



Improving accessibility to rural health services: The maximal covering network improvement problem

Lisa Murawski^a, Richard L. Church^{b,*}

^a California Legislative Analyst Office, 925 L Street - Suite 1000, Sacramento, CA 95814, USA

^b Department of Geography, University of California at Santa Barbara, Santa Barbara, CA 93106-4060, USA

ARTICLE INFO

Article history:

Available online 21 June 2008

Keywords:

Network design
Infrastructure
Planning
Access
Optimization

ABSTRACT

Accessibility to health facilities is a critical factor in effective health treatment for people in rural areas of lesser-developed countries. In many areas accessibility is diminished by the lack of all-weather roads, making access subject to weather conditions. Location–allocation models have been used to prescribe optimal configurations of health facilities in order to maximize accessibility, but these models are based on the assumption that the underlying transport network is static and always available. Essentially, past work has ignored the potential impacts of improvements to the transport system in modeling access. In this paper we propose a model that treats the opposite side of the location/transport equation; that is, a model that treats existing facility locations as fixed and improves health service accessibility by upgrading links of the transport network to all-weather roads. This new model, called the Maximal Covering Network Improvement Problem (MC-NIP) is formulated as an integer-linear programming problem. An application of the MC-NIP model to the Suhum District of Ghana is presented, which shows that even a modest level of road improvement can lead to substantial increases in all-season access to health service.

© 2008 Elsevier Ltd. All rights reserved.

1. Introduction

In analyzing the efficacy of health services provision, the ability of patients to access facilities, in terms of acceptable distances and adequate transport provision, is the key factor enabling effective treatment. These patients include mothers in all stages of natal care, children receiving immunizations and routine checkups, persons requiring emergency treatment of injury and illness, and persons receiving routine care. The problem of health services accessibility is particularly pronounced in rural regions of lesser-developed countries; this has been well documented by studies in a number of countries including Nigeria [16,22], Ghana [2,5], Bolivia [18], Haiti [3], and Zimbabwe [11].

Recently, governmental agencies, NGOs, and international development organizations like the International

Labor Organization, International Forum for Rural Transportation and Development, and the World Bank have emphasized the link between transport and health, noting the importance of transport in reaching health-related Millennium Development Goals [13]. Leipziger et al. [13] suggest that better access to basic infrastructure plays an important role in improving child health outcomes.

Until this point, models addressing health care accessibility have focused attention almost exclusively on the efficient location of health facilities. Selected examples include: Eaton et al. [9] who used the maximal covering location model to locate rural health workers and clinics in Colombia; Rahman and Smith [19], who addressed the problem of finding additional suitable sites for health facilities in Bangladesh with a maximal covering location model; Eaton et al. [10], who studied the problem of locating ambulances in Santo Domingo, Dominican Republic to maximize multiple coverage of demand; and Mehretu et al. [15], who used a *p*-median approach with constraints on maximum distance traveled to find clinic locations that

* Corresponding author.

E-mail address: church@geog.ucsb.edu (R.L. Church).

minimized total weighted travel distance from villages to facilities. For a comprehensive review of location-allocation models applied to health facility location in developing areas, see Ref. [20].

Location-allocation (LA) models, while very useful for defining efficient configurations of health facilities, are necessarily limited by their exclusive focus on facility location. These models ignore accessibility gains that could be provided by improvements to the underlying transportation network. Most location models have assumed either that (1) the underlying network will remain static and underdeveloped, ignoring the potential of road improvements for improving access or (2) all roads in the network are all-season accessible, ignoring the characteristics of different road classes. Oppong [17] noted that many applications of LA modeling in third-world settings have failed to explicitly treat the unique characteristics of a rural, third-world transportation infrastructure, such as dirt roads being completely washed out in the rainy season. Accessibility gains made on paper by the use of an LA model mean little when there is no viable means of transport between patients and facilities for much of the year.

