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Full Length Research Paper

Location of ambulance emergency medical service in the Kumasi metropolis, Ghana

S. K. Amponsah, Gordon Amoako*, K. F. Darkwah and E. Agyeman

Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi-Ghana.

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Location of emergency medical services such as an ambulance in urban locations has been under study for a long time. Several approaches have been employed in solving this very sensitive location problem. In this paper, a case study of the ambulance location problem in an urban setting as the Kumasi metropolis in Ghana is solved. The Non-Linear Maximum Expected Covering Location Problem (MEXCLP) implemented by Saydam and Aytug (2003) was used. To solve the problem, Genetic Algorithms (GA) that uses random key coding was implemented. A formula for renormalization has been introduced. Real route distances were used for computation and statistical deviation was introduced in the selection of our optimal route.

Key words: Location, maximum expected covering location problem, genetic algorithm.

INTRODUCTION

Emergency Medical Service (EMS) is a service that provides out-of-hospital acute care and provides transport to place of definitive care, to patients with illnesses and injuries, which the patient believes, constitute a medical emergency. The most common and recognized EMS type is an ambulance organization (US DOT, 1995). There has been significant evolution in the development of ambulance location. In Ghana, cases requiring emergency medical services have been left unattended to over a long period. Many accident cases recorded over the years, suggest the country has left this very important sector of health in a neglected state. Until 2004, the country had no working pre-hospital unit and this accounted for several avoidable deaths. The May 9 stadium disaster that claimed one hundred and twenty-six lives at the Ohene Djan Sports Stadium (formerly Accra Sports Stadium) is clear evidence of the failure to respond to emergencies in the country.

Related works

A lot of location models have been employed in health care. Covering models are the most widely used location models for solving the emergency facility location problem. The objective here is to provide coverage to the demand points. A demand point is considered as covered only if a facility is available to service the demand point within a coverage distance limit which is normally referred to as a critical distance. At the heart of the set covering and maximal covering models is the notion of coverage.

Toregas et al. (1971) formulated the Set-Covering Location Problem (SCLP) to minimize the number of stations such that all demand points are covered. An important step after this formulation was the development of the Maximum Covering Location Problem (MCLP) by Church and ReVelle (1974). The main objective of the MCLP is to choose the location of facilities to maximize the population that has a facility within a maximum travel distance (or time). Thus, a population is considered covered if it is within a predefined service distance (or time) from at least one of existing facilities.

Daskin (1983), proposed the Maximal Expected Covering Location Problem (MEXCLP) as extension to the (MCLP) formulated by Church and ReVelle (Church and Revelle, 1974; Chiyoshi et al., 2003). This was mainly to account for possibility of server unavailability due to a congested system. The interest here is for demand to be covered by a located facility that is

*Corresponding author. E-mail: kwesiamoako@gmail.com. Tel: +233(0)208127706

available when a demand for service arises. The approach attempted to maximize expected coverage given that the servers are busy and unavailable with a calculable system-wide probability (p), (Daskin, 1982). ReVelle and Hogan (1989a) later developed the Maximum Availability Location Problem (MALP) which distributed a fixed number of servers to maximize the population covered with a server available within the response-time standard with reliability. They presented two versions of MALP, one with a system wide busy probability which is somewhat similar to MEXCLP, and the other version computed the local busy fractions for servers assuming that the immediate area of interest is isolated from the rest of the region (Aytug and Saydam, 2002).

Saydam et al. (1994), compared the accuracy of the predicted expected coverage of adjusted MEXCLP and found that MEXCLP provides optimal or near-optimal sets of locations, but, that there can be a significant over- or underestimation of coverage.

Batta et al. (1989) suggested adjustments to the MEXCLP to improve the accuracy of the expected coverage predicted by it. They proposed a two step heuristic that utilizes Larson's hypercube optimization procedure (Larson, 1974). Unlike MCLP, MEXCLP can locate multiple units (ambulances) at the same station (facility node), limited by the capacity of the station. Given that ambulances are typically busy at least 30% of the time, MEXCLP is considerably more realistic than MCLP.

