study are the occurrence frequency and the time of cardiac arrest in a given location. The spatial variation considered is the distance between EMS facilities and the convenience stores. Installing AEDs in convenience stores that are far from EMS facilities may compensate for the time lost when there are long distances between OHCA patients and EMS. With these considerations, we established two models, a temporally weighted model (TWM) and a spatially weighted model (SWM).

Temporal weight of an OHCA patient. In the TWM, we divided the cardiac arrest time of the OHCA occurrences by 12 months and into two half-days (8:00 am–5:00 pm as daytime and the remainder as nighttime) to determine whether the incident occurred during the day or night. The OHCA positions in each month are the union of the total OHCAs. First, for each OHCA, x_i, we set the monthly value u_i of each month ($x_{i,m}$) as 1 or 0.5 according to whether it occurred during the night or day, respectively. To determine the monthly temporal weight of OHCA, $u(x)$, if OHCA exists (suppose the OHCA is x_i) in position i, we chose the value u_i. Otherwise, we interpolated the value that is the sum of the weighted OHCA standardized by inverse distance weighting (Eq. (1)) (Shepard, 1968).

$$u(x) = \begin{cases} u_i & , \text{ if } x = x_i \\ \sum_i \dfrac{w_i(x)u_i}{\sum_i w_i(x)} & , \text{ if } x \neq x_i \end{cases}, \tag{1}$$

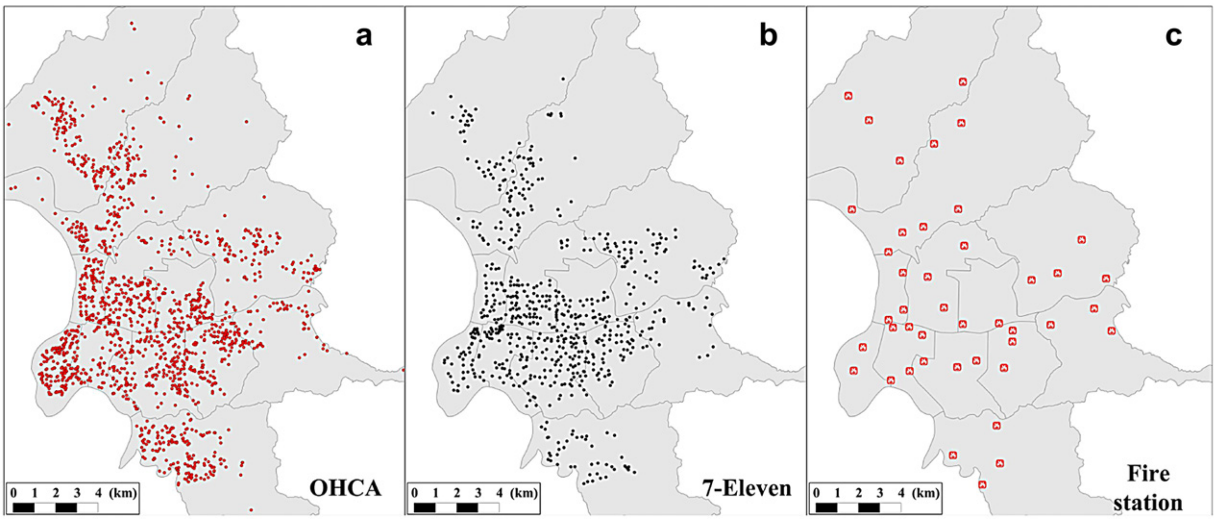

Fig. 1. Geographical distribution of (a) out-of-hospital cardiac arrest (OHCA) cases in 2010, (b) 7-Eleven chain of convenience stores, and (c) fire stations in Taipei City.

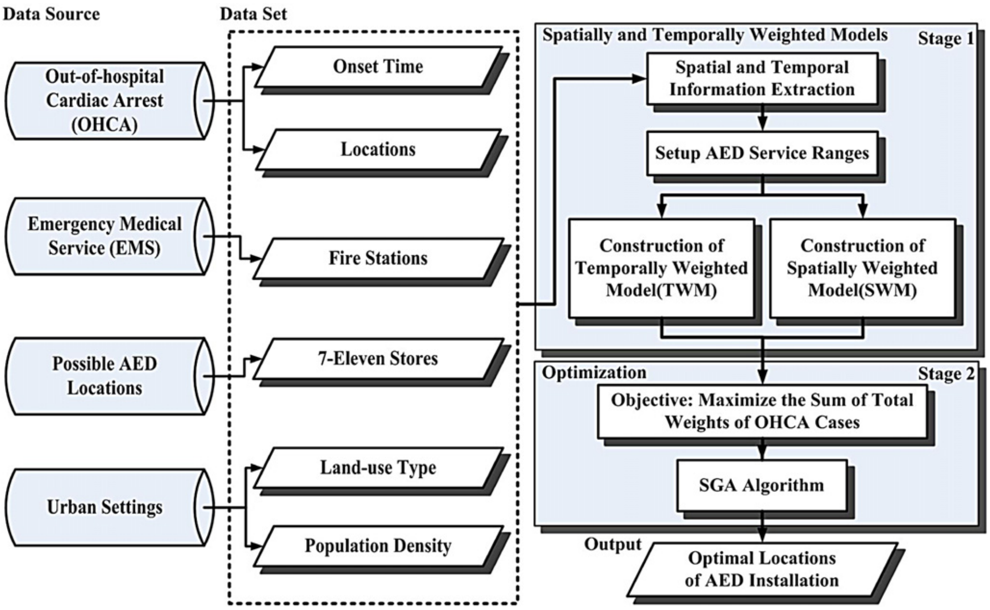

Fig. 2. Data and methodological framework.

