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LOCATING FACILITIES FOR EMERGENCY RESPONSE SERVICES: INSIGHTS FOR GHANAIAN PROFESSIONAL ENGINEERS

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ABSTRACT

Optimal location of Emergency Response Services (ERS) is important for reducing emergency-related fatalities. To enable engineers in Ghana increase their level of contribution to the design, control and operation of these systems, this paper explains the nature of the decision problem associated with locating depots for ERS; presents a method for solving the problem; illustrates the problem formulation and solution methodology with a simple numerical example, solved using a spreadsheet model; and demonstrates the effect of key inputs on the decision and an important characteristic of the system. Results point to the need to support the decision-making process with some form of quantitative modelling, since failure to do so may lead to sub-optimal decisions, resulting in inefficient and/ or ineffective system designs.

Keywords: *EMERGENCY RESPONSE; FACILITY LOCATION; SET-COVERING; OPTIMIZATION*

1 INTRODUCTION

Optimal siting of facilities for emergency response services (ERS) is important for safety, health and economic reasons. Such emergency response systems may consist of medical emergency rooms with ambulances; fire stations with fire tenders; and police posts that are sited to respond swiftly to violent crimes. Examples of recent studies on siting emergency response facilities include locating a fleet of ambulances in France (Moeini et al., 2015) and in Kumasi (Amponsah et al., 2011); assigning emergency response services for disaster management in Peloponnesus, Greece (Mitsakis et al., 2014); and determining the locations of additional fire stations to build in Istanbul, Turkey (Aktas et al., 2013).These municipal facilities respond to disasters or emergency-related incidents by either dispatching response teams to the location of the emergency or by receiving affected individuals for shelter and/or treatment. Undoubtedly, the efficient operation of these facilities depends on public infrastructure systems designed by engineers.

Through the design and construction of these public infrastructure systems, for example road networks, traffic control systems, and communications systems, engineers contribute immensely to the development and operation of emergency response systems. In order to increase this level of contribution, the Ghana Institution of Engineers has been concerned recently with how ERS facilities can be well-distributed in order to reduce fatalities in emergencies. The decision on the number and location of these facilities for emergency purposes is crucial for their performance and methods for making these decisions include some form of mathematical programming (Green and Kolesar, 2004). Although the simplest of such problems can be modelled directly in a spreadsheet without specifying the underlying mathematical model, there are scientific reasons for indicating the underlying math. In the absence of such programming and or modelling, these decisions may be based on ad-hoc criteria, leading to the development of sub-optimal systems that may fail to satisfy the purpose for which they were designed. Consequently, a clear understanding of the scientific basis for deciding how many and where to site ERS depots would appear useful to engineers in Ghana, if they are to increase their role in the design, operation and control of such systems.

Therefore, the purpose of this study is to provide insight on how depots for ERS can be well-distributed so that emergency-related fatalities can be reduced. To achieve this purpose, the study was designed to accomplish two main objectives. The first objective is to present a method for locating ERS depots. Hence in Section 2, we explain the nature of the decision problem associated with locating ERS facilities, and provide a general mathematical formulation for solving such problems. The presentation will focus on simple problems that can be modelled and solved with a spreadsheet. More complicated formulations exist, and the interested reader can obtain further information from the literature cited in the references list of this paper, including those contained in recent independent reviews by Li et al., (2011) and Farahani et al., (2012).

The second objective is to illustrate how the decision problem on locating ERS depots can be solved in practice, and how decisions on key inputs affect important features of the system. This objective is accomplished with a numerical example in Section 3. Here, we describe a hypothetical case, provide an expanded mathematical formulation of the problem, and develop a spreadsheet model for its implementation. We then evaluate how the

Response Time Criterion (RTC)—which refers to the time limit within which emergencies must be responded to—affects the decision on the number and locations of depots; and demonstrate how arbitrary decisions on the number and locations of depots affect *Percentage Coverage* (PC). PC is a key characteristic of the system, and is defined as the percentage of locations in the system that can be reasonably reached in an emergency within the RTC. Section 4 discusses the implications of the results for siting ERS facilities in Ghana. We present conclusions, and recommendations for future research in the country in Section 5.

2.0 FACILITY LOCATION PROBLEMS AND A SOLUTION METHOD

The optimal distribution of emergency response facilities for reducing fatalities in emergency situations is a well-known and solved problem in operations research, management science or systems engineering (Labi, 2014; ReVelle et al., 2004). The problem falls within the general class of problems known as Location Set-Covering Problems (LSCP) and their solution requires the specification of either a travel time or distance criterion (Toregas et al., 1971).