Saydam and McKnew (1985) studied the same problem and offered a separable programming formulation that they found could solve larger instances to optimality than Daskin's formulation (Daskin, 1983). Widner et al. (2007) noted that an accurate model for EMS can be quite complex since elements of uncertainty appear in time, location and amount of required services with particular dispatching policies.

Chuang and Lin (2007), proposed a new MEXCLP-DS model which combined MEXCLP with DSM to solve a double standard coverage ambulance location problem under a probabilistic situation, to provide sufficient coverage of EMS once an ambulance is dispatched to a call. The proposed MEXCLP-DS model presented the benefits of relocation of emergence vehicles. At the end of their research, their results clearly demonstrated that not only did their model satisfy 100% of demands within 8 min standard arriving time at (5.3 km coverage distance), but it also achieved 95% of demands within 5 min standard arriving time at (3.3 km coverage distance) while locating only 4 facilities.

Aytug and Saydam (2003) compared the performance of Genetic Algorithms (GAs) on large-scale maximum expected coverage problems to other heuristic approaches. They focused their attention on a particular formulation with a nonlinear objective function that was optimized over a convex set. They went on to compare the solutions obtained by the best Genetic Algorithm (GA) to that of Daskin's heuristic and the optimal or best solutions obtained by solving the corresponding Integer Linear Programming (ILP) problems.

Simple genetic algorithm

GA is a computational method inspired by evolution. The algorithm encodes a potential solution to a specific problem on a simple chromosome-like data structure and applies recombination operators to these structures so as to preserve critical information. GA are often viewed as function optimizer, although the range of problems to which GAs have been applied is quite broad. It was first proposed by John Holland in 1975, (Whitley, 1994) as an adaptive search procedure. It is primarily inspired by Darwin's theory of 'the survival of the fittest'. An implementation of a GA begins with a population of chromosomes (solutions). One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the target problem are given more chances to "reproduce" than those chromosomes which are weak solutions.

The "goodness" of a solution is typically determined by the relative performance of other solutions of the current population (Whitley, 1994). A simple GA is as follows:

(i) Produce an initial population of individuals of the population.
(ii) Evaluate the fitness of all individuals.
(iii) WHILE (termination condition not met).
(iv) SELECT fitter individuals for reproduction.
(v) RECOMBINE between individuals to obtain offsprings
(vi) MUTATE offsprings.
(vii) Evaluate the fitness of the modified offsprings.
(viii) Generate a new population.
(ix) END WHILE.

GA’s have been used to successfully solve a number of facility location problems. Chuang and Lin (2007) used GA in solving their MEXCLP-DS model and obtained very promising results. Aytug and Saydam (2003), solved a large-scale MEXCLP with a GA implementation. Location of EMS in Ghana and the Kumasi metropolis has not been done with any known location model. They have been intuitively attached to “fire stations” without any know mathematical or facility location model. This paper will seek to optimally place a limited number of ambulances in Kumasi submetro centres in order to optimally cover emergency medical cases while achieving coverage of over 95% of the generated demand.

Background study

Kumasi is the capital city of the Ashanti Region, a very important and historical centre for Ghana. It is located about 250 km (by road) northwest of Accra. Kumasi is approximately 300 miles north of the equator and 100 miles north of the Gulf of Guinea. It is the second largest city of Ghana with a population of 1,517,000. The metropolis is made up of 119 submetros.

There are five ambulances currently located in Ashanti Region, and one is in the Kumasi metropolis. The one in Kumasi is located at the Komfo Anokye Teaching Hospital (KATH) and the other four ambulances are located at Mamponten, Ejisu, Konongo and Ahwia Nkwanta. All except the KATH and Ahwia Nkwanta services are located at “fire stations”. Cases handled by the Regional Ambulance Service (RAS) range from Gynaecology to road accidents.

The RAS is housed in a separate building at the KATH polyclinic. The EMTs here run two shifts; day and night. Communication is the key to running of the ambulance service.