where,

$$w_i(x) = \frac{1}{d(x, x_i)^2} \tag{2}$$

and $d(x,\ x_i)$ is the distance from x to x_i (Eq. (2)). Second, we computed the temporal weight of the OHCA by combining the 12 values of the OHCA weights, and we used the quotient of the mean $(\overline{\alpha_i})$ to standard deviation (std(α_i)) as the OHCA weight (Eq. (3)), as in,

$$\sigma_i = \frac{\overline{\alpha_i}}{\mathrm{std}(\alpha_i)}, \tag{3}$$

where $\overline{\alpha_i}$ and std (α_i) are computed as follows (Eqs. (4) and (5)):

$$\overline{\alpha_i} = \sum_{m=1}^{12} u(x_{i,m})/12, \tag{4}$$

$$\mathrm{std}(\alpha_i) = \sqrt{\sum_{m=1}^{12} \left(u(x_{i,m}) - \overline{\alpha_i}\right)^2 /12}. \tag{5}$$

Spatial weight of an OHCA patient. In the SWM, a higher weight signified a longer distance from a fire station. Therefore, we assumed the spatial weight would be the minimal square of the Manhattan distance to every fire station (μ_k) as in (Eq. (6)).

$$\sigma_i = \min_k H(\sigma_i, \mu_k)^2. \tag{6}$$

Note that we used the square of the distance to amplify the effect of distance from fire stations.

Considering the grid-like street networks in urban settings, Manhattan distances were used as the covering distance to compute the distance from a given convenience store to the OHCA patient (Eq. (7)):

$$H(a,b) = |a_x - b_x| + |a_y - b_y|, \tag{7}$$

where $H(a,b)$ is the Manhattan distance between two two-dimension points, $a = (a_x,a_y)$ and $b = (b_x,b_y)$.

Implementation of the optimization model

Objective function. Assume that there are M OHCA patients and N convenience stores. Each OHCA patient has different weights (W) based on his/her spatial and temporal characteristics. The optimization problem can be formulated as a choice of the limited K-sized subset of convenience stores that covers the OHCAs with the greatest weights. We formulated the problem as a set cover of a medical resource location-allocation problem (MRLAP) and proposed a genetic algorithm for the optimization (Eq. (8)).

$$\begin{aligned} &\text{maximize} \sum_{i=1}^{M} W_i \circ x \\ &\text{Subject to,} \\ &\sum_{i=1}^{N} x_i = K \end{aligned} \tag{8}$$

where W_i is the i-th row of the constant M by N weighting matrix W (whose element w_{ij} represents the weight of the i-th OHCA covered by the j-th 7-Eleven). We define the operator ○ as the maximum value among the sequentially chosen elements (Eq. (9)):

$$W_i \circ x = \max_j (w_{ij} \cdot x_j), \tag{9}$$

where x is of a 0–1 array of length N corresponding to the index x_i of the convenience store candidates, with an element value of 1 for the index chosen and 0 for the index not chosen. The weighting matrix W is determined by the temporal or spatial characteristics of the OHCA patients described above.

The covering set is all 7-Eleven convenience stores in Taipei City, and for each 7-Eleven convenience store, the coverable object is an OHCA. Accordingly, we denote each 7-Eleven as C_j and each OHCA as o_i. We assume that the coverable OHCAs for C_j cut off using a constant threshold d are as follows (Eq. (10)):

$$o_i \in C_j \text{ if and only if } H(o_i, C_j) \le d. \tag{10}$$

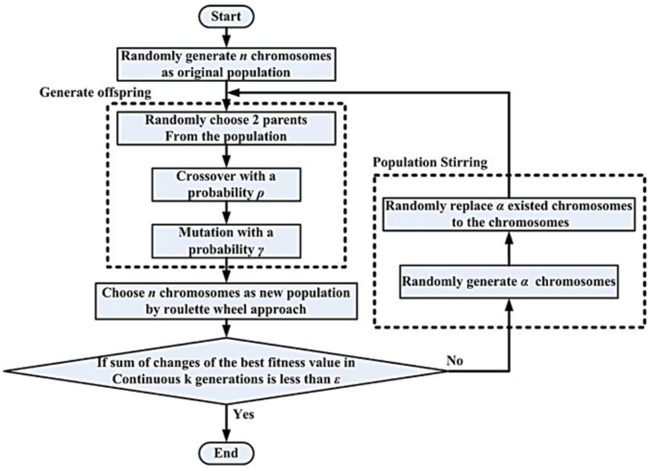

Fig. 3. The procedure of the stirring genetic algorithm (SGA).