In abstract terms, LSCP involves minimizing the cost in covering all members of a set, say, S = {1,2,3,…,m}, by using members of a class L, each of which is a subset of S, having unit cost (Williams, 1999). For example,

if *S = {1, 2, 3, 4, 5}*

and *L = {(1, 2); (1, 3, 5); (2, 4, 5); (3), (1); (4, 5)},*

Then a cover for S would be
C = {(1, 2), (1, 3, 5), (2, 4, 5)}

It is clear that C ⊆ S, and implies that three out of the six members of class L can be used to cover the five elements of set S. Here, the choice of elements in C is arbitrary; any combination of the elements in L can be used, provided it covers all the elements of S. We classify set C as effective because it provides 100% coverage, but inefficient because it uses more members of L than is required for 100% coverage.

To prevent inefficient solutions, the LSCP is formulated and solved as a mathematical model. We provide a generic Integer Linear Programming (ILP) formulation of the LSCP along the lines of ReVelle et al., (2004, p. 196), using the following variable definitions: Let

$i = 1, 2, \ldots, n$ be the index of potential sites for the deployment of emergency facilities;

$j = 1, 2, \ldots, m$ be the index of total number of demand nodes (i.e. locations that will need emergency response services);

t_{ij} = the shortest time from a potential deployment site i to demand node j;

T = the *response time criterion* (RTC), say 10 min. RTC defines the maximum time it should take for a facility deployed at a particular location i to reach an assigned demand node j;

N_j = the set of sites i eligible, by virtue of time, to cover demand node j. This is equal to the set $\{i | t_{ij} \leq T\}$, interpreted as the set $\{i\}$ such that the time from i to j is less than or equal to T;

x_i = the decision on whether to deploy a facility at site i or not. It takes value 1 if a facility is sited at i and, 0 otherwise.

The decision problem is to determine the minimum number of deployment sites such that all demand nodes can be covered within the response time criterion (Toregas et al., 1971). Mathematically, the problem is formulated in a compact form as presented in equations (1) to (3). This model minimizes the sum of potential deployment sites with a constraint for each demand node, such that each demand node is covered by at least one depot.

$$\text{Minimize} \quad Z = \sum_{i=1}^{n} x_i \qquad (1)$$

$$\textit{Subjected to:} \quad \sum_{i \in N_j} x_i \geq 1, \ \forall\, j = 1, 2, \ldots, m \qquad (2)$$

$$x_i \in \{0,1\}, \forall\ i = 1, 2, \ldots, n \qquad (3)$$

The problem formulated in equation (1) to (3) is based on the assumption that the cost of deploying a facility at a location is equal for all locations and is unity. Where this is not the case, a cost coefficient, $cost_i$, for each potential deployment site is included in the objective function (Equation 1). The problem then becomes one of minimizing total costs (see for example, Coskun and Erol, 2010). This variant formulation is known as the capacitated location set-covering problem. Li et al., (2011)chronicles extensions to the basic LSCP model, including the Maximal Covering Location Problem and the Double Standard Model. In Section 3, we explain the method of formulating and solving simple LSCPs with a numerical example for a hypothetical system. We first solve the main problem, and then illustrate the effects of changing the RTC (T), and of arbitrary location decisions, on the solution and on the percentage coverage, respectively.

3.0 NUMERICAL EXAMPLE

3.1 Case Description

Supposing city authorities are interested in locating depots for emergency response in a city of six suburbs. City engineers have collected the data presented in Table 1, which shows the travel times between each pair of suburbs. The decision problem confronting the policy makers is three-fold: first, to determine the minimum number of depots to site; second, to decide where to locate these depots, so that the response time in an emergency is not more than a policy limit of 15min; and third, which depot(s) to assign to emergencies that arise in specific suburbs. In addition to this main decision problem, it is of interest to evaluate how changes in the policy criterion of 15min affects the decision (i.e. the number and locations of depots), and how arbitrary decisions on the number and locations of depots affects the percentage coverage (PC).