METHODOLOGY

The MEXCLP was formulated by Daskin (1982, 1983). The aim is to locate M ambulances at possible facility sites on a network so as to maximize the demand expected to be covered within an endogenously determined coverage radius, r, when the probability of each vehicle being busy is (p). Critical to Daskin’s formulation is the fact that if M units must cover a point geographically, and if each unit is busy with probability p, then the probability that the point is covered by at least one unit is $1-p^m$. Daskin (1983), maximized the expected coverage as follows:

Maximize $\sum_{i=1}^{n}\sum_{j=1}^{M}(1\ \ p)\cdot p^{j-1}\cdot h_i\ \cdot y_{ij}$ (1)

Subject to:

$$\sum_{i=1}^{M} y_{ij} - \sum_{i=1}^{n} a_{ij}x_i \leq 0, \forall j \quad (2)$$

$$\sum_{i=1}^{n} x_i \leq M \quad (3)$$

$$x_i = 0,1,2,\ldots,M, \forall i \quad (4)$$

$$y_{ij} = (0,1)\ \forall i,j \quad (5)$$

where

M = Maximum number of ambulance facilities to be located, n = Number of nodes or submetros, x_i =Number of ambulances located at facility node I, h_j = Demand generated at node j.

$$y_{ij} = \begin{cases} 1 \text{ if node } j \text{ is covered by the facilities } i \\ 0 \text{ Otherwise} \end{cases}$$

The objective (1) is non-linear and it maximizes the expected number of demands that can be covered. Constraint (2) computes the number of times demand node j is covered and relates the decision variables y_{ij} to the first set of decision variables, x_i. Constraint (3) specifies the maximum number of facilities to be located on the network. Constraint (4) allows multiple ambulance units to be located at any candidate node. Finally, we note that the number of facilities capable of covering node j is given by $a_{ij}x_i$. In this paper, a reformulated variant of the MEXCLP due to Saydam and McKnew (1985).

Let y_j = The number of times demand node j is covered, n = number of demand nodes, $h(1-p^{y_j})$ = the expected coverage for each of he demand nodes for all demand nodes.

The nonlinear equivalent form of (1) can then be formulated as:

Maximize $\sum_{j=1}^{n} h_j\,(1-p^{y_j})$ (6)

Subject to:

$$\sum_{i=1}^{n} a_{ij}x_i = y_j, \forall j \quad (7)$$

$$\sum_{i=1}^{n} x_i \leq M \quad (8)$$

$$x_i = 0,1,2,\cdots,M\ ,\forall i \quad (9)$$

$$y_j = 0,1,2,\cdots,M\ ,\forall j \quad (10)$$

Aytug and Saydam (2003), state that, although the two formulations 1 and 6 are theoretically identical; the reformulation of Daskin's MEXCLP due to Saydam and McKnew (1985) makes its implementation easier with GA.

Solving the model

We shall solve the proposed ambulance location in Kumasi metropolis by means of a GA that employs random key coding as proposed in Aytug and Saydam (2003), however, we introduced a formula for renormalization of the random key codes. GAs are known to work very well on unconstrained optimization problems without any further engineering on its search operators (Aytug and Saydam, 2002). When the search space is constrained the regular search operators like crossover and mutation do not guarantee feasible solutions and thus there is the need to then engineer the genetic operators in order to guarantee feasible solutions (Cleveland et al., 1989) or one needs to impose penalties on infeasible solutions to make their survival less likely (Anderson and Ferris, 1994; Michalewicz, 1996; Palmer et al., 1989).

Genetic algorithm design using random key coding

In designing any GA there are important steps and factors one has to consider. As described by Aytug and Saydam (2002), five key factors or issues are considered when designing a GA.

(I) Selecting an appropriate representation of solution space
(II) Select an effective crossover operator
(III) Select an effective mutation operator
(IV) Select a feasible initialization
(V) Select appropriate crossover and mutation rates that will create

Table 1. Unnormalized table of random numbers.

0.7803, 0.2348	0.5470, 0.9294	0.6443, 0.2077	0.3111, 0.5949

Table 2. Normalized table of random numbers.

0.1194, 0.0359	0.0837, 0.1423	0.0986, 0.0318	0.0476, 0.0911

the best answer when the algorithm stops.