Therefore, we define the weighting matrix W in the following equation (Eq. (11)):

$$w_{ij} = \begin{cases} \sigma_i & , \text{ if } H(o_i, C_j) \le d \\ 0 & , \text{ if } H(o_i, C_j) > d \end{cases}, \tag{11}$$

The SGA algorithm. To solve this problem, a stirring genetic algorithm (SGA) was proposed; the relevant procedure is shown in Fig. 3. The population is randomly generalized by n chromosomes initially. Each chromosome is encoded with a limited length, and each element corresponds to a unique 7-Eleven convenience store index. To evolve the offspring, a crossover rule and a mutation rule are adopted in turn with a large probability ρ and small probability γ, respectively. For the adoption of a crossover rule, two of the chromosomes in the population are randomly chosen as parents and then interchanged as elements between two random positions (Fig. 4). Avoiding results containing repeated elements, the elements of the parents are rearranged before the interchange such that the same elements of both are moved in front of the chromosome. After two new chromosomes are generated for each crossover, the mutation rule is adopted for both the chromosomes. If the chromosome is mutated, only one element in the chromosome is changed to a random but existing index (Fig. 4).

After the offspring is created, the next generation is then generated using chromosomes chosen from both the previous generation and the offspring using a roulette wheel approach; the chosen probability of a chromosome is in proportion to its fitness value. For each generation, the chromosome with the best fitness value is recorded. The fitness value of each chromosome is defined by the weight summation of the OHCA within the covering range of the selected index (Eq. (1)). To avoid falling into the local optimum solution, if the amount of changes of continuous k generations is smaller than ε (a sufficiently small number), then a number of newly random chromosomes is added to the generation to stir the convergence. The stop criterion of evolution is the convergence of the fitness value after another k generation.

Therefore, the time to stir the population occurs when the evolution is stable enough that the sum of the difference of optimal fitness values in a number of rounds (default: 20 rounds) is smaller than a tolerance value (default: 10^{-10}). Then, new and random chromosomes (default: 20%) are placed in the population in another few rounds (default: 20 rounds). Evolution stops when the sum of the difference of the optimal fitness values in the other rounds is smaller than the tolerance value.

Table 1
Percentages of OHCA cases and 7-Eleven stores in different service range.

Service range	7-Eleven ($n = 677$)	Out-of-hospital cardiac arrest (OHCA) ($n = 1625$)
100 m	262 (38.70%)	323 (19.88%)
300 m	623 (92.02%)	1271 (78.22%)

Results

We considered the two service ranges of 100 and 300 m from 7-Eleven convenience stores in Taipei City to evaluate the coverage rate of OHCA patients in Taipei City (Table 1). When the service range is set to 100 m, only approximately 20% of OHCA patients can be covered. When the service range is increased to 300 m, approximately 78% of OHCA patients are covered, and over 90% of 7-Eleven stores can be covered.

The distribution of the spatial and temporal weights of the OHCA cases is different in the TWM and the SWM (Fig.5). The size of the dots represents the level of weight computed in the TWM and the SWM. As shown, in the TWM, the weight of the OHCA cases is concentrated in western Taipei City (Fig. 5a-1, 5b-1), which has a greater population density than the average of Taipei City. However, OHCA cases in the SWM are uniformly distributed throughout Taipei City (Fig. 5a-2, 5b-2).

The SGA with the stirring population helps to raise the fitness value. We compared the performance of the SGA with a classic GA using four different parameter settings (Fig. 6). Stirring the population helps improve the chromosome selection and increases the fitness value. Although the initial population would be composed

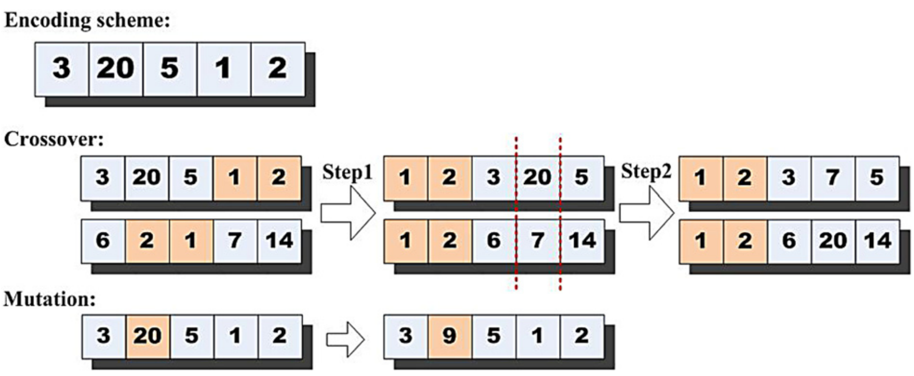

Fig. 4. The encoding scheme and rules of crossover and mutation in a stirring genetic algorithm (SGA).