To solve the main decision problem, we formulated a mathematical model as presented in Section 3.2.To evaluate how changes in the RTC affects the decision, we varied T from 5min to 35min in increments of 5min, and solved for the optimal solution and optimal value in each case. In the language of operations research, the optimal solution refers to the decision on where facilities are to be deployed. The optimal value, on the other hand, is the numerical value of the objective function that results from solving equations (4) to (11); it represents the minimum number of depots required to achieve 100% coverage.

Arbitrary decisions can be sub-optimal because they may either result in more depots than required (inefficient), or may not provide 100% coverage (ineffective). One of several possibilities could exist: either the optimal number of depots is chosen but the depots are wrongly sited, leading to less than 100% coverage; or more than the optimal number is deployed. In this paper, we will characterize decisions with an optimal number of depots as *efficient* and those that provide 100% coverage as *effective*. We will not examine the scenario where fewer than optimal depots have to be deployed because such a system will certainly not provide 100% coverage. If in practice such a decision is necessitated by budgetary constraints, then the locations of the depots must be optimally chosen to maximize the percentage coverage. This can be modelled as a Maximal Coverage Location Problem (MCLP), as depicted in Li et al., (2011, p. 286).

Table 1. Inter-suburb travel times

	Suburb 1	*Suburb 2*	*Suburb 3*	*Suburb 4*	*Suburb 5*	*Suburb 6*
Suburb 1	0	10	20	30	30	20
Suburb 2	10	0	25	35	20	10
Suburb 3	20	25	0	15	30	20
Suburb 4	30	35	15	0	15	25
Suburb 5	30	20	30	15	0	14
Suburb 6	20	10	20	25	14	0

3.2 Model Formulation

To formulate the mathematical model for the main decision problem, let x_i be the decision on whether to locate a depot at Suburb$i$ or not, "iÎ{1, 2,…,6}. Thus, x_1, x_2, x_3,…,x_6 can be defined as the decision to locate an emergency facility in suburbs 1 to 6 respectively, or otherwise. Let Z be a count of the number of locations where facilities are deployed.

Based on these definitions, the mathematical model for solving the main problem can be formulated as follows:

Minimize $Z= x_1 + x_2 + x_3 + x_4 + x_5 + x_6$ (4)

Subset to:-

$1x_1+1x+0x_3+0x_4+0x_5+0x_6 \geq 1$ constraint on covering suburb1 (5)

$1x_1+1x_2+0x_3+0x_4+0x_5+1x_6 \geq 1$ constraint on covering suburb 2 (6)

$0x_1+0x_2+1x_3+1x_4+0x_5+0x_6 \geq 1$ constraint on covering suburb 3 (7)

$0x_1+0x_2+1x_3+1x_4+1x_5+0x_6 \geq 1$ constraint on covering suburb 4 (8)

$0x_1+0x_2+0x_3+1x_4+1x_5+1x_6 \geq 1$ constraint on covering suburb 5 (9)

$0x_1+1x_2+0x_3+0x_4+1x_5+1x_6 \geq 1$ constraint on covering suburb 6 (10)

$x_i \in \{0,1\}, \forall\ i = 1, 2, \ldots, 6$ (11)

The objective function formulated in equation (4) minimises the number of locating for siting depots. Based on the assumption that the cost of locating a facility is the same in each suburb, the objective function is simply the summation of all the decision variables. The constraints to this problem are that each suburb must be served by at least one depot. Thus, one constraint is needed for each suburb. Table 2 indicates which inter-suburb travel times (the t_{ij}'s) satisfy the response time criterion, and which suburbs can be served if a facility is located at a given deployment suburb. For each demand suburb (the *j*'s), it assigns a 1 to potential deployment sites (the *i*'s) that can provide coverage, and a 0 otherwise, taking into consideration the travel times provided in Table 1 and the policy response time criterion of 15min.

Thus, from Table 2, the following assignments define the constraints formulated in equations (5) to (10), respectively:

-*Suburb 1* can be served if facilities are located in suburbs 1 and 2;

-*Suburb 2* can be served if facilities are located in suburbs 1, 2 and 6;

-*Suburb 3* can be served if facilities are located in suburbs 3 and 4;

-*Suburb 4* can be served if facilities are located in suburbs 3, 4 and 5;

