Optimal Siting of Fire Stations Using GIS and ANT Algorithm

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Abstract: Safety and emergency response are being given greater importance while planning infrastructure and transportation projects. This is particularly so, when transporting hazardous materials (HAZMAT) within a heavily urbanized area such as Singapore. The number and location of fire stations significantly influence the efficiency of emergency response during fire accidents. This paper presents an approach to suitably situating new fire stations, considering multiple objectives, using geographic information systems (GIS) and ANT, a novel Ant algorithm. The efficiency of the current fire station locations in covering HAZMAT transport routes is studied using a GIS. The ANT algorithm is implemented within a GIS environment to locate the additional fire stations so as to reduce the response time to an accident occurring on HAZMAT transport routes from 8 to 5 min. Other considerations include incorporating proper distance among fire stations and maximizing the area that can be served by these fire stations in 6 min. Computational experiments reveal that the proposed algorithm performs stably under different parameter settings and outperforms the conventional genetic algorithm. Furthermore, the integration of GIS with ANT offers enhanced spatial analytical capabilities, and our approach can be employed to solve further intricate optimization problems in transportation and infrastructure.

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Introduction

Each and every major civil engineering (CE) application has a profound impact on human life and transportation and infrastructure are CE disciplines that are intricately intertwined in our day to day life. The employment of software applications and the use of spatial analytical tools such as the geographic information system (GIS) within the realm of civil engineering have increased tremendously over the past decade. These tools, in addition to facilitating conventional tasks, save considerable time and effort. While the increasing use of such information technologies are revolutionizing civil engineering practices, such practices have necessitated the use of advanced computing tools such as genetic algorithms (GAs) and various other advanced optimization techniques to solve intricate problems in the CE field. We propose a comprehensive methodology in this paper, which is applicable to a wide range of problems involving multiobjective models.

Safety is of utmost priority in the design of any modern urban infrastructure environment. Following the September 11 terror attacks in the United States and the recent July 7 attacks in London, nations around the globe are beginning to take a renewed look at the safety of their infrastructure environment and providing relief operations in the unfortunate event of a mishap. Fire stations offer the necessary personnel and paraphernalia for saving life and property during a fire accident and are inevitable components of any infrastructure environment. While it is imperative that fire stations are properly situated, their access to transportation routes and their promptness in offering services are also of considerable importance. Fire stations must not only be located such that maximum area may be served, but also strategically placed so as to minimize the response times to accident sites.

The effectiveness of the fire stations in covering the transportation routes of hazardous materials (HAZMATs) through Singapore is of primary concern to this study. HAZMATs are inherently dangerous due to their volatile explosive nature, and can result in severe devastation if misused by terrorists. Extra care has to be taken to provide additional safety measures during their transportation. While taking every possible care in their transportation, the authorities must also remain prepared for responding to an emergency arising from their transportation (for instance explosion and crashing). This requires a proper assessment of the existing fire stations in terms of their location and their ability to promptly reach the accident sites along the transportation routes. Currently Singapore has 17 fire stations positioned around the island (Fig. 1), each equipped with at least one fire engine, one Red Rhino (light fire attack vehicle), and one ambulance.

With just 647 km^2 of land supporting more than 4.6 million people, Singapore's urban planners had to restrict highway construction, and had to undertake public transportation network ventures only after meticulous planning. Hence, much planning is required when transporting HAZMATs along roads. The Singapore Civil Defense Force (SCDF) has approved specific routes for transporting HAZMATs and other petroleum products in Singapore (see also Fig. 1). These routes (henceforth referred to as

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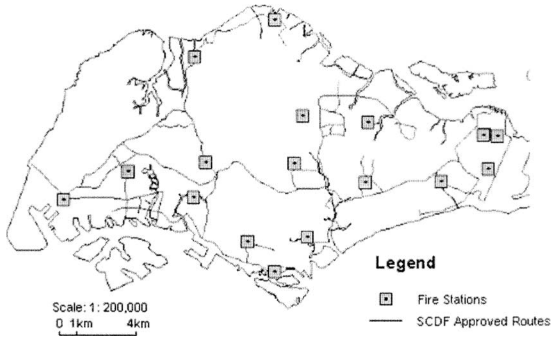

Fig. 1. Approved HAZMAT transport routes and fire stations in Singapore

SCDF routes) avoid densely populated areas and water catchment areas and HAZMAT transportation is only allowed between 7:00 a.m. and 7:00 p.m., when sufficient daylight exists for remedying any accident. The vehicles are not allowed to ply along expressway tunnels, which may otherwise lead to major pileups during accidents.

According to SCDF, the targeted response time is 8 min, from the moment of receipt of an emergency call to that of the arrival of a fire engine on the accident site. Local authorities have proposed to set up six additional fire stations with the primary intention of reducing the response time from 8 to 5 min. Other objectives considered in this project include determining a suitable distance between the fire stations and maximizing the areas that can be served by fire stations within 6 min. The above discussion evinces that the problem under discussion is a linear feature covering problem consisting of multiple objectives. Moreover, it will be shown later that the problem is a complex one indeed and needs to be formulated by means of a suitable model. The relevant approaches must also be developed.

This paper proposes a multiobjective (MO) model supported by a GIS and an Ant algorithm, ANT, to solve the problem. GIS lacks advanced optimization capabilities and hence it is integrated with a heuristic algorithm. The combined system is used to solve complex spatial optimization problems, which otherwise cannot be solved using GIS and its built-in functions alone. However, the initial input data to the optimization algorithms are accomplished using GIS.