Solution representation

Unlike the usual facility location problem where only one facility is located at a candidate site, the present problem requires the possibility of more than one facility (ambulance) be located at a candidate site. A solution or chromosome consists of $n \cdot k$ bits or alleles. This breaks down into n blocks representing the *n* vertices or nodes in the network with each block containing *k* random numbers. The argument k represents the number of bits (alleles) in each of the n block of our solution and also gives information on the maximum number of ambulance units *U* that can be placed at a candidate node, that is $U_{max} = 2^k - 1$. Thus 2k is the smallest integer greater than the number of ambulances allowed at one node. Argument U actually takes on the binary format such that the number of ambulances (*U*) at any one node can be calculated from the formula:

$$U = a_{k-1}2^{k-1} + a_{k-2}2^{k-2} + \cdots + a_0 \qquad (11)$$

where a_k =0,1

Random key code representation scheme

The chromosome representation of the genetic algorithm used in this work is based on random key coding. A solution is represented by a random key coded string s of length $n \cdot k$ where s_i is assigned a uniform random value. The number of ambulances in a given node is determined from *k* uniform random numbers and their relative values. *k* is selected such that, 2^k is the smallest integer greater than the maximum number of ambulances allowed at one node.

The formula is verified in the illustration below. Aytug and Saydam (2002), provided for each string the normalization constraint

$$2^{k-1-(i \bmod k)} \cdot s_i = M \qquad (12)$$

so as to eliminate the potential that a parent with high random numbers can eliminate the solution from a parent with very low random numbers. Equation (12) is same as the constraint Equation 8 in problem P2. In applying Equation (12), Aytug and Saydam (2002) state that random initialization requires creating feasible solutions randomly. Random key coding requires no feasibility check since the decoding algorithm guarantees feasibility.

In this paper we provide a renormalization formula that can be applied to non-feasible random key codes and convert them to the feasible ones that satisfy Equation (12). The formulation is given by

$$\frac{1}{\sum_i\left(\frac{1}{M}\sum_i 2^{k-1-(i \bmod k)} \cdot s_i\right)}\left(\frac{1}{M}\sum_i 2^{k-1-(i \bmod k)} \cdot s_i\right) = 1 \qquad (13)$$

Illustration

For example if we have say a network with nodes n = 4 and the number of bits at each node (block) is k = 2 the solution space in the example is $n \cdot k = 4 \cdot 2 = 8$. This implies we have chosen k = 2 and $2^k = 2^2 = 4$, what it means is that we are allowing a maximum of $U_{max} = 3$ ambulances to be located at any candidate site. The data values (alleles) for the elements of the solution space are of the set

$$S = S_i = S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8$$

and they are represented by uniform random numbers. Choosing eight random numbers uniformly we may get the random numbers as shown in Table 1.

We use the condition $\sum_i 2^{k-1-(i \bmod k)} \cdot s_i = M$ to check for normality with M = 5. If $\sum_i 2^{k-1-(i \bmod k)} \cdot s_i \neq M$ which is so in our case for the above uniformly generated random numbers, then we normalize the S_i values. We thus normalize the S_i values as follows:

$$\frac{1}{\sum_i\left(\frac{1}{M}\sum_i 2^{k-1-(i \bmod k)} \cdot s_i\right)}\left(\frac{1}{M}\sum_i 2^{k-1-(i \bmod k)} \cdot s_i\right) = 1 \qquad (14)$$

Once Equation 14 is satisfied, we finally do an element wise division of the set with $\sum_i 2^{k-1-(i \bmod k)}$ to obtain the individual random numbers that have been completely normalized. Thus the elements in Table 1 are normalized to obtain normalized Si values in Table 2. Thus the Table 2 satisfies condition (14).

Generation of binary code

The random key code is decoded to obtain a binary coded chromosome solution. The decoding process starts with assigning integer indices to the corresponding random number value. From left to right we assign indices from 0 to $n \times k - 1$ to the random numbers. We then map the random numbers onto the indices. Retaining the mapping we arrange the random numbers in order of decreasing magnitude so that the index of the largest random number is in first position on the permuted list of indices I. Now

Table 3. Binary and decimal representation.