-*Suburb 5* can be served if facilities are located in suburbs 4, 5 and 6; and

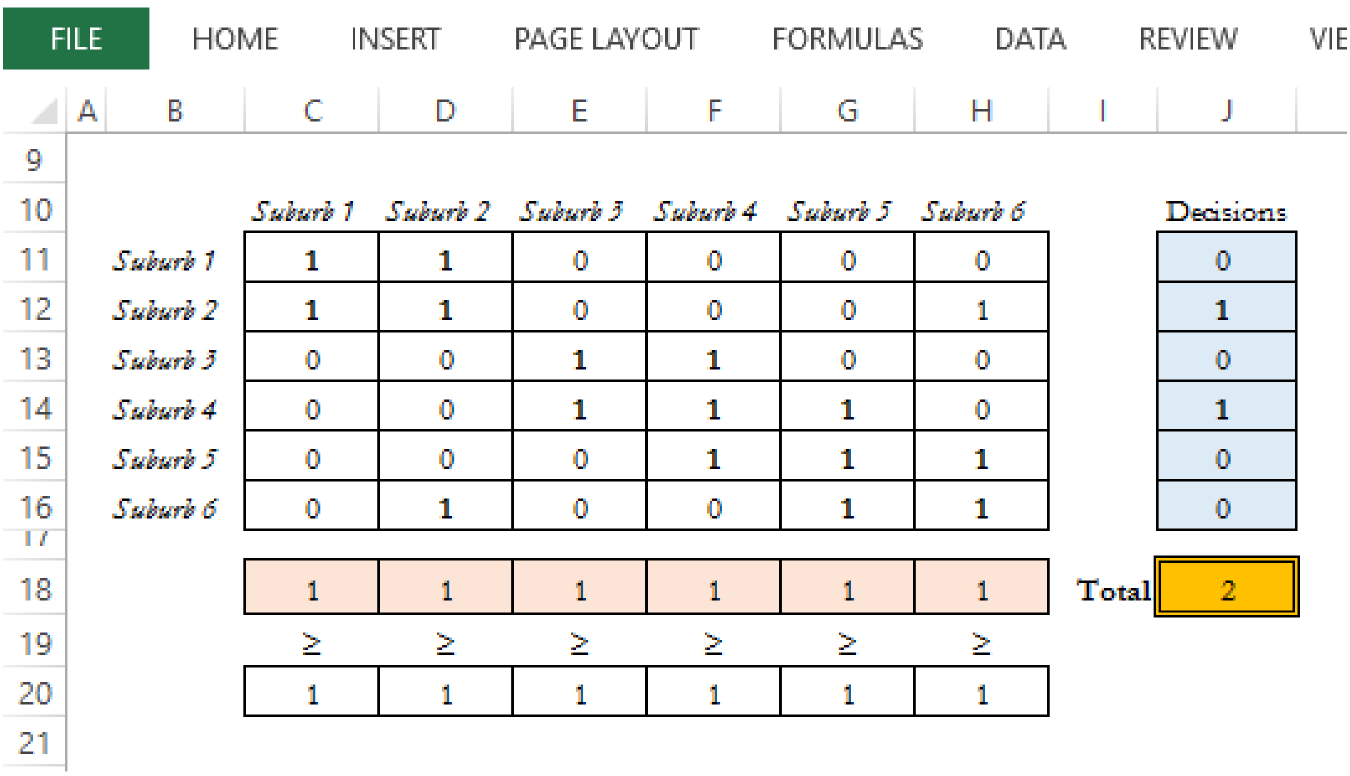
-*Suburb 6* can be served if facilities are located in suburbs 2, 5 and 6.

Table 2. Indicator variables for siting facilities.

	Suburb 1	*Suburb 2*	*Suburb 3*	*Suburb 4*	*Suburb 5*	*Suburb 6*
Suburb 1	1	1	0	0	0	0
Suburb 2	1	1	0	0	0	1
Suburb 3	0	0	1	1	0	0
Suburb 4	0	0	1	1	1	0
Suburb 5	0	0	0	1	1	1
Suburb 6	0	1	0	0	1	1