The Ant algorithm, inspired by the nature, is based on the capability of ants to locate the shortest path between their nest and the food source while searching for food. The Ant algorithm is an adaptive construction heuristic combined with a local search measure. The original Ant algorithm, Ant system (AS), initially proposed by Dorigo (1992), drew a great deal of attention leading to various innovations on the original algorithm. Typical examples are Ant Colony System (ACS) (Dorigo 1992), ANTS (Maniezzo 1998), MAX-MIN Ant System (MMAS) (Stützle and Hoos 1997), Fast Ant (FANT) (Taillard and Gambardella 1997), Ant-Q (Dorigo and Gambardella 1995), Rank-based Ant System (AS_{rank}) (Bullnheimer et al. 1997), and Hybrid Ant System (HAS) (Gambardella et al. 1997). In this paper, the Ant algorithm is improved to solve the location optimization problem of fire stations.

The remainder of this paper is as follows. "Related Work" reviews the associated work and discusses the way in which the proposed problem differs from other location problems. "Problem Analysis" gives a preanalysis to the problem. In "Methodology" the proposed methodology using the MO optimization model and the ANT developed in this study are described. The computational results and their comparison with a GA are presented in "Computational Results and Discussion." Finally, "Conclusion" presents the conclusion of the paper.

Related Work

The optimal location of fire stations has been extensively studied and a range of models has been developed. Doeksen and Oehrtman (1976) used a general transportation model based on alternative objective functions to obtain optimal fire station locations for the rural fire system. The different objectives used to obtain the optimal sites include: minimizing response time to fire, minimizing total mileage for fighting rural or county fires, and maximizing protection per dollar's worth of burnable property. Plane and Hendrick (1977) used the max covering distance concept to develop a hierarchical objective function for the set-covering formulation of the fire station location problem. The objective function permitted the simultaneous minimization of the number of fire stations and the maximization of the existing fire stations within the minimum total number of stations. Hogg (1968) used a set-covering technique, which minimizes the total number of fire appliance journey times to fires for any given number of fire stations, and applied this to the city of Bristol. Badri et al. (1998) underline the need for a multiobjective model in determining fire station locations. The authors used a multiple criteria modeling approach via integer goal programming to evaluate potential sites in 31 subareas in the state of Dubai. Their model determines the location of fire stations and the areas they are supposed to serve. It considers 11 strategic objectives that incorporate travel times and travel distances from stations to demand sites, and also other cost-related objectives and criteria—technical and political in nature. Most of the aforementioned researchers employed the discrete location model or its variations to site fire stations. The modeling techniques and solution algorithms of this category of problems have been methodically reviewed in Mirchandani and Francis (1990) and Daskin (1995). However, the objectives in these works are different from ours, which result in different models and approaches.

Tzeng and Chen (1999) used a fuzzy multiobjective approach to determine the optimal number and sites of fire stations in Taipei's international airport. A GA was then executed to weigh against the brute-force enumeration method. The results proved that GA is suitable for solving such location problems. Nevertheless, its efficiency still remains to be verified by means of large-scale problems.

Within the realm of GIS, location problems have also been studied extensively. Dobson (1979) utilized a GIS to identify site for a power plant in the State of Maryland. Estochen et al. (1998) used a GIS to determine the location/allocation of emergency response vehicles in the state of Iowa. Through GIS, the response times were estimated and compared to actual response times. Church (2002) exhaustively reviewed the existing work linking GIS and location science and asserted that GIS can support a wide range of spatial queries that aid location studies. He also discussed some of the potential research areas relating GIS and location modeling. Following the spirit, this research explores the integration of a heuristic algorithm into GIS for spatial optimization of fire station locations, which has rarely been discussed in the GIS literature aforementioned. This is a novel approach to solving optimization problems and can ultimately lead to a paradigm shift in solving spatial analytical problems of a similar nature in the disciplines of transportation, networking, and infrastructure design.

Problem Analysis

The island nation of Singapore, the feasible solution space considered in this study, can be mathematically viewed as a continuous plane with irregular shapes (Fig. 1) consisting of infinite x-y coordinate pairs (location candidates). This is not a classical continuous p-maximal covering problem (Watson-gandy 1982; Drezner and Hamacher 2002) that locates p facilities with determined coverage in a continuous plane for maximizing the number of demand nodes. If demands originate from nodes, then the objective can be easily judged by counting the number of nodes that can be served by the supply sides. However, in this study, the fire stations need to cover polylines (and polygons) and not nodes. While determining the coverage in the case of nodes might be a simple task, it is not easy to determine whether or how much of the polylines (polygons) have been covered. This can be done by comparing the coverage distance with the Euclidean (network or user defined) distance between the node and the supply node. Computing the portion of polylines covered involves greater complexity than computing the portion (number) of nodes covered. Simply stated, it is rather difficult to directly evaluate the objectives considered in this problem. Tzeng and Chen (1999) have shown that these kinds of location problems belong to the NP-hard category.

The problem is an MO optimization problem, which further adds to the complexity of the study. MO optimization offers a framework for sorting out decision-making problems involving multiple objectives. Many spatial and location problems inherently possess multiple conflicting objectives. There is no single best solution to multiple conflicting objectives and for this reason the resultant MO optimization problem opts for tradeoff optimal solutions (Pareto-optimal). Pareto-optimal solutions for MO problems can typically be characterized by three methods: the weighting method, the constraint method, and the weighted minimax method. Sakawa (1993) provided detailed reviews on these three methods applicable to both MO linear and nonlinear programming problems. The λ transformation, which is the equal-weighted minimax method, is employed in this research.