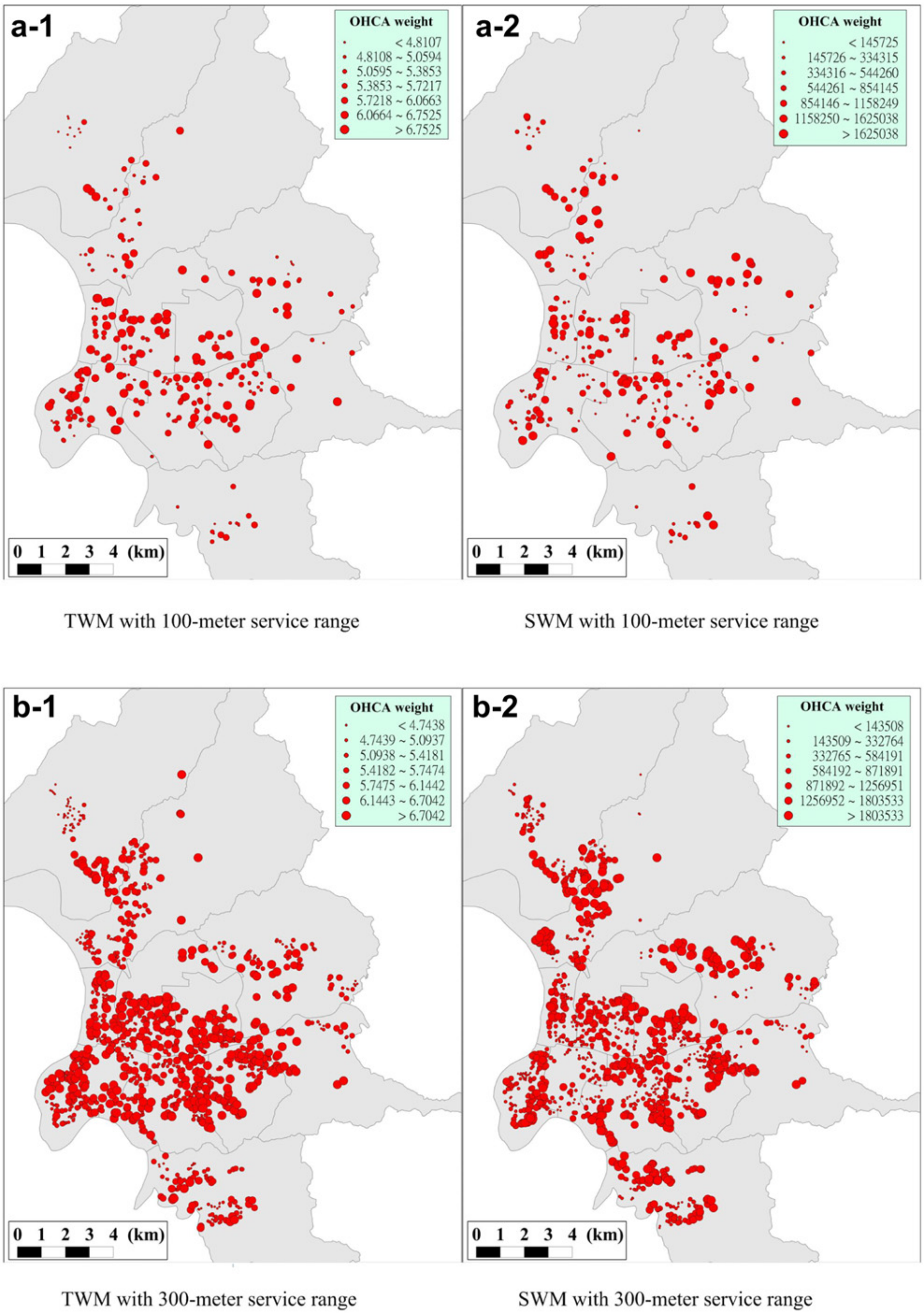

Fig. 5. Distribution of spatial and temporal weights of the OHCA cases in the temporally weighted model (TWM) and the spatially weighted model (SWM).

of lower-valued chromosomes, the SGA can gradually improve fitness values (over 200–300 generations) by stirring the population.

Fig. 7 shows the performance of the SGA in the TWM with a covering range of 100 m over one round. The results showed that the SGA (the red line) has a better performance than the classical GA (represented by the blue line). The increase in performance is shown in the gap of average fitness values (represented by the dark line). The increase in the average fitness value in the stirring stage represents the evolution toward a better population with better overall fitness values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The summary statistics showing the optimal convenience store locations for installing AEDs selected by the SGA are shown in Table 2. With the chosen number of convenience stores limited to 100 and the service range fixed, the coverage to OHCA is higher in the TWM than in the SWM. When the service range is set to 100 m, 177 OHCA patients (54.89%) are covered in the TWM, and 150 cases (46.44%) are covered in the SWM. When the service range is increased to 300 m, 659 cases (51.85%) are covered in the TWM, and 522 cases (41.07%) are covered in the SWM. When comparing the coverage rate of convenience stores with the different service ranges under consideration using the coverable OHCA cases (totaling 323 cases in the range of 100 m and 1271 cases in the range of 300 m), the coverage rate for the service range of 100 m in