An additional problem with relying on LA models for improving accessibility lies in the political, financial, and logistical difficulty of reconfiguring a system of health facilities. Rarely are analysts faced with a greenfield situation. Often, health facilities are established in certain locations due to other factors besides maximal coverage of population, such as availability of an adequate labor pool, existing infrastructure, or strategic government mandates. There are many reasons a region cannot or will not reconfigure locations of a system of health facilities, rendering location-allocation models of limited use in these scenarios. For the remainder of this paper, we will assume that health facilities are fixed in location.

2. Infrastructure investment for health services access

In addition to facility location, several authors have also addressed problems incorporating road condition and using road investment to improve accessibility. Oppong [17] attempted to address particular circumstances of a third-world LA application by accommodating the rainy season in a prescriptive study of health facility locations in Suhum region, Ghana. The approach in this study was a *p*-median LA model that took into account the reality that roads would not be serviceable during the rainy season. The solution approach was to locate clinics of two types (full service and somewhat limited service) only on paved roads, assuming that the facilities could then remain functional throughout the year. Kumar and Tillotson [12] propose a model for rural road development that seeks to provide all-weather road access to every village in the study area, while minimizing the sum of travel cost as a function of the traffic flow, road dimensions, and construction costs. The network resulting from solution of his model is a spanning tree that provides all-weather connection to every node on the network. Scaparra and Church [21] introduce a model that provides support for deciding paving strategies in a rural third-world setting. The model

identifies the highest-priority links to upgrade to all-weather in order to improve both all-season road connectivity and route efficiency, given a fixed budget. This is operationalized by simultaneously maximizing the volume of people served by an all-weather roads and minimizing the vehicle-kilometers traveled on the inter-village network. This bi-criterion objective is the weighted sum of the two individual objectives. Antunes et al. [1] define a nonlinear combinatorial model that represents an accessibility-maximization approach to long-term planning of an intra-urban road network. Accessibility is defined as the spatial interaction between centers, and is assumed to be related to the size of centers and distance between centers. The model is solved both by a local search and a simulated annealing heuristic to yield the decisions to upgrade and/or create new links between urban centers. Both the Scaparra and Church model and the Antunes et al. model address connectivity, an important long-term objective for the design of a rural road network. However, neither of these models addresses the need to access specific locations such as health facilities within the network, since they do not distinguish nodes with critical facilities from those without. Given the assumption that road network design has a significant effect on basic access to health services, we turn our attention to how improvements in the transport network can improve access to health care.

While others have focused on the location and relocation of clinics to maximize access to health services, or road improvements to optimize some other objective, our focus here is on increasing health service access by making road improvements. For the remainder of this paper, we will assume that established clinic and hospital locations are fixed. Over the near term (*e.g.* 5–10 years), current locations are likely to change very little if any, so this assumption is not very restrictive and is quite realistic. The question that we wish to address is: how much can access to health services be improved by making improvements to the road network? In the region of our study, the Suhum District of Ghana, the quality of road segments can be classified into three basic categories. The lowest quality category is the trail. Trails are very poor quality roads which are easily rendered impassable during the rainy season. The next category is the dirt road. Dirt roads are better than trails, as they are often wider and can better accommodate vehicle traffic. Unfortunately, these too are compromised by the weather. The third category is the paved road. Paved roads are considered passable during all seasons of the year.

In the bulk of past work, a village is considered access-covered when the distance between the village and the clinic or hospital is less than a maximal service distance standard. Thus, a village could be too far from the nearest clinic to be considered covered. Unfortunately, even when a village is within a reasonable distance to a clinic, the roads between the clinic and the village may not be passable during the rainy season. Thus, if a village is close enough but the road is dirt, then health service access coverage would be seasonal at best. Recognizing this additional limitation, we append the traditional definition of access-coverage to include the restriction that access-coverage must be provided on all-season roads.

Clearly, the better the existing roads, the greater the access provided. However, underdeveloped areas usually have a limited budget to spend on road improvements, raising the question of how best to spatially allocate such scarce resources to maximize the improvement in health service access. Our infrastructure planning problem can be defined in a formal way as:

Maximize the number of people who can be provided with year-round health service coverage within a limited budget by determining which roads should be improved.