The discussion hitherto has clearly demonstrated that this problem varies significantly from the conventional location problems and is very difficult to solve. Therefore a MO modeling approach using GIS and an Ant algorithm (ANT) is proposed and implemented. The GIS data requirements for this study include: a GIS map of the region to build fire stations, i.e., the Singapore map, the feasible areas to build fire stations excluding unusable lands, e.g., water bodies etc., and the existing fire station locations and the SCDF routes.

GIS is adopted to convert the continuous plane into a coordinate grid system consisting of rows and columns, following which the polylines and polygons can easily be configured. As a result, the number of candidate locations for facilities to be sited in this problem is more than 113 times larger than that in Tzeng and Chen (1999). Owing to the fairly larger size of the problem, enumeration method is not feasible. Subsequent computational comparison illustrates that the GA by Tzeng and Chen (1999), efficient in solving small-scale problems, is unsuitable for large-scale problems. Ensuing discussions show that the ANT proposed herein provides much better solutions than the GA in Tzeng and Chen (1999).

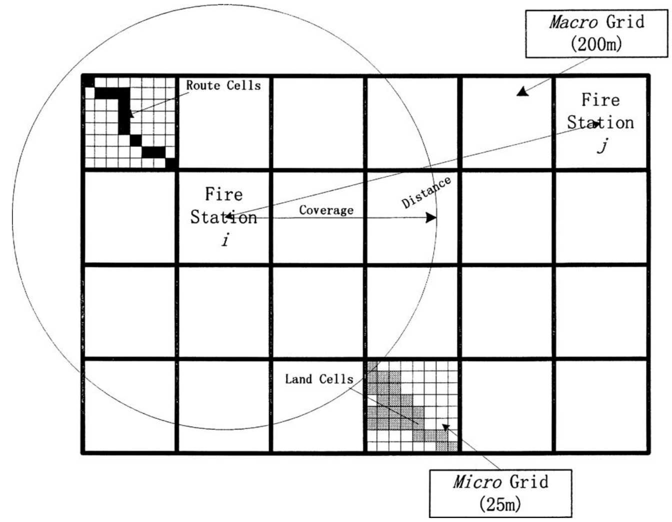

Fig. 2. Macro- and microgrids

Methodology

Two-Level Discrete Grids Construction

The continuous map ought to be converted into a raster map in order to make the map elements mathematically recognizable. In a raster map the continuous plane is represented using a grid coordinate system by means of a specific number of discrete cells. The cell size is of foremost consideration while converting a continuous map into a raster map. It can neither be too large as to cause intolerable errors, nor be too small leading to unnecessary computational or storage demands. Two scalars of the cell size with respect to two raster systems (macro and micro) are employed to keep the computational burden within tolerable range, while simultaneously assuring data accuracy.

The area for siting the fire stations is represented by a macroraster map (125 rows $\times$ 215 columns) with a larger cell size of 200 m. The location of a fire station is represented by the centroid of the cell it stands in. This larger cell size is reached by considering the present customary size of Singaporean fire stations and their surroundings, 200 m $\times$ 200 m. The macromap is used to locate additional fire stations in order to reduce the computational burden, hence reducing processing time.

The microraster map employs a smaller cell size, no lesser than the width of SCDF routes, 25 m. The micromap snaps its extent to the macromap, thus ensuring that the microgrid coincides with the macrogrid. The location of the microcell is also represented by its centroid. The micromap is used to determine the coverage of fire stations on SCDF route cells and land cells in Singapore.

In Fig. 2, the macrogrids of 200 m $\times$ 200 m are represented by the larger squares. The microgrids of 25 m $\times$ 25 m are the smaller squares located within the larger macrosquares. Those microroute and land cells inside the macrocells falling under the coverage (buffer) of a fire station are shown in black. The uncovered microroutes and land cells are shown in grey. The distance from one fire station to its nearest fire station is measured in a Euclidean norm.

Calibration of Response Time Function

Fig. 1 shows the SCDF routes and the existing fire stations distributed in Singapore. Current regulations require that the fire engines reach any part of SCDF approved routes within 8 min. The response time function of a fire station (Haupt and Haupt 1997) can be estimated as follows:

$$T = t_0 + K \cdot r \tag{1}$$

where T=response time of the fire station; r=distance (kilometers); t_0(minutes)=operational readiness time (the time taken for the fire engine to leave the fire station upon receiving the call), which is 1.0 min given by the SCDF; and K=traffic impedance factor.

An experiment was conducted in GIS environment to estimate the value of K using data obtained from local fire stations and transport authorities. The smallest radius of the fire station buffer covering all the SCDF routes was estimated to be 5.30 km. Then K was calculated by substituting 5.3 km for r and 8.0 min for T in the response time function. The final estimated response time function is as follows:

$$T = 1.0 + 1.32 \cdot r \tag{2}$$

Multiobjective Optimization Model

In accordance with the project requirements, the three objectives considered are:

1. Maximizing the coverage of the routes uncovered by the original buffers. Using ArcGIS, the uncovered SCDF routes were converted into a raster map, i.e., the polylines used to represent the uncovered routes were converted into grid cells. The newly located stations must cover maximum uncovered area (grid cells) to complement the existing fire stations.
2. Achieving a reasonable distance between fire stations. The intention here is to obtain optimal coverage and efficient cooperation among fire stations. Investigations by local authorities revealed that the distance between one fire station and its nearest fire station must be within 1–9 km. This is a reasonable distance, since it is neither too long for efficient cooperation among stations nor too short to cause overlapping and redundancies of their services.
3. Maximizing the area that can be served by fire stations within 6 min. The third goal is to maximize the coverage of the uncovered grid cells by means of the additional fire stations. Above and beyond combating the HAZMAT accidents on the SCDF routes, fire stations will have to render a whole lot of additional services to places located elsewhere. This research therefore takes into account those urban and suburban areas nonreachable in 6 min by the existing fire stations.