Binary representation			
1 0	0 1	1 0	0 0
Decimal representation			
2	1	2	0

Table 4. Two parents p_1 and p_2.

p_1	0.1194, 0.0359	0.0837, 0.1423	0.0986, 0.0318	0.0476 , 0.0911
p_2	0.0134, 0.1010	0.0182, 0.1781	0.1315, 0.0976	0.0916, 0.1138

based on the newly ordered arrangement of the indices we use the formula $M = 2^{k-1-(U(i) \bmod k)}$ to calculate the corresponding decimal value at the index element $l(i)$ at the ith position and sum up until the U_i values so far encountered is equal to our M. Once we obtain our M all other locations without entries are set to 0. While retaining the mapping, the permuted indices list is arranged back to the original index list. The permuted binary list is now put into a binary set of n blocks each of k binary elements. For each block of k binary elements we use the formula of Equation (11) to convert the k binary elements into integer values to reflect the number of ambulances to be placed at each of the n candidate facility sites.

From Table 2 of normalized feasible solutions above, ranking the bits based on the random numbers, 0.1423 at position 3 happens to be the highest, followed by 0.1194 at position 0, 0.0986 in position 4 follows and this continues until we obtain the set of unordered integer indices (3, 0, 4, 7, 2, 6, 1 and 5). Now setting bit 3 to 1 is equivalent to placing 1 ambulance on node 2, setting bit 0 to 1 is equivalent to placing 2 ambulances on node 1 and setting bit 4 to 1 is equivalent to placing 2 ambulances on node 3. Since all of M = 5 ambulances have been assigned, bits (7, 2, 6, 1 and 5) are set to 0. Thus the example in Table 2 gives the binary representation in Table 3.

GA operators

As with every GA, setting the genetic operators is important in the solutions one would obtain. Aytug and Koehler (2007) suggested that in the worst case a large population size and a high mutation rate regardless of the crossover rate reduces the number of iterations required before the optimal is seen for a given probability. A crossover rate of 0.7 and mutation rates of 0.03 yielded the best results regardless of the crossover and initialization types employed.

Selection

Our members of the crossover pool are based on a selection rate, X_{rate}, which randomly selects a fraction of the initial population size which will survive the next step of mating or crossover. The population to keep for mating, $N_{keep} = X_{rate} \times N_{init\_pop}$, where N_{init} pop is the number of members of the initial population. We are using a selection rate, Xrate = 0:75. Thus, if the initial population were to 100 we select N_{keep} = 0.75 x 100 = 75 for mating. The seventy-five will be selected according to the magnitude of their objective function values.

Crossover

Crossover as a genetic operator is used to generate offsprings and solutions of a chromosome from parent solutions such that some traits or data information in two parents are exchanged to obtain offsprings. It is analogous to reproduction and biological mating or fusion. Many crossover types exist. To effect crossover we define location points(s) among the alleles in the chromosome after which alleles of two chromosomes will be exchanged. The traditional one-point crossover implemented in Aytug and Saydam (2002) is the one employed in this work. After this, we start at the top of the list and pair the chromosomes two at a time until N_{keep} chromosomes are selected for mating. Here we pair odd rows with even rows. Two parents p_1 and p_2 are illustrated in Table 4.

p_1 and p_2 are two random key coded parents from the set of parent chromosomes N_{keep}. We now proceed with a crossover rate of cX_{rate} = 0.70 as suggested in [22] to obtain a crossover point with the formula $C_p = ceil(cX_{rate} \times S)$, where S is the length of our chromosome. This means our crossover point is then $C_p = 6$ and the corresponding offsprings are obtained in Tables 5 to 7.

Mutation

Mutation is a genetic operator that alters one or more gene values in a chromosome from its initial state. This can result in entirely new gene values being added to the gene pool. Mutation is an important part of the genetic search as it helps prevent the population from getting stuck in a local optima and find a new neighborhood with a potentially more promising solution. Mutation occurs according to a user-defined mutation probability. As suggested by Aytug and Saydam (2002), we use a mutation rate, m=0.03. We obtain the number of mutations as:

No. of mutations = $ceil(mX_{rate} \times (N_{pop} - 1) \times N_{bits})$

where N_{pop} is the number of members in the population and N_{bits} is the number of bits of each member. The bits are then mutated base on the above.

GA for location of the ambulance

The GA used here is one implemented in Aytug and Saydam (2002) and based on Bean's work (Bean, 1994). In this representation, each bit is encoded with a random number (encoding). The genetic operator and function evaluator decodes the bits so as to guarantee feasibility. Based on parameters

Table 5. Corresponding offsprings.