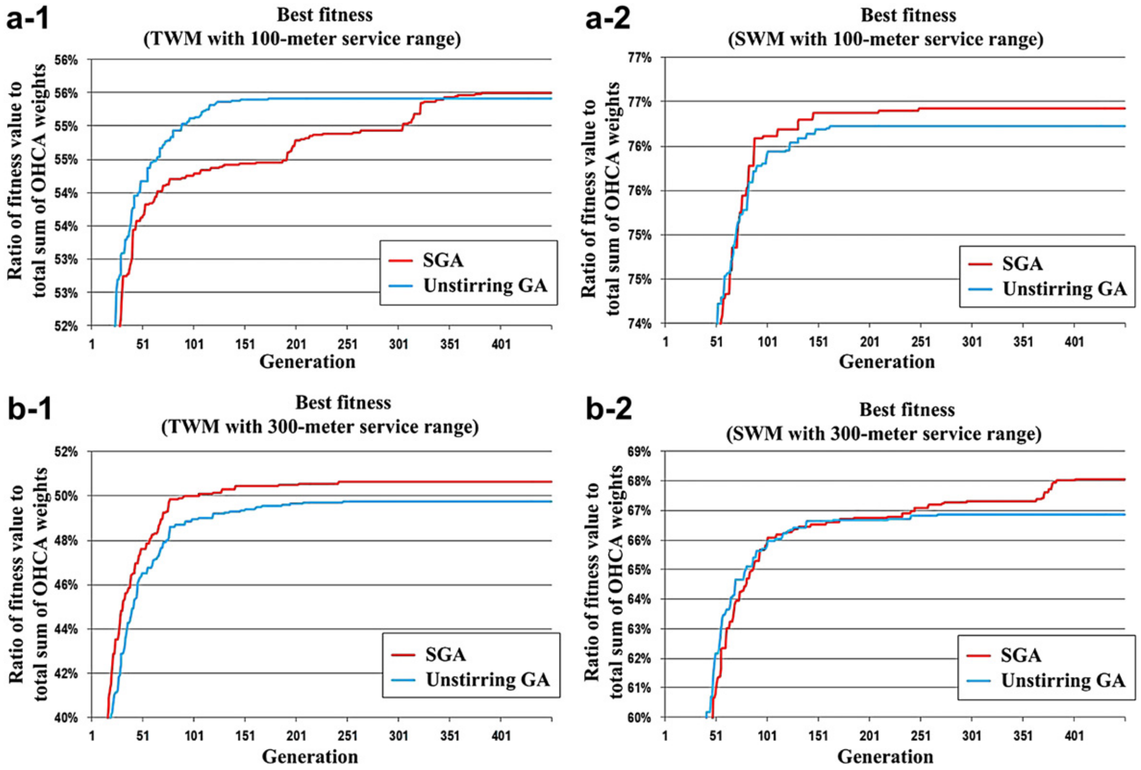

Fig. 6. Comparison of best fitness between SGA and GA: The *x*-axis represents the round of generation; the *y*-axis represents the ratio of the fitness value (the sum of weights of OHCA cases covered by the selected 7-Elevens) to the total sum of OHCA weights.

both the TWM and the SWM (54.89% and 46.44%, respectively) is higher than that of the 300-m range (51.85% and 41.07%, respectively).

The selected locations of convenience stores in the TWM are located in high-population areas, whereas the locations in the SWM are distributed in high and low-population areas (Table 3 and Fig. 8). More convenience stores located in high-population areas are selected in the SWM than in the TWM (42 versus 39 in the 300-m range in Table 3). This difference may result from the fact that in the TWM, the model preferred selecting the locations with a higher nighttime frequency, and the selected positions (represented by the blue dots) are primarily located in southwestern Taipei City, which is downtown and a highly populated area. In the SWM, the model preferred selecting locations away from fire stations; thus, the selected positions (represented by the green dots) are located primarily in suburban Taipei City. In addition, the average distance from a selected convenience store to the nearest fire station in the SWM is larger than that found in the TWM (1.23 km versus 0.87 km in the 100-m range, and 1.3 km versus 0.88 km in the 300-m range) (Table 4). The overlap (represented by the dark dots) reflects the areas with the highest priority for the installation of AEDs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Differences in urban land-use types in both models are shown in Fig. 9. The stores selected only by the TWM are represented by blue dots, while only SWM-selected stores are represented by green dots. The stores that are selected in both models are represented by black dots. It can be observed that most of the selected convenience stores in both models are located primarily in residential areas. However, in the TWM, more convenience stores are selected in commercial areas than in the SWM (31 versus 27 in the 100-m

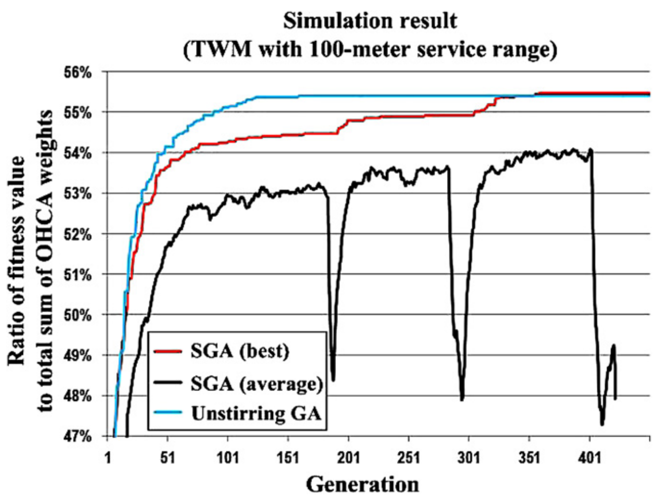

Fig. 7. A result of SGA simulation. The performance shows even SGA has a worse start but better fitness value than GA when it achieves convergence. The fitness value of SGA is raised during the generations with the gaps (caused by the stirring chromosomes) exist in average fitness value.