A λ transformation formulation is then modeled as follows:

$$\max_{L} \lambda \tag{3}$$

Subject to

$$\lambda \leqslant \mu_i[L], \quad \forall\, i = 1,2,3 \tag{4}$$

$$\mu_i(L) = \frac{x_i(L)}{x_i^+}, \quad \forall\, i = 1,3 \tag{5}$$

$$\mu_2(L) = \min[x_2(l), \forall\, l \in L] \tag{6}$$

where

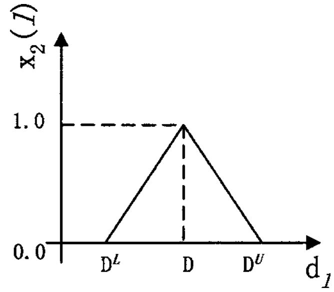

Fig. 3. Achievement level function of individual fire station

$$x_2(l) = \begin{cases} 1 & \text{if } d_l = D \\ (D^U - d_l)/(D^U - D) & \text{if } D^U \geqslant d_l > D \\ (d_l - D^L)/(D - D^L) & \text{if } D > d_l \geqslant D^L \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where L=set (solution) that represents the locations of new fire stations; $\mu_i[L]$=normalization function of objective i which turns the objective value to its achievement level (a real number between 0 and 1); $x_i(L)$=value of objective i given a solution L; x_i^+=optimistic value of objective i; $x_2(l)$=achievement level of Objective 2 with respect to the fire station located at l; d_l=distance between the fire station located at l and its nearest counterpart; D=desired distance between two fire stations; D^U=upper bound of the distance between two fire stations; and D^l=lower bound of the distance between two fire stations.

The objective function Eq. (3) and the constraint Eq. (4) are meant to maximize the minimal achievement level among every one of the different objectives. Eq. (5) is the normalization function of Objectives 1 and 3. The optimistic value x_1^+ in Objective 1 is the total number of all the grid cells representing the routes uncovered by the buffer of existing fire stations. Also, the optimistic value x_3^+ in Objective 3 is the sum total of all the land cells not covered by the buffer of current fire stations. Eq. (6) furnishes the normalization function of Objective 2. The function calculates the minimal achievement level of the newly built fire stations as the overall achievement level of Objective 2. The achievement level of an individual fire station is a segmented linear function of its distance from its nearest counterpart as shown in Eq. (7). A graphical representation of Eq. (7) is shown in Fig. 3.

Ant Algorithm

GIS data conversion turns the complex continuous plane of the feasible solution space into a simple discrete grid. Yet, the number of feasible solutions still remains a huge figure, i.e., $(C_{15,388}^6) \approx 1.84 \times 10^{22}$ where 15,388 is the total number of the macrocells and 6 is the number of new fire stations to be built.

Under a discrete coordinate system, Objective 1 can be modeled into a typical maximum set covering problem provided the other two objectives are not considered. The same applies to Objective 3. Unlike the other two objectives, Objective 2 is difficult to model into a straightforward optimization problem. This is so because: (1) the problem is discrete in nature; and (2) a segmented linear function is used in the evaluation of the objective.

If it were a MO programming problem with Objectives 1 and 3, it could have been solved by formulating an integer linear programming problem (ILPP), which can typically be solved by a branch-and-bound method or cutting plane method. However, the problem remains a huge one even after formulating an ILPP, in-

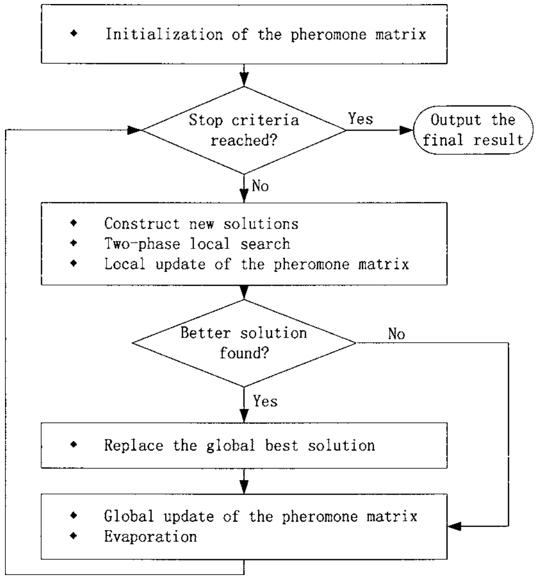

Fig. 4. Flowchart of ANT algorithm

volving 19,618 integer variables, 4,232 rows of constraints, and 3,699,548 nonzero coefficients. If Objective 2 is also considered, it becomes rather difficult to formulate an ILPP with no ready-to-use solutions for such a MO problem except through the use of the GA in Tzeng and Chen (1999). Nonetheless, the aforementioned GA has not been proved to be competent in solving this kind of large-scale problem.

As a result, ANT has been proposed and implemented here to solve this "highly intractable" MO programming problem. Six artificial ants are used in the ANT to represent the locations of the six fire stations to be built. Within a number of iterations, the six artificial ants are kept moving on the macrogrid system in accordance with specific principles trying to locate the optimal sites for the six fire stations. The generic flowchart of the algorithm is given in Fig. 4.