We will call this problem the maximal covering network improvement model (MC-NIP). Although this problem is defined within the context of improving health service access by making road improvements, it is also applicable for other services, such as access to schools or market centers. In the next section we will formulate this model as a mathematical programming model.

3. Formulating the maximal covering network improvement model

We assume that a limited road network of varying quality exists between towns and villages. Let this network be represented by a graph G which is a set of nodes, N , representing towns and villages and a set of arcs, A , representing the road links connecting the towns and villages. Formally, the graph $G = (N, A)$. To put the infrastructure planning problem into a quantitative framework, consider the following notation:

i, j, a, b, k = indices used to represent the nodes (villages) of the network.

$A = \{(i, j) \mid i < j, \text{ where nodes } i \text{ and } j \text{ are directly connected by a road or trail}\}$.

B = the budget for road improvement.

S = the maximal distance standard for measuring access to health services.

a_i = the population of village i .

d_{ij} = distance of arc $(i, j) \in A$.

c_{ij} = cost of upgrading road arc $(i, j) \in A$ to an all-season road, based upon current road condition.

SP_{ij} = the shortest distance between nodes i and j on network G .

$U = \{(i, j) \mid (i, j) \in A \text{ and } c_{ij} > 0\}$, the set of road arcs that are not "all-season".

$F = \{j \mid \text{village } j \text{ houses a medical clinic}\}$, the set of villages housing a health clinic.

$D = \{i \mid \text{village } i \text{ does not currently receive all weather access to clinic services}\}$.

$D_s = \{i \in D \mid \text{village } i \text{ is within } s \text{ distance of a clinic}\}$, the set of villages that are not currently served with all season road access, but are candidates for such access by virtue that they are within s distance of one or more clinics.

$F_i = \{j \mid SP_{ij} \leq s \text{ where } j \in F\}$, the set of clinics that are within the maximal access distance s to village i .

$\Omega_{ij} = \{(a, b) \mid \text{arc } (a, b) \in A \text{ and could be used in an accessible path between } i \text{ and } j\}$.

There are three types of decision variables that are needed to build the MC-NIP model. The first type of

decision is which arcs or road links are to be upgraded to all-season use. For each arc that can be upgraded, i.e. $(a, b) \in U$, we define the following road investment decision variable:

$$H_{ab} = \begin{cases} 1, & \text{if arc}(a, b) \text{ is upgraded to an all season road} \\ 0, & \text{otherwise} \end{cases}$$

The model also needs to track which villages have been provided access by virtue of the road investment decisions. Thus, for each village that does not currently have year-round access to health services and has one or more clinics within a maximal service distance of s , i.e. $i \in D_s$ where

$F_i \neq \emptyset$, we define the following decision variable,

$$y_{ij} = \begin{cases} 1, & \text{if village } i \text{ and health clinic at } j \text{ are connected} \\ & \text{by an all season route within coverage distance } s \\ 0, & \text{otherwise} \end{cases}$$

This variable is also used to track which specific clinic j has been made accessible to village i . Finally, we need the capability to delineate an accessible path between a village and a clinic. This is done by the use of "path" variables, P_{ab}^{ij} , defined for each arc $(a, b) \in \Omega_{ij}$ such that $i \neq a$ (we exclude any variables P_{ib}^{ij}). These variables are defined as follows:

$$P_{ab}^{ij} = \begin{cases} 1, & \text{if a paved all season route between } i \text{ and } j \\ & \text{uses arc}(a, b) \text{ in the direction of } a \text{ to } b \\ 0, & \text{otherwise} \end{cases}$$

$$P_{ba}^{ij} = \begin{cases} 1, & \text{if a paved all season route between } i \text{ and } j \\ & \text{uses arc } (a, b) \text{ in the direction of } b \text{ to } a \\ 0, & \text{otherwise} \end{cases}$$

It should be noted here that we delineate paths in the model oriented from clinics to villages. This choice of direction is somewhat arbitrary and the model could have just as easily been formulated using path directions oriented from villages to clinics. It is also important to note that there are network nuances where a specific road arc may be a candidate for path delineation in either direction. Hence, the path variables on a given arc may be associated with one direction or both directions.