Table 2
Percentage of OHCA patients with the number of 7-Eleven stores limited to 100.

Service range	SGA results	
	Model	OHCA
100 m	TWM	177 (54.89%)
	SWM	150 (46.44%)
300 m	TWM	659 (51.85%)
	SWM	522 (41.07%)

TWM: temporally weighted model; SWM: spatially weighted model.

Table 3
Comparison of selected 7-Elevens at different levels of population density.

Population density	Only TWM		Only SWM		TWM and SWM	
	100 m	300 m	100 m	300 m	100 m	300 m
Low	30	22	31	30	13	11
Middle	30	39	29	28	15	16
High	40	39	40	42	23	18
Total	100	100	100	100	51	45

TWM: temporally weighted model; SWM: spatially weighted model.

range, and 29 versus 22 in the 300-m range in Table 5). Conversely, the SWM selects more convenience stores in residential areas than the TWM (53 versus 47 in the 100-m range, and 62 versus 54 in the 300-m range in Table 5). Because there is a greater frequency of human activity in commercial areas than in residential areas, the commercial areas show a higher OHCA incidence. Contrarily, because fire stations are not generally located in residential areas, the SWM selects convenience stores in residential areas. Comparing urban settings and urban land uses between the TWM and the SWM, we found that in urban settings, the SWM selects convenience stores more uniformly in both high and low population density locations than the TWM. However, in urban land uses, the TWM selects more commercial locations than the SWM, which selects more residential locations (Tables 3 and 5). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Discussions

We used different weighting schemes to incorporate the spatial and temporal characteristics of each convenience store and OHCA patient for allocating AEDs in both the TWM and SWM. First, our optimization models show that convenience stores located in high population density areas are selected under both temporal and