Pheromone Matrix

The pheromone matrix is a mechanism used in the Ant algorithm to store the historical "good" information. In the ANT being used here, the pheromone matrix is a 125×215 dimension matrix corresponding to the macrogrid system. Each cell of the matrix is filled with a positive float value, representing the "desirability" of choosing the corresponding cell (i,j) under the macrogrid system (i is the row number, j is the column number) as a location for one of the six fire stations. Those cells representing the unsuitable areas, e.g., water body, are assigned a zero value thus avoiding their selection as the candidate sites for the new fire stations. This coding method has an important advantage such that it can also be used to restrict the feasible region for siting fire stations. For example, if all fire stations need to be sited along a roadway within 0.5 m, then the only thing we need to do is to set a 0.5 m buffer for all roadways and then assign a zero value to those cells lying outside the buffer. This can easily be done by GIS software.

As no information is contained in the trace matrix when the algorithm is initialized, the same value is assigned to all the feasible cells. Typically, this initial value for the feasible cells is the local enhancement level (as described below).

ANT determines the locations for the new fire stations by controlling the artificial ants to detect such "desirability" and directing them to move to those "desirable" cells. The probability of an ant choosing one cell is the function of the "desirability" of that cell. The higher the "desirability" of a cell, the higher the probability an ant will be moving to that cell.

The aforementioned mechanism and the associated storing of historical good information can also be possibly used in other civil engineering disciplines such as urban planning or infrastructure design which involve selection from among given pixels or from an array of basic elements. The notion of "ant migration" into a cell of higher probability to determine the suitability of that particular cell can be fruitfully employed to enhance decision-making capabilities and thus selection processes which may otherwise be cumbersome.

The pheromone matrix is updated by means of the iterations in the ANT's running process. The update policy of ANT consists of two subroutines (Taillard and Gambardella 1997), the global update, and the local update. Such a combined update policy is capable of taking full advantage of both local and global information. The global update enhances the "desirability" values of the cells that constitute the global best solution (the best solution found until then). The local update aims to fortify the "desirability" of those cells that constitute the local best solutions (the best solutions found in the local search process during current iteration). The matrix update policy is based on the rationale that the cells forming good solutions have larger probabilities of constituting the optimal solution.

The mathematical formulation of the update policy is as follows:

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}^{\text{local}} \cdot x_{ij} + \Delta\tau_{ij}^{\text{global}} \cdot y_{ij} \tag{8}$$

where $\tau_{ij}(t)$ = "desirability" value of the cell (i,j) at iteration t; x_{ij} = dummy variable, which equals 1 if the cell (i,j) is included in the local better solution, otherwise zero; y_{ij} = dummy variable, which equals 1 if the cell (i,j) is included in the global best solution, otherwise zero; and $\Delta\tau_{ij}^{\text{local}}$ and $\Delta\tau_{ij}^{\text{global}}$ = local and global enhancement levels, respectively.

Solution Construction

The solution construction is based on the pheromone matrix. The construction is implemented as a linear search through a roulette wheel with slots weighted in proportion to cell values in the pheromone matrix. Simply stated, the probability of choosing the cell (i,j) as a location for one of the six fire stations to be built is calculated by

$$P_{ij}(t) = \frac{\tau_{ij}(t)}{\sum_i \sum_j \tau_{ij}(t)} \tag{9}$$

where $P_{ij}(t)$ = probability of choosing the cell (i,j) at iteration t. Other notations are the same as already mentioned.

Two-Phase Local Search

The local search is performed immediately after the newly constructed solution is obtained. The local search repeatedly tries to improve the current solution by introducing local changes in the new solution. As and when a better solution is found in the "neighborhood" of the current solution, it replaces the current solution and the local search restarts from this better one.

A novel two-phase local search algorithm has been developed in ANT. The first phase of the local search is called the neighbor-