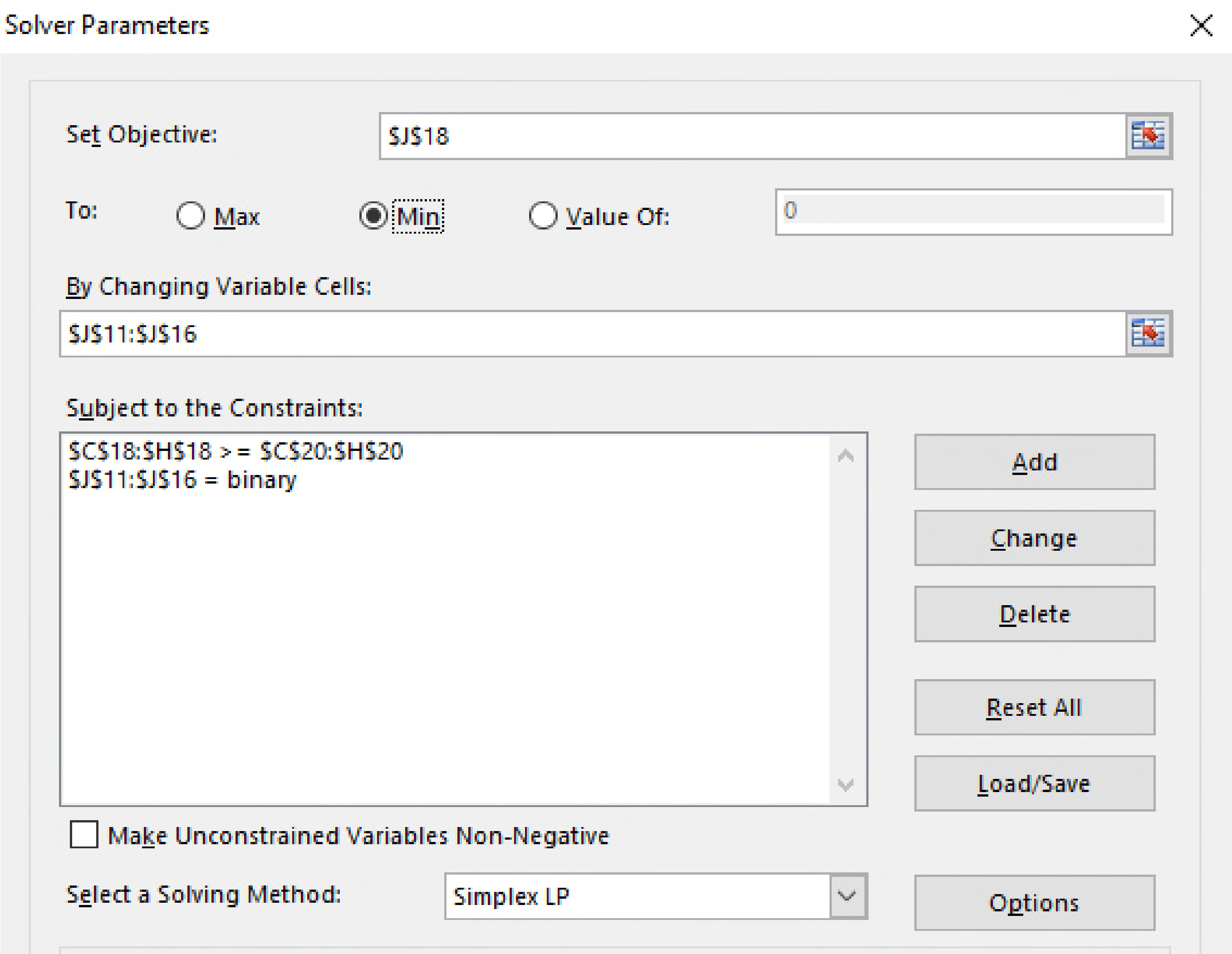
Source: adapted from Albright and Winston (2014)

Figure 1: Snapshot of spreadsheet model for implementing equation (4)-(11)



	A	B	C	D	E	F	G	H	I	J
9										
10			Suburb 1	Suburb 2	Suburb 3	Suburb 4	Suburb 5	Suburb 6		Decisions
11		Suburb 1	1	1	0	0	0	0		0
12		Suburb 2	1	1	0	0	0	1		1
13		Suburb 3	0	0	1	1	0	0		0
14		Suburb 4	0	0	1	1	1	0		1
15		Suburb 5	0	0	0	1	1	1		0
16		Suburb 6	0	1	0	0	1	1		0
17										
18			1	1	1	1	1	1	Total	2
19			≥	≥	≥	≥	≥	≥		
20			1	1	1	1	1	1		
21										

Figure 2: Solver parameters for equations (4)-(11)



Finally, equation (11) specifies that all decision variables must be binary.