We can define the MC-NIP model based upon the above notation. This model maximizes the population that can be provided all-season access coverage based upon new road investment.

4. MC-NIP

$$\text{Maximize } Z = \sum_{i \in D_s} \sum_{j \in F_i} a_i y_{ij} \quad (1)$$

$$\sum_{(a,i) \in \Omega_{ij}} P_{ai}^{ij} = y_{ij} \quad \text{for each } i \in D_s \text{ and } j \in F_i \quad (2)$$

$$\sum_{(a,k) \in \Omega_{ij} \text{ or } (k,a) \in \Omega_{ij}} P_{ak}^{ij} - \sum_{(a,k) \in \Omega_{ij} \text{ or } (k,a) \in \Omega_{ij}} P_{kb}^{ij} = 0 \quad (3)$$

for each $i \in D_s$ and $j \in F_i$ where $k \neq i$ and $k \neq j$

$$P_{ab}^{ij} + P_{ba}^{ji} \leq H_{ab} \quad \text{for each } (a, b) \in Q_{ij}, \text{ where } i \in D_s \text{ and } j \in F_i$$

when $(a, b) \in U, i \neq a, i \neq b, j \neq a, j \neq b$ (4)

$$P_{ab}^{ij} \leq H_{ab} \quad \text{for each } (a, b) \in Q_{ij}, \text{ where } i \in D_s \text{ and } j \in F_i$$

when $b = i$ and $(a, b) \in U$, or when $a = j$ and $(a, b) \in U$ (5)

$$\sum_{(a,b) \in Q_{ij}} (P_{ab}^{ij} + P_{ba}^{ji}) d_{ab} \leq s^* y_{ij} \quad \text{for each } i \in D_s \text{ and } j \in F_i \quad (6)$$

$$\sum_{j \in F_i} y_{ij} \leq 1 \quad \text{for each } i \in D_s \quad (7)$$

$$\sum_{(a,b) \in U} c_{ab} H_{ab} \leq B \quad (8)$$

$$H_{ab} \in \{0, 1\} \quad \text{for all arcs } (a, b) \in U, \quad (9)$$

$$P_{ab}^{ij} \in \{0, 1\} \quad \text{and} \quad P_{ba}^{ji} \in \{0, 1\}$$

for all $i \in D_s$ and $j \in F_i$ and arcs $(a, b) \in Q_{ij}, \quad (10)$

$$y_{ij} \in \{0, 1\} \quad \text{for all } i \in D_s \text{ and } j \in F_i \quad (11)$$

The objective (1) of this model is to maximize the number of people who are provided access-coverage by virtue of road investment decisions. The MC-NIP is based upon an existing set of health clinic locations, F . Some villages already have “all-season” access to health services because they have a clinic located within their village. Others have all-season access because an all-season road route links them to a clinic within the maximal acceptable access distance of S . The remainder of the villages can be classified into two types: those that can be provided all-season access within the maximum coverage distance by making certain road investments, i.e. set D_s , and those that are too far from a clinic to be considered accessible regardless of the road condition, $D - D_s$. The model involves making investment decisions in order to improve access for those villages in set D_s . A node (village) is considered covered if a route on an all-weather road exists between it and a facility, within the specified maximum service distance S .

To describe this model, it is first helpful to note constraints (7) and (8). Constraint (7) establishes that access-coverage for a village can be counted at most once. Let us say that a village lacks all-season access but is close to several clinics (i.e. $i \in D_s$). Then, it may be possible to provide all-season access by improving separate routes to two different clinics. This constraint limits counting access-coverage to at most once for each village. Constraint (8) establishes a limit on the amount spent on road improvements.