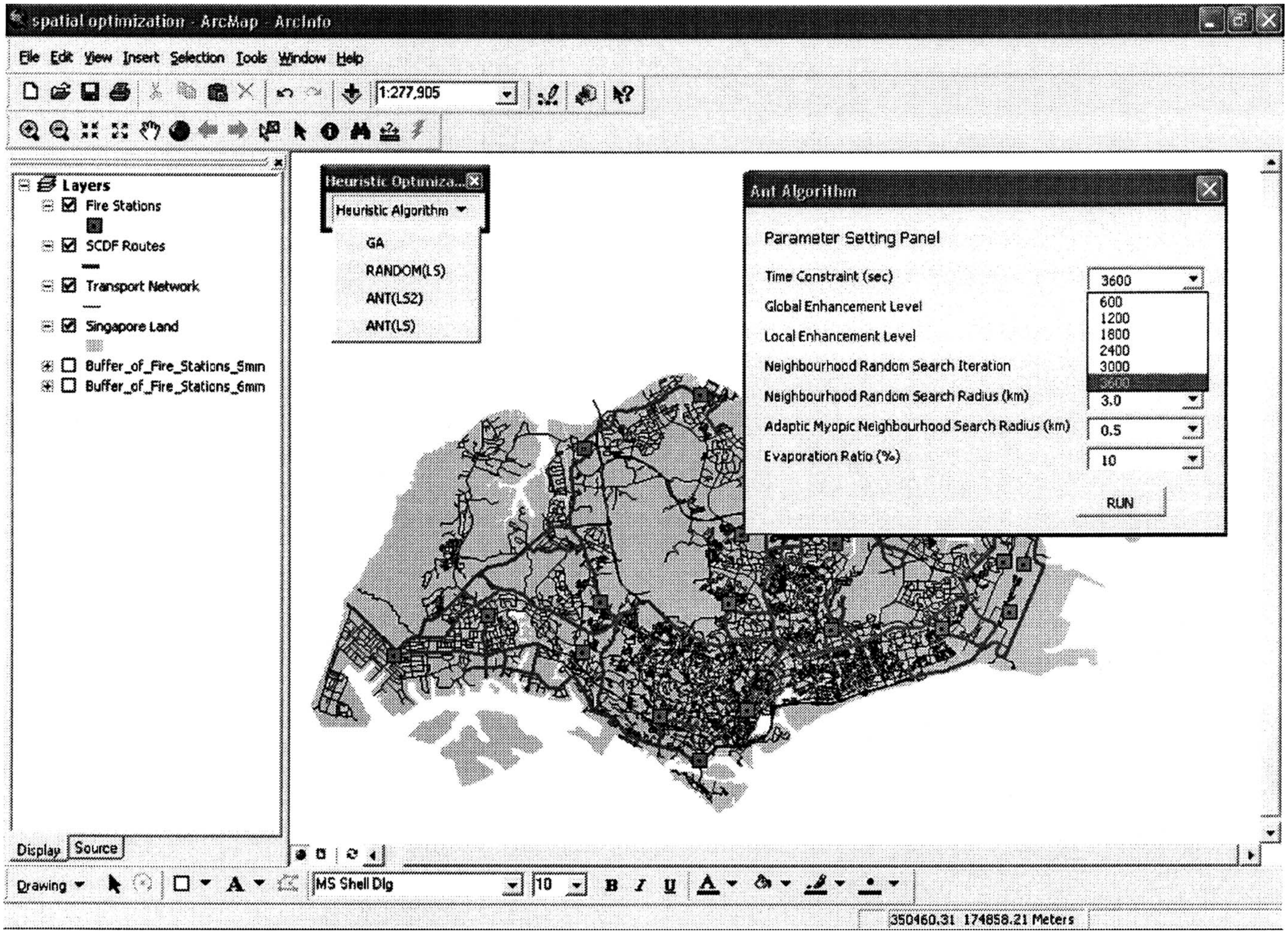

Fig. 5. Interface of prototype

hood random search (NRS), which is conducted for a specific number of iterations. Within a single iteration of NRS, the ants randomly move from its current cells to other cells in a limited distance, e.g., 3 km. The objective is then revaluated. If a better solution is found, the ants move to the cells constituting the better solution; if not, they remain on the original cells.

Subsequent to the first phase local search, the second phase local search named adaptive enumeration neighborhood search (AENS) is activated. In AENS, each of the six ants moves to every cell within a certain distance from its current cell while keeping the other five ants fixed on their original cells. As stated previously, upon revaluation, if the objective improves, the ant enters the cell that improves the objective and restarts a new AENS.

The AENS is a thorough and rigorous local search method, since it continues until no movements of the ants can improve the objective. To be noted, the "myopic" characteristic of the AENS lies in that it only considers the effect of moving only one ant, while not taking into account the interactive effect of moving multiple ants. Thus it might lose a better solution that can only be obtained by moving multiple ants simultaneously. However, the use of AENS can be attributed to computational complexity. For

Table 1. Computational Comparison between GA and ANT

Algorithms	1	2	3	4	5	6	7	8	Ave (λ)	COV (λ)
GA[a]	0.495	0.487	0.541	0.480	0.488	0.524	0.502	0.502	0.502	4.09
RANDOM (LS)[b]	0.623	0.578	0.623	0.622	0.630	0.599	0.611	0.623	0.614	2.85
ANT (LS2)[c]	0.590	0.588	0.542	0.564	0.555	0.564	0.591	0.566	0.570	3.15
ANT (LS)[d]	0.644	0.650	0.632	0.644	0.638	0.615	0.623	0.614	0.633	2.20

[a]GA = genetic algorithm in Tzeng and Chen (1999).

[b]RANDOM(LS) = random start two-phase local search.

[c]ANT(LS2) = ANT with only the second phase local search.

[d]ANT(LS) = ANT with the two-phase local search.

Table 2. Computational Results of ANT under Different Parameter Settings

	1	2	3	4	5	6	7	8	Ave (λ)	COV (λ)
Varied global enhanced level										
$\Delta\tau_{ij}^{\text{global}}=1.0$	0.621	0.606	0.622	0.600	0.618	0.632	0.644	0.618	0.620	2.22
$\Delta\tau_{ij}^{\text{global}}=3.0$	0.625	0.621	0.647	0.644	0.644	0.601	0.648	0.611	0.630	2.89
$\Delta\tau_{ij}^{\text{global}}=9.0$	0.609	0.623	0.613	0.651	0.602	0.641	0.621	0.656	0.627	3.16
Varied NRS search radius										
1.0 km	0.644	0.658	0.645	0.647	0.653	0.660	0.659	0.656	0.653	1.00
2.0 km	0.629	0.649	0.637	0.623	0.631	0.648	0.644	0.644	0.638	1.50
Base case										
	0.644	0.650	0.632	0.644	0.638	0.615	0.623	0.614	0.633	2.20

example, supposing that an ant has n alternative cells to move, the computational complexity of using the AENS will be proportional to $6n$; on the contrary, if moving multiple ants is considered, the computational complexity will be proportional to n^6, which can be insupportable if n is large.

Evaporation

Evaporation is a commonly used measure in some other Ant algorithms, e.g., ACS (Dorigo 1992), to force ants to forget the "bad" information collected before and prevent the algorithm from falling into a local optimum. Toward the end of each iteration, the evaporation mechanism is activated in the ANT and controlled by a parameter called the evaporation ratio. This results in the reduction of the cell values of the pheromone matrix. For example, if the evaporation ratio equals 10%, then the value of each cell in the pheromone matrix will be reduced to 90% of its original value.