3.3 Model Implementation

The spreadsheet model we developed for solving the problem is presented in Figure 1, showing information from Table 2. The decision variables are modelled in cells [J11:J16]. Cell [J18] sums the total number of facilities and so implements equation (4), the objective function. Cell range [C18:H18] sums the total number of facilities that can serve each of the suburbs listed in range [C10:H10].Thus, it implements equations (5) to (10), the demand node constraints. We solved the problem using Microsoft Excel, constraining all decision variables to be binary as specified in equation (11). The solver dialogue box for implementing the model is shown in Figure 2.

Testing the effect of changes in the RTC requires repeated solving of the spreadsheet model using the alternative values of T as specified in Section 3.1. We used the same spreadsheet model to obtain percentage coverage values when arbitrary decisions are made. However, this second set of tests do not need the spreadsheet to be solved for decisions. Instead, we input the decisions on the number of depots and where they are to be deployed, and then computed the resulting percentage coverage by counting the number of suburbs covered under each of those decisions and dividing the result by the total number of suburbs. The experimental decisions we used can only by specified *a posteriori* since they depend on the results from solving the main decision problem. We therefore reserve their specification until Section 3.6.

3.4 Results 1: Main Decision Problem

The solution to the problem is shown in Figure 1. All constraints are satisfied; each suburb listed in the row will be served by exactly 1 facility, and all decision variables are binary. The solution can be stated and interpreted as follows:

$$x_1=0; \quad x_2=1; \quad x_3=0; \quad x_4=1; \quad x_5=0; \quad x_6=0; \quad Z = 2$$

It means that the decision is to locate facilities at Suburb 2 and at Suburb 4, for an obvious optimal value of 2. The facilities in these two suburbs will then serve the entire city as follows:

Table 3. Effect of response time criterion on the number and location of emergency depots

Response Time (min)	No. of facility locations (optimal value)	Location of facilities (optimal solution)
5	6	{1, 2, 3, 4, 5, 6}
10	4	{2, 3, 4, 5}
15	2	{2, 4}
20	2	{3, 6}
25	1	{6}
30	1	Any
35	1	Any

-the facility at Suburb 2 will respond to emergencies that arise in suburbs 1, 2, and 6

-the facility at Suburb 4 will respond to emergencies that arise in suburbs 3, 4 and 5

3.5 Results 2: Effect of Response Time Limit on the Number and Locations of Depots

Results regarding the effect of changes in the RTC on the optimal value and optimal solution are presented in Table 3. It shows how the number and deployment sites change as the response criterion changes. The results indicate that number of facility locations reduces as the RTC increases or becomes less stringent. For example, a 5min performance standard requires depots to be sited in each suburb. This is so because the travel time between any pair of suburbs in the data set is more than 5min. RTC values greater than or equal to 30min will require a depot to be sited in any suburb. This is the case since the RTC is greater than all the travel times shown in Table 1. By implication, a single depot, irrespective of where it is located, can reach any emergency site within 35min. It is important to note that both a RTC of 15min and of 20min require two depots, but the locations are completely different in each case. This shows that the interaction between travel times and RTC influences the siting decisions, even if the optimal number of sites required to provide 100% coverage are equal.

Table 4. Effect of siting decisions on percentage

Scenario	Experimental Siting Decisions	Number of Depots	Percentage Coverage
Main problem	{2,4}	2	100%
Case 2	{2, 3, 6}	3	100%
Case 3	{2, 6}	2	67%
Case 4	{1, 2, 5, 6}	4	83%

3.6 Results 3: Effect of Arbitrary Decisions on Percentage Coverage

With *a priori* knowledge on the optimal decision, we tested the effect of arbitrary siting decisions on the percentage coverage by locating facilities in suburbs {2, 3, 6}, {2, 6} and {1, 2, 5, 6} independently, and computed the resulting percentage coverage for each case. The results, including those for the main decision problem, are reported in Table 4, showing that different siting decisions may result in different percentage coverage values, even in cases where the number of depots sited are the same. In the latter case, the key is where these depots are located. In terms of our efficiency and effectiveness classification system, the results indicate that the decision for the main problem

(Z = 2; PC = 100%) is efficient and effective;

Case 2 (Z = 3; PC = 100%) is inefficient but effective;

Case 3 (Z = 2, PC = 67% is efficient but ineffective; and

Case 4 (Z= 4, PC = 83%) is inefficient and ineffective.