O_1	0.1194, 0.0359	0.0837, 0.1423	0.0986, 0.0318	0.0916, 0.1138
O_2	0.0134, 0.1010	0.0182, 0.1781	0.1315, 0.0976	0.0476, 0.0911

Table 6. The corresponding binary solutions.

***bO_1* =**	1 1	0 1	0 0	0 1
***bO_2* =**	0 1	0 1	1 1	0 0

Table 7. The offspring integer solutions for the facilities to be located.

iO_1 =	3	1	0	1
iO_2 =	1	1	3	0

obtained and motivation from the simple GA, the algorithm for our program is as follows:

(i) Load_Parameters()
(ii) Create_Boolean_Matrix of aij's
(iii) Initialize population For i=1:no_of_runs current population
(iv) doNormalisation()
(v) Decode random key coded solution into binary code solution()
(vi) Evaluate FITNESS of the solutions
(vii) Store GLOBAL BEST solution For j=1:no_of_generations
(viii) SELECT Fitter Individuals from the population for Reproduction
(ix) doCROSSOVER to get offspring solutions
(x) doMUTATION on offspring solutions
(xi) Normalise and decode
(xii) Evaluate FITNESS of offspring solutions
(xiii) Obtain new generatioin of population from the current population and offsprings
(xiv) End
(xv) Store new generation in current population
(xvi) End

Experimental setup

Our computational study involves solving the problem defined in problem P2 of related work. The application instance is fully defined by the number of nodes, the distance matrix, the coverage radius of the servers, the number of servers, distribution of calls among the nodes, and the system wide probability of a server being busy when it is called to service. With our implementation, uniform random solution set is created based on the number of nodes on the network and the number of ambulances to be located. The network consists of 54 nodes among which ambulances are going to be located. The 54 nodes were selected based on a Geographic Information Systems (GIS) buffering technique. The edge matrix used in the work is based on real road distances and not Euclidean distances as used by Aytug and Saydam (2002) in their model. This work is different in that the distance matrix is obtained from the All-Pairs Shortest Path (APSP) of the edge distances between all nodes on the network using the Floyd-Warshall Algorithm.

Parameters for computational work

Average response time (ART)

One important parameter in EMS circles is the average response time which is defined as the time interval between the time a call is received and the time an ambulance arrives at the scene. Daily data was obtained from RAS over a 5-month period from July 2007 to November 2007. There was a total of 363 calls with total time T = 4198 min. Thus the ART) is then given by

$$ART = 4198 = 363 = 11.56 \approx 12mins$$

Thus the measured average response time for emergency calls over a 5-month operation period was 12 min.

Coverage radius

The terms coverage radius and critical distance will be used interchangeably. We will base this work on two coverage radii, r_1 and r_2. The first coverage radius, r_1 is calculated from the 5-month RAS data and the second, r_2 will be based on the 10 minute response time set by the US EMS 1973 Act for all emergency cases in urban areas.
Coverage radius, r_1, of our ambulances was computed from basic information of the known allowable constant ambulance speed of $V_A = 40km/h$ and the average response time calculated from the 5-month data obtained from the RAS. From our known allowable, constant ambulance speed, the first coverage radius based on the average response time of 12 min gives

$$r_1 = \frac{V_A \times ART}{60} = \frac{40 \times 12}{60} = 8km$$

A 10 min response time based on VA = 40 km=h will correspond to a coverage radius of

$$r_2 = \frac{V_A \times ART}{60} = \frac{40 \times 10}{60} = 6.67 \approx 7km$$

System-wide probability

We consider the total period of 5 months within which the data was taken: July, August and October are made up of 31 days and September, November are 30 days. Thus the total number of days

is

$$D_T = [(31 \times 3) + (30 \times 2)] = 153$$

Converting to minutes we have 220320 min. The number of ambulances, NA, used over the period was just a single ambulance. Thus our calculation will yield the system-wide probability p:

$$p = \frac{T}{D_T \times N_A} = 0.02$$

Table 8. Solutions with parameters: p = 0:02, response time = 12 min, coverage radius = 8 km, M = 7.