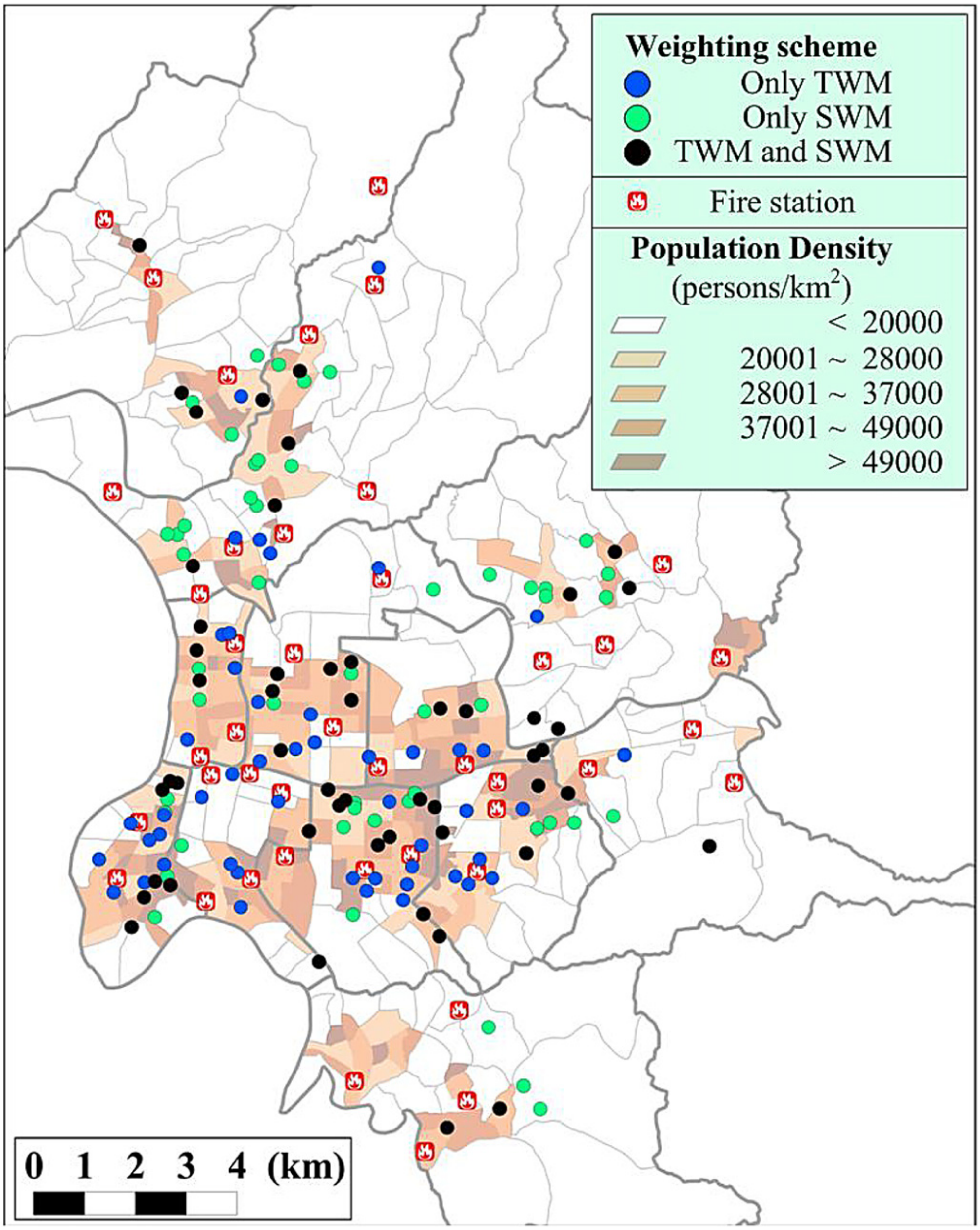

Fig. 8. Spatial distributions of population density overlaid by locations of 7-Elevens selected by the SWM and TWM with 100-m service range.

Table 4
Average distance from each 7-Eleven to the nearest fire station (unit: meter).

Service range	TWM		SWM	
	Mean	STD	Mean	STD
100 m	869	429	1230	344
300 m	881	458	1303	432

TWM: temporally weighted model; SWM: spatially weighted model.

spatial considerations (Fig. 8), which is consistent with previous studies (Malcom et al., 2004). The reason for this selection could be that OHCA incidence may be in proportion to the population density. Therefore, it would be important that the convenience stores be located in high population density areas. Second, for land use types, the optimized locations of convenience chain stores are more likely in commercial than in residential areas. The reason for this increased likelihood could be that most convenience chain stores have been built in areas of high human activity because of commercial considerations (Fig. 9). Third, optimized locations in the TWM are more likely in commercial areas, whereas the SWM is more likely to predict optimized locations in residential areas. When spatial variation is considered, our results would be consistent with the suitable area for AED placement (Folke et al., 2010). However, our results also show the importance of temporal variation and the priority of AED locations in commercial areas. Compared to commercial areas, most residential areas have less business activity and are located farther from fire stations. Therefore, the convenience stores selected in the SWM helps to compensate for poor EMS efficiency because of the long distances from fire stations to residential areas.

The SWM reflects the high priority of locations that are distant from fire stations, whereas the TWM prefers locations where OHCA cases occur at night. The overlap reflects the importance of installing AEDs in locations that compensate for the gap of EMS, for example, in locations with a high frequency of OHCA incidents that are far from fire stations. Moreover, reducing the service range of an AED installation would require that it be close to the OHCA location to reduce transport time, which could improve EMS treatment but would require the installation of more AEDs in convenience stores. Conversely, a larger service range may reduce the quantity of AEDs but can also increase the distance from the AED locations to OHCA patients. Heavy traffic, of course, may increase the time of service delivery, increasing the danger to the patient. Therefore, the setting of service ranges for installing AEDs in convenience stores can be