These results show that deploying the optimal number of sites at suboptimal locations deprives the system of being effective. Secondly, deploying more sites than optimal will not necessarily provide 100% coverage, especially when the optimal locations are not included in the siting decision.

4.0 DISCUSSION

In order to enable engineers in Ghana increase their level of contribution to reduction of fatalities resulting from emergency events, this study made an attempt to explain the nature of the decision problem associated with distributing facilities for emergency response services, and illustrated the solution method with a numerical example. The numerical example gives a solution for such a problem assuming the public infrastructure system to support the decision is available and in good state. The state of road infrastructure must be such that the travel time required for effective response can be satisfied within the response time criterion. For example, suppose the required response time is 15min and the actual travel time between the closest suburbs is 25min due to traffic congestion, poor accessibility, pot-holes, etc., then each suburb must be serviced by its own facility as indicated in Table 3.

Thus, improving the performance of any system in practice calls for continuous monitoring of the system's performance, making investments in infrastructure development where needed. With increases in population and vehicular traffic, actual response times may deteriorate. When this happens, the road infrastructure system may require the provision of extra lanes and/or improved traffic control systems. Therefore, continuous monitoring and evaluation, such a tracking the actual response times and comparing them with the policy RTC, may signal the need for improvement in the infrastructure system.

For efficient and effective emergency response, policy makers must set the required response criterion. For example, when a disaster or emergency occurs, how long should it take a response team to reach the emergency site in order to minimize fatalities? This policy will contribute immensely in designing an optimal system. The results to the numerical example in this study has shown that the facility location decision becomes flexible, requiring fewer depots, as the response time criterion becomes less restrictive. This leads to lower costs for facilities deployment. On the other hand, if the response time criterion becomes more stringent, more care is required to determine the number and locations of a greater number of depots. This makes it more expensive for achieving 100% coverage.

5 CONCLUSIONS AND RECOMMENDATIONS

In conclusion, the answer to the question on how emergency response facilities can be well-distributed in order to minimize emergency-related fatalities is that, Engineers contributing to the design of such systems should model the problem mathematically as a location set-covering problem. The decision depends on existing travel times among locations, as well as the response time criterion. A more flexible response time criterion results in fewer deployment sites, and vice versa. Unless one models the decision problem quantitatively, with or without specifying the underlying mathematical details, there is the likelihood of siting more facilities that is required (being inefficient) to provide 100% coverage (being effective); the likelihood of siting more facilities than required (being inefficient) without achieving 100% coverage (being ineffective); the likelihood of siting the optimal number of facilities (being efficient) without achieving 100% coverage (being ineffective).

As the numerical example has indicated, several data inputs will be required for designing optimal emergency response systems. To start with, policy makers will need to specify the response time criterion. Data on the list of locations to be served by such facilities (the demand nodes), the travel times between all potential facility sites and locations to be served, and the cost of siting facilities in each potential deployment site will be required.

In Ghana, practical research in this area may focus on evaluating whether the number and locations of depots for emergency response services in the major cities, municipalities and districts are optimal. The author has initiated a study in this regard, to evaluate whether the major metropolitan areas in seven regions, plus Tema, have optimal fire response coverage.

Another potential set of questions to study is whether the existing response time criterion (if any) for emergency response services in Ghana is realistic, given the travel times between locations, and whether the performance of the responsible agencies actually meet the set criterion. For example, the Ghana National Fire Service may be targeting 4mins response time, but what is the probability that this performance standard can be met in practice? This question is relevant because if travel times between locations are more than the policy criterion, then it will be virtually impossible for emergencies that arise in one location to be serviced by a depot located in a different location using ground travel. Regarding the second part of the question, the Auditor General's report on the preparedness of the Ghana National Fire Service for emergency response suggests an average performance of 12.5min from a sample of 57 data values collected from 2006-2010 (AG, 2013). Would this average be different if the data were split into two: one for responses within the same location as the fire depot, and the other for fire incidents that were responded to by depots sited outside the location of the incident?

Finally, apart from using LSCP to site emergency response facilities, the method can also be innovatively applied to problems that require satisfying maximum travel distances between service points and customer locations. Such problems include the location of standpipes in community water supply systems; location of public toilet facilities, where permissible; locating skip containers for solid waste collection; and locating pay-points for public utilities such as the GWCL and ECG. Hopefully, the explanation provided in this paper will contribute to providing the analytical skills needed by the engineers in the associated institutions and firms to formulate and solve such problems.

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