Run	Nodes (No. of facilities)	Min	Average	Max
1	11(2), 15(1), 48(4)	359.5280	361.8305	362.9997
2	1(4), 34(2), 49(1)	361.4397	362.1359	362.9997
3	1(4), 17(2), 37(1)	359.6264	362.5669	362.9997
4	30(2), 31(4), 43(1)	360.8752	362.4097	362.9997

Table 9. Table of deviations.

No.	Average object	Object value deviation
1	361.8305	1.1692
2	362.1359	0.8638
3	362.5669	0.4328
4	362.4097	0.5900

Table 10. Table of solution selection.

No.	Node	Facilities	Covered nodes
3	Kokobeng	1	Aboabo,Adum,Ahinsan,Amakom,Anloga,Asafo,Asokwa,Bantama,Bomso,Bompata Buokrom,Dichemso,Fanti Newtown,KATH,Kokobeng,Kejetia,Manhyia,Asuoyeboa
	Asuoyeboa	2	Abrepo,Adiebeba,Adum,Ampabame,Asafo,Asuoyeboa,Bantam,Bohyen,Breman,Fanti, Newtonw,KATH,Kejetia,Kwadaso Estate,Suame,Tafo,Tarkwa Maakro,Aboabo
	Aboabo	4	Aboabo,Abrepo,Adiebeba,Adum,Amakom,Ampabame,Anloga,Anwomaso,Asafo, AsawasiZongo,Ashanti,Newtown,Asokore,Mampong,Asokwa,Ayeduase,Ayigya,Bantama Bohyen,Bomso,Bompata,Buokrom,Dichemso,Bompata,Buokrom,Dichemso,Fanti ,Newtown,KATH,Kejetia,Kentinkrono,Kwadaso,Estate,Kentinkrono,Kwadaso Estate,Manhyia,Oduoum,PankronoSipe Tinpon,Suame,Tafo

RESULTS AND DISCUSSION

A MATLAB program based on the GA with random key coding was written to optimally locate seven ambulances at the submetro centres of the Kumasi metropolis. We performed 30 runs of the program with each run consisting of 100 iterations. The program for obtaining our solutions was run on an Intel Pentium (R) with 1.8 GHz processor speed and 1GB RAM running Ubuntu 8.04 LTS with a Linux 2.6.24-19 Kernel and the algorithm was implemented in MATLAB (Release, 2007b). The best results out of the 30 runs are displayed in Table 8. It contains the demand covered using the algorithm. Each solution has three candidate sites (nodes) each having the number of ambulances to be placed entered beside it in bracket.

Facility sites were selected based on the results of program run that produced the maximum objective function value. This was 362.9997. However, the solution was not unique. To determine the optimal solution from the four solutions we introduce in this paper the statistical measure of deviation in the analysis of the solutions. The deviation measure gives the absolute difference between the maximum value and the average value. We thus consider the optimal solution to be the one with the highest average objective function value. As Table 9 shows such a solution is the one with the minimum deviation between the maximum objective function value and the mean objective function value. Thus solution three is the optimal solution. Figure 1 indicates facility sites for the optimal solution and the number of ambulances for each facility site. Table 10 shows the selected sites and their covered nodes.

Conclusion

We have been able to solve the ambulance location problem using a reformulation of the MEXCLP by Saydam and McKnew (1985), modeled with a random-key