The role of the remainder of the constraints is to identify which villages are provided access-coverage based upon the selected road projects. This is achieved in two parts: a set of path constraints and a set of constraints linking possible path selection to road improvements. A set of path variables are defined for each demand i that is within S distance of clinic j . These variables, P_{ab}^{ij} , are defined for

only those road links (a, b) that it is possible to include on a path between demand i and clinic j , without exceeding the maximal service distance S . Basically, the variable, P_{ab}^{ij} , represents traveling from clinic j to demand i , along an arc connecting a and b in the a to b direction. If $P_{ab}^{ij} = 1$, then an accessible path from j to i travels from a to b . If an accessible path reaches demand i , then constraint (2) allows y_{ij} to equal 1. Otherwise, y_{ij} will remain at 0. What makes this a connected path is the “node balance” constraints (3). Essentially, at every possible intermediate node between i and j , if a path between i and j enters an intermediate node k , the path must exit that node heading away from node k . Also, if a path does not enter a given node k , then constraint (3) ensures that the path cannot leave node k . Thus, a feasible path between i and j starts at clinic node j , and cannot terminate at any node except village node i . Of course, if a feasible path cannot connect node i and j , then all path variables P_{ab}^{ij} associated with demand i and clinic j are 0 in value.

Path variables are not restricted in value for any existing all season road links (in either direction). However, path variables are restricted for those road links that need updating. This is established in constraints (4) and (5). Essentially, using a road link by a path from clinic j to demand i is limited by the decision to upgrade the road, when the current road arc is not yet all-season. A path variable that represents traversing arc (a, b) can be positive only if the investment decision for arc (a, b) has been made, i.e. $H_{ab} = 1$. Together, constraints (2) through (5) ensure that only paths that traverse all-season roads from clinic j to demand i are allowed. The last key constraint (6) tracks the distance of the path selected between demand i and some clinic. Constraint 6 ensures that the length of the identified path must have a distance that is less than or equal to S , otherwise the path is not feasible. Altogether, constraints (2) through (6) ensure that only feasible all-season paths of lengths less than S are counted, and that at most one such path for each demand $i \in D_s$ is allowed. Finally, constraints (9–11) represent the integer conditions for the decision variables. It is important to note that restrictions (10) are not necessary when solving the problem, as the path variables can be set up as bounded variables between 0 and 1. If a solution exists, where some or all path variables associated with a path between a given i and j are fractional (i.e. between 0 and 1), it would represent the case where alternate feasible paths exist.

The MC-NIP as formulated is an integer-linear programming problem. Although this is a new design problem, it is related functionally to a problem called the maximum population shortest path problem [6–8] and the multiple-path covering-routing problem [4]. The maximum population shortest path (MPSP) problem involves minimizing the path length between a fixed origin and a fixed destination, while maximizing the population of the nodes in which the path traverses through. For the MPSP problem, the objective is to optimize both path length and the population of the nodes along the path. Although the MC-NIP problem contains multiple potential paths of fixed origins (clinics) and fixed destinations (villages), the similarity stops there. The differences between MC-NIP and the MPSP type problems include: (1) all paths are optional; (2) no two paths

can be used to reach the same destination; only population at the end node of the path is counted; (3) the length of each access path cannot exceed a distance of S to be feasible; and (4) paths are constrained by arc improvements.

The Maximal Covering Route Extension Problem (MCREP) of Matisziw et al. [14] is a valuable extension of the Maximal Covering Shortest Path problem and is designed to extend multiple transit routes by path variables and extend service by locating transit stops along the extended route. The basic similarity between MC-NIP and MCREP is that one can view a route extension as a covering path. But a route extension can be of any length and contain many stops, whereas in MC-NIP an access path cannot be longer than a distance S , has no stops and cannot travel along a dirt road or trail, unless the road arc has been selected for improvement. Thus, MC-NIP can be classified as a new model within the genre of maximal covering routing problems.

5. Solving the MC-NIP model

The MC-NIP formulation contains a rather small set of coverage and road investment variables. The bulk of the model is made up of path defining variables and constraints associated with identifying feasible access-coverage paths for a given set of road investment decisions. Consequently, the size and layout of the network will dictate the exact number of path variables and constraints. It is not an easy task to estimate the problem size, without a close examination of the network being solved. That said, the two most important factors in model size are the number of road arcs within S distance of villages not yet served by all-season road access and the number of clinics that are potentially eligible to serve a village not yet served with all-season roads. Suffice it to say, the model can be quite large in application.