Computational Results and Discussion

In order to appraise the proposed ANT, it was compared with a GA and a random start local search procedure. The GA from Tzeng and Chen (1999), the only algorithm available for a similar problem as we know so far, was used for comparison. In order to test the performance of the two-phase local search an ANT using only the second phase local search was executed.

All the algorithms were coded in the C programming language and assembled in the form of functions within a dynamic link library (DLL). The DLL is seamlessly linked to a macro VB script in ArcGIS so that ArcGIS can call upon any of the aforementioned algorithms (functions) in the DLL to perform optimizations. The prototype runs on a Windows XP PC with Intel PIII processor (733 MHz) and 512 MB of RAM. Its interface within ArcGIS is shown in Fig. 5.

The parameters of GA and ANT are set as follows. The population number of GA is 100. The global and local enhancement levels of ANT are set as 6.0 and 1.0, respectively. The NRS is restricted to 100 iterations and the search radius to 3 km. The scope of the AENS is set at 0.5 km from the original ant location. The evaporation ratio is 10%. Eight independent runs of all the algorithms have been conducted under the same time constraint (3,600 s). Results including the objective (λ) values for eight independent runs, the mean value of λ[Ave(λ)], and the coefficient of variation of λ[COV(λ)] are listed in Table 1.

It must be noted that the ANT here refers to the ANT with two-phase local search, i.e., ANT (LS). However, ANT with only the second phase local search [ANT (LS2)] was also tested. From the results it can be established that ANT outperforms GA in all the eight independent runs. The best solution found by ANT (0.650) is 20.15% better than the one found by GA (0.541) and the average solution found by ANT (0.633) is 26.10% better than GA (0.502). Moreover, the performance of ANT is much more stable than GA, as the coefficient of variance of the solutions acquired by ANT (2.20%) is much lower than GA (4.09%).

A random start local search procedure [RANDOM (LS)] was also compared with ANT to corroborate the utility value of pheromone information. The results show that ANT outperforms RANDOM (LS) in the seven independent runs excluding one, wherein the performance is still quite competitive. The RANDOM (LS) is found to outperform the GA, which indicates that the local search measure proposed in this research provides a good solution method. This also shows that the heuristics using local search principles (Hertz and Widmer 2003), e.g., Ant algorithm, is more efficient than the one using population search principles, e.g. GA, in solving this problem.

ANT (LS2) was run to testify whether the first phase local search, which involves randomness and is typically handled by the Ant part, is of any special effect. The results show that ANT (LS2) performs worse than ANT (LS) in terms of all the criteria mentioned herein.

A series of computational experiments are also performed in the same computing environment to test the performance of ANT under different parameter settings (varied global enhancement

Table 3. Computational Results of ANT with Different NRS Iteration Numbers

Varied NRS iteration number	1	2	3	4	5	6	7	8	Ave (λ)	COV (λ)
50	0.644	0.651	0.648	0.661	0.663	0.651	0.644	0.653	0.652	1.10
100	0.644	0.658	0.645	0.647	0.653	0.660	0.659	0.656	0.653	1.00
150	0.651	0.648	0.660	0.649	0.652	0.652	0.651	0.649	0.652	0.56

Table 4. Best Objective Achievement Levels

Objective i	Achievement level (μ_i)
1	0.663
2	0.669
3	0.664

levels and varied search radius). The results are shown in Table 2. It should be noted that the base case is referred to as the parameter setting previously mentioned. Each time the ANT is executed, only one parameter is changed while keeping the others constant.

The computational results evince that ANT performs very stably under different parameter settings. The average final objective values achieved by ANT under different parameter setting are all above 0.620. It is found that the global enhancement level does not have a significant impact on the performance of ANT. To test the effect of the local and global enhancement levels, we only need to consider the ratio between them as only this ratio affects the solution construction process. However, the NRS search radius seems to have an evident influence on the performance of ANT. The smaller the search radius, the better the performance of the ANT. When using a smaller search radius, ANT performs a more thorough first-phase local search around its neighborhood. This may give more information to ANT, thus enabling it to find better solutions.

The results in Table 2 show that the combination of the global enhance level as 6.0 and the NRS search radius as 1.0 km offers the best in terms of the average final objective value. Using these two parameter values, some computational experiments are performed with different NRS iteration numbers to test the effects of them. The results are shown in Table 3.

It is observed that the NRS iteration number has very little impact on the performance of ANT in terms of the average final objective value. The smaller the NRS iteration number, the less thorough the first-phase local search and the greater the local search performance, and vice versa. The computational results do not show a clear preference to a large NRS iteration number or a small one. This may be so since doing more (two-phase) local searches can make up for a less thorough first-phase local search and vice versa.

The best result given by ANT in all the computational experiments is shown in Table 4 and the corresponding location of six additional fire stations is mapped in Fig. 6. Recall that μ_i is the achievement level of objective i.

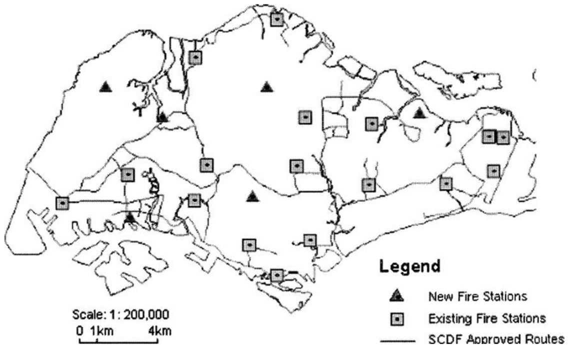

Fig. 6. Locations of new fire stations

Conclusion

This paper has presented an approach to optimally siting fire stations with a multiobjective model implemented by integrating GIS with an Ant algorithm. The locations of additional fire stations need to take into consideration three objectives: maximizing the coverage of the SCDF routes uncovered by the existing fire stations, achieving a reasonable distance between fire stations, and maximizing the area served by fire stations within 6 min. In this study, the model is formulated in a λ transformation. Other formulations may be used in different scenarios to establish various multiobjective models.