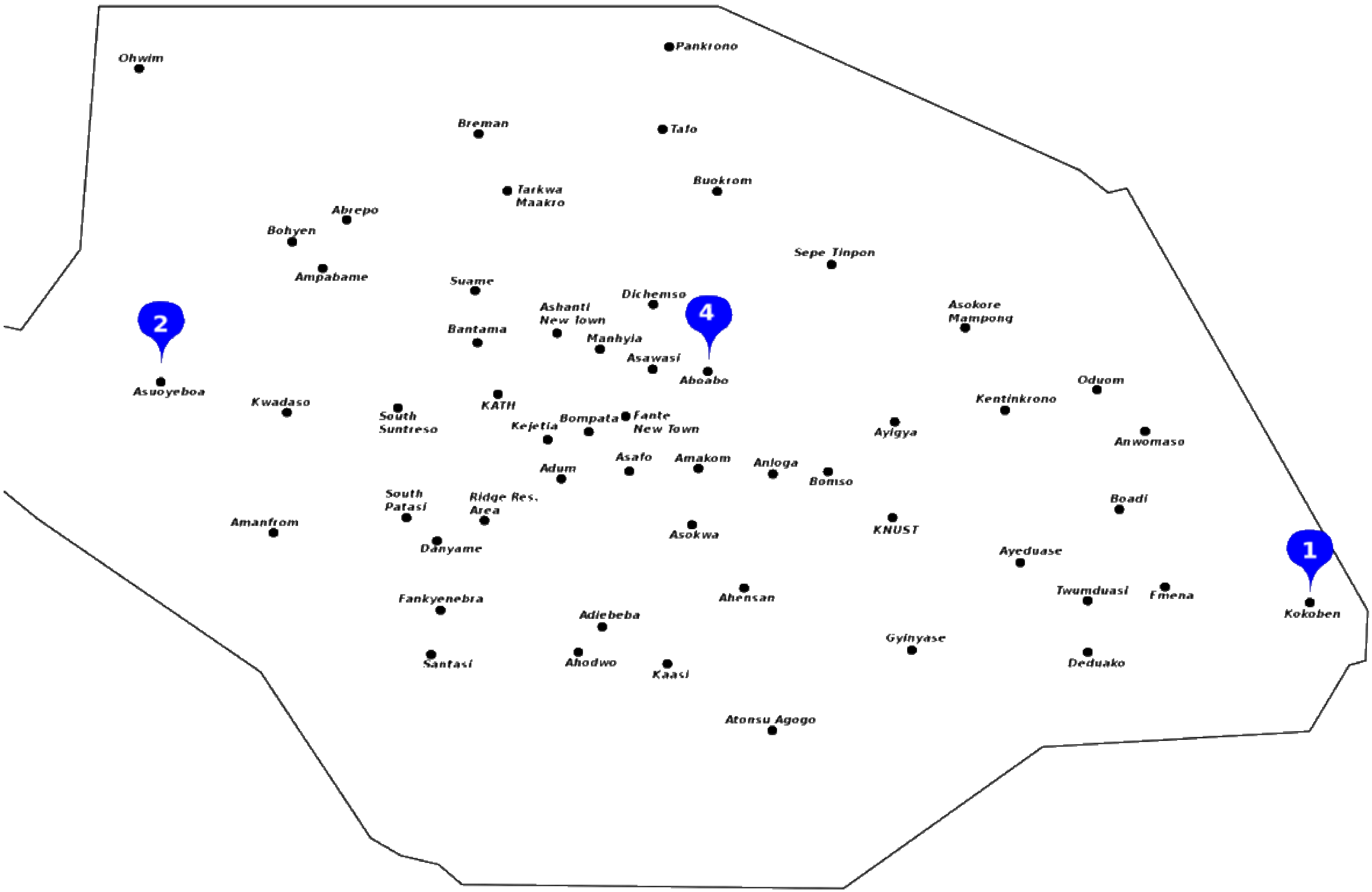

Figure 1. Map of Kumasi metropolis with buffered nodes and chosen optimal facility site.

genetic algorithm implementation. It is been seen from the results that 99.9999% of the total demand was covered within the RAS computed coverage radius of 8 km (12 min response time) with system-wide probability, p=0.02 and total number of ambulances, M =7.

The ambulance locations were finely distributed based on the model and the demand generated at the various nodes. Four ambulances are being assigned to a location that is surrounded by high concentration of sub-urban centres which can facilitate easy reach. It is also complemented by the other two locations which are on either side of it. Using our algorithm the requirements of 10 min response time set by the US (1973) Federal EMS was tested on our data. The parameters were coverage radius of r_2 = 7 km, system-wide probability p=0:02, number of ambulances M=7 and the US (1973) Federal EMS Act requirement of 10 min response time with over95% of demand coverage. We obtained solutions that exceeded the coverage stipulated for the EMS Act. The minimum percentage coverage encountered was 98% which still exceeds what the act stipulates.

The minimum percentage coverage encountered was 98% which is still exceeds what is stipulated. The percentage of total demand covered in both cases are far above the standard set by the US (1973) Federal EMS Act and this clearly demonstrates how the model used can be efficient.

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