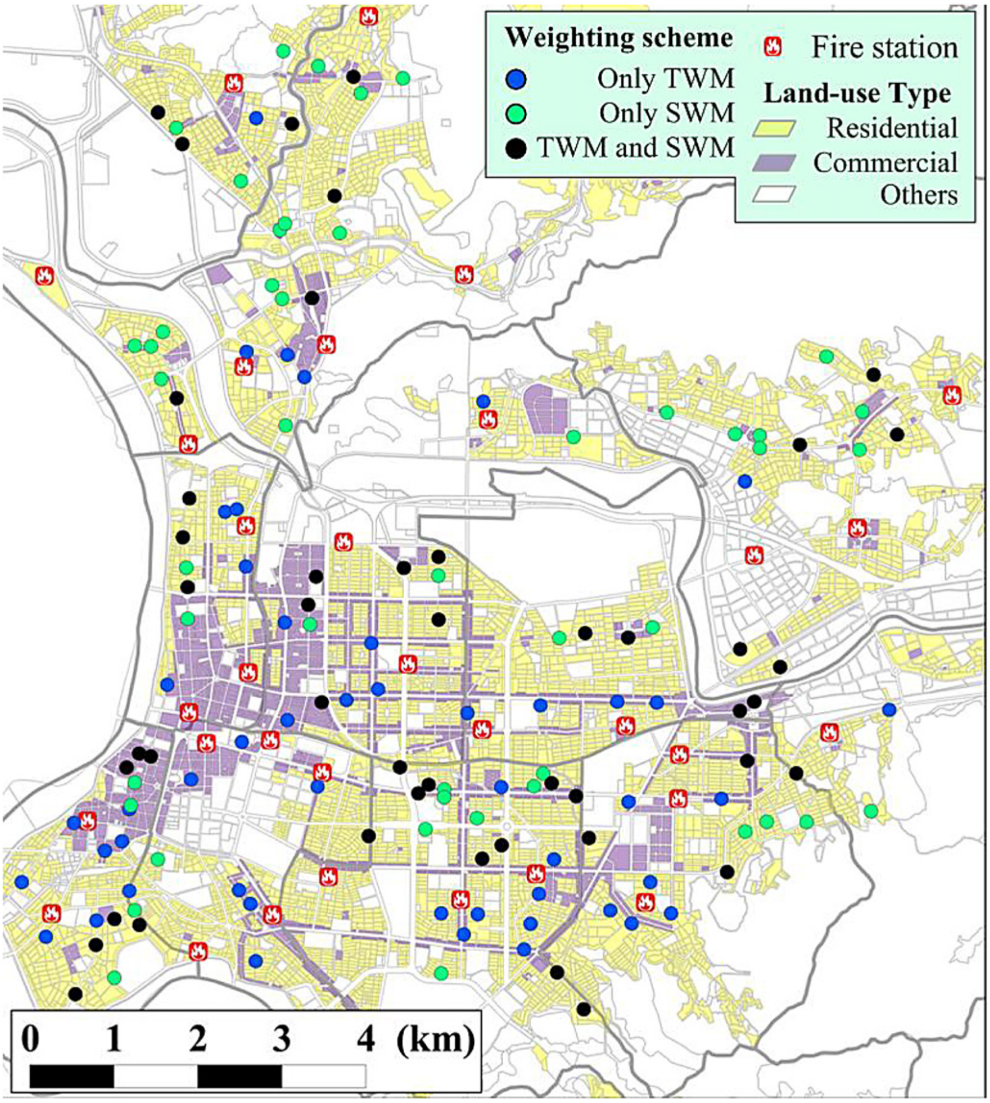

Fig. 9. Spatial distributions of land-use types overlaid by locations of 7-Elevens selected by the SWM and TWM with 100-m service range.

Table 5
Comparison of selected 7-Elevens at different types of land-use categories.

Land-use type	Only TWM		Only SWM		TWM and SWM	
	100 m	300 m	100 m	300 m	100 m	300 m
Commercial	**31**	**29**	27	22	14	11
Residential	47	54	**53**	**62**	25	28
Others	22	17	20	16	12	6
Total	100	100	100	100	51	45

TWM: temporally weighted model; SWM: spatially weighted model; comparing TWM and SWM, the larger numbers in the commercial and residential types are shown in bold.

different depending on the frequency of occurrence of OHCA cases and the traffic volume in a given area. The policy implications of installing AEDs suggest that AEDs with a small service range can be installed in areas with a high incidence of OHCA (Folke et al., 2009). Moreover, we also suggest the use of large service ranges in areas with low traffic volume.

Methodologically, a genetic algorithm (GA) is a heuristic method to solve NP problems, such as set-cover problems. Although convergence to a local optimum can be avoided in the mutation stage, it may not ensure that the GA finds global optimal solutions, even after a long period of evolution (Aickelin, 2002; Goldberg, 1989). This study demonstrated that stirring chromosomes in an SGA would be a suitable approach that satisfies both evolution time and performance. When evolution converges, the new random chromosomes stir the solution and help improve the space. Therefore, although it may have generated a poorer-performing evolution in the first several generations, the SGA may improve the performance in the final analysis. Furthermore, the SGA contains two important parameters that may be adjusted for stirring chromosomes: the length of the stable period and the number of random new chromosomes. A long period of stability would decrease the computational performance so that the SGA converges after more computation time. However, short stability periods may not ensure convergence. Large numbers may also break the evolutionary pattern with numerous random chromosomes, but small numbers may not effectively help move out from the local optimum. Therefore, the two parameters are in a trade-off, and balancing the length of the stable period with the number of newly random chromosomes in SGA models may warrant further study.

This study had notable limitations. First, this study used OHCA patient data from 2010 for AED allocation and deployment. The study period may be too short to capture long-term spatial and temporal trends of OHCA. Second, this study assumed ambulances that always deployed from fire station. Therefore, the distance between the locations of the fire stations and OHCA patients could be measured as geographical obstacles to timely EMS treatment in this study. We did not consider the situation that ambulances could be “on the road” and directed straight to the OHCA location. It is difficult to quantitatively measure the frequency and locations of “on-the-road” ambulances. However, the historical routes and volumes of ambulances could be evaluated to account for “on-the-road” EMS in further studies. Last, the 7-Eleven convenience stores were used as potential AED locations in this study because of their high-density distribution and hours of operation (24 hours a day, 7 days a week). Therefore, this study does not imply that the methods used are applicable to other areas or countries, as there may be important differences in demographics and infrastructure.

Conclusions

In this study, we proposed a framework to solve the NP problem of allocating AEDs in a limited number of convenience stores. We refined a genetic algorithm by improving the searching strategies by adding new chromosomes to the stable generation to exceed the local optimum. We established two spatially and temporally weighted optimization models, the SWM and the TWM, which considered the spatial and temporal characteristics of convenience stores and OHCA patients to validate the feasibility of using the SGA in solving the location-allocation problem.

The results suggest that the highest priority locations for AED installations would be in convenience stores in high population density areas. Each convenience store has a different role in an urban setting for allocating AEDs. For convenience store chains in commercial areas, the installation of an AED helps compensate for the temporal gap in EMS for nighttime OHCA cases and the high incidence of OHCA in general. For convenience stores in residential areas, an AED installation helps compensate for the spatial gap of areas that are far from fire stations.

Conflict of interest

The authors declare no conflict of interest related to this work.

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