The result of this study is founded on the pheromone matrix that gathers and stores the historical "good" information. The guiding principle behind matrix updating is that the cells composing the good solutions have better probabilities of making up the final optimal solution. An innovative two-phase local search algorithm has been developed in ANT, which keeps executing incessantly until such time when the objective can no longer be enhanced by the movements of the ants.

Computational results show that ANT outperforms the conventional GA and performs stably under different parameter settings. This finding is very promising since one can get good results without spending much time fine tuning the parameters. Moreover, this makes it possible to use ANT to solve problems with larger size and greater complexity, e.g., real-time applications and problems with more practical constraints.

Some extensions to this study can be done in our future research. For example, one of them would be to use a network buffer instead of a Euclidean distance buffer in determining the coverage of a fire station. However, this may necessitate much more computational effort as we need to determine network buffers whenever evaluating objectives. Another is to obtain the collision accident rate data along the SCDF routes and the fire accident data over the whole island, so that the solution could be relatively oriented to the accident-prone areas.

Furthermore, the approach proposed herein is a wide-ranging one, which can be applied to a broad spectrum of civil engineering applications involving multiple objectives. The union of heuristic algorithms and GIS greatly complements and enhances the spatial analysis functions of GIS. The data from the GIS environment are fed into the heuristic algorithm that provides the optimal solution, which in turn can be evaluated by a GIS platform. This continuous process serves as a prototype for the development of a decision support system combining GIS with heuristics algorithms. Such a system will be valuable in decision making for emergency facility location and other real-life spatial optimization problems.

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References

Badri, M. A., Mortagy, A. K., and Colonel, A. A. (1998). "A multiobjective model for locating fire stations." *Eur. J. Oper. Res.*, 110(2),

243–260.
Bullnheimer, B., Hartl, R. F., and Strauss, C. (1997). "A new rank based version of the ant system—A computational study." *Technical Rep. Prepared for Institute of Management Science*, Univ. of Vienna, Austria.
Church, R. L. (2002). "Geographical information systems and location science." *Comput. Oper. Res.*, 29(6), 541–562.
Daskin, M. S. (1995). *Network and discrete location: Models, algorithms, and applications*, Wiley, New York.
Dobson, J. (1979). "A regional screening procedure for land use suitability analysis." *Geogr. Rev.*, 69(2), 224–234.
Doeksen, G., and Oehrtman, R. (1976). "Optimum locations for a rural fire system: A study of a major county in Oklahoma." *South. J. Agric. Econ.*, 12(1), 121–127.
Dorigo, M. (1992). "Optimization, Learning and Natural Algorithms." Ph.D. thesis, Politecnico di Milano, Milano, Italy.
Dorigo, M., and Gambardella, L. M. (1995). "Ant-Q: A reinforcement learning approach to the traveling salesman problem." *Proc., ML-95, 12th Int. Conf. on Machine Learning*, Morgan Kaufmann, 252–260.
Drezner, Z., and Hamacher, H. W. (2002). *Facility location applications and theory*, Springer, Berlin.
Estochen, B. M., Strauss, T. R., and Souleyrette, R. R. (1988). "An assessment of emergency vehicle response predeployment using GIS identification of high-accident density locations." *Proc., Crossroads—2000*, Ames, La., 221–226.
Gambardella, L. M., Taillard, E. D., and Dorigo, M. (1997). "Ant colonies for the QAP." *Technical Rep. No. IDSIA-4-97*, IDSIA, Lugano, Switzerland.
Haupt, R. L., and Haupt, S. E. (1997). *Practical genetic algorithms*, Wiley, New York.
Hertz, A., and Widmer, M. (2003). "Guidelines for the use of metaheuristics in combinatorial optimization." *Eur. J. Oper. Res.*, 151(2), 247–252.
Hogg, J. (1968). "The siting of fire stations." *Oper. Res. Q.*, 19(3), 275–287.
Maniezzo, V. (1998). "Exact and approximate nondeterministic tree-search procedures for the quadratic assignment problem." *Technical Rep. No. CSR 98-1*, Computer Science, Univ. of Bologna, Bologna, Italy.
Mirchandani, P. B., and Francis, R. L. (1990). *Discrete location theory*, Wiley, New York.
Plane, D., and Hendrick, T. (1977). "Mathematical programming and the location of fire companies for the Denver fire department." *Oper. Res.*, 25(4), 563–578.
Sakawa, M. (1993). *Fuzzy sets and interactive multiobjective optimization*, Plenum, New York.
Stützle, T., and Hoos, H. (1997). "The MAX-MIN ant system and local search for the traveling salesman problem." *Proc., ICEC'97—1997 IEEE 4th Int. Conf. on Evolutionary Computation*, IEEE, New York, 308–313.
Taillard, Ě. D., and Gambardella, L. M. (1997). "Adaptive memories for the quadratic assignment problem." *Technical Rep. No. IDSIA-87-97*, IDSIA, Lugano, Switzerland.
Tzeng, G. H., and Chen, Y. W. (1999). "The optimal location of airport fire stations: A fuzzy multi-objective programming and revised genetic algorithm approach." *Transp. Plan. Technol.*, 23(1), 37–55.
Watson-gandy, C. (1982). "Heuristic procedures for the *m*-partial cover problem on a plane." *Eur. J. Oper. Res.*, 11(2), 149–157.