For some applications it is reasonable to suggest the use of general-purpose mix-integer programming software in order to identify optimal solutions. When this approach is not possible due to problem size, heuristics and special procedures like Lagrangian relaxation techniques should be pursued. In this paper we present results utilizing a general purpose optimization code called ILOG-CPLEX.

We designed a five-step approach to apply the MC-NIP model. The first step involved the use of GIS software (ARC/GIS) to store a representation of road network of the planning region, along with road attributes, clinic locations and village populations. Data from the geo-database was extracted using ARC/GIS functions and exported to an Excel file. The second step involved the development of a Visual Basic program that read the network data and created a problem instance using the well-known MPS format. Each problem instance was stored in a problem file. In the third step, we used ILOG-CPLEX to solve the problem specified in the problem file. In solving each problem path variables, p_{ab}^{ij} , were set as continuous variables, since path variables will be integer at optimality, unless there exists multiple feasible access paths. In either case, a feasible access path exists whether integer restrictions are imposed or not. Coverage variables, y_{ij} , were also set as continuous variables, since coverage variables will be integer whenever road investment variables are integer. Thus, the MC-NIP was solved to integer optimality by restricting only

the road investment variables H_{ab} to be binary integer. Results of CPLEX were directed to an output file. For the fourth step, a Visual Basic program was written that could read the CPLEX output file and extract the road investment decisions associated with the optimal solution. In the fifth step, the extracted results were then imported into ARC/GIS and the solution was mapped. The maps that are presented in the next section are products produced by the GIS software. The design of this approach was a loosely coupled system of five independent tasks; however, each step is relatively easy to apply, making a useful decision support system associated with this specific model. In the next section we present results of the MC-NIP model applied to the Suhum District of Ghana.

We used ILOG-CPLEX version 9.0 on a Sun workstation (SunBlade 2500) running Solaris 5.7. This system has a clock speed of approximately 500 mghz. ARC/GIS and Visual Basic programs were executed on an Intel Pentium 4. Computer times given in the next section are associated with solving the MC-NIP model using CPLEX on the SunBlade.

6. An application of the MC-NIP model

Several past studies on health services delivery have been applied to the Suhum District of Ghana. Oppong [17] applied the p -median and maximal covering models to analyze the impact of seasonal road conditions on the optimal placement of health facilities. Because of this past work on the Suhum district, we chose to use the Suhum District as a test application of the MC-NIP model. Fig. 1 presents a map of the district. The road network contains 205 nodes and 240 arcs. Locations of the 20 small clinics (C-type), 6 large clinics (B-type) and the regional hospital (A-type) are given on the map, as well as the conditions of each of the road arcs in terms of trail, dirt road, and paved road. Only paved roads are considered to be all-season. We assumed that the cost of updating road arcs is proportional to the distance of the arc, where the cost of upgrading a dirt road to all-weather was set equal to the distance of that arc and the cost of upgrading a trail was equal to 1.5 times the distance of the arc. The majority of seasonal roads are dirt.

We first solved the MC-NIP model for the Suhum District using a maximal service distance of 7 km. (4.2 miles). This maximal service distance is the same used by Oppong [17]. Whereas Oppong analyzed how access could be increased by relocating clinics, this study determines how road improvements can be used to improve access-coverage. In using a maximal service distance of 7 km, we first needed to identify those villages who receive all-season access within the 7 km distance. Fig. 2 depicts a breakdown of the population by access type. Of the 102,531 people in the region, approximately 50% (51,781) receive services because they live in a village or town that has a clinic or hospital. This is not surprising, since there are 27 existing health facilities and many of these are located at the most populous villages. About 14% (14,286) of the people have an all season route that is within 7 km of a health clinic. Thus, the current system serves approximately 65% of the people within the standards of all season access and 7 km. Eight percent of the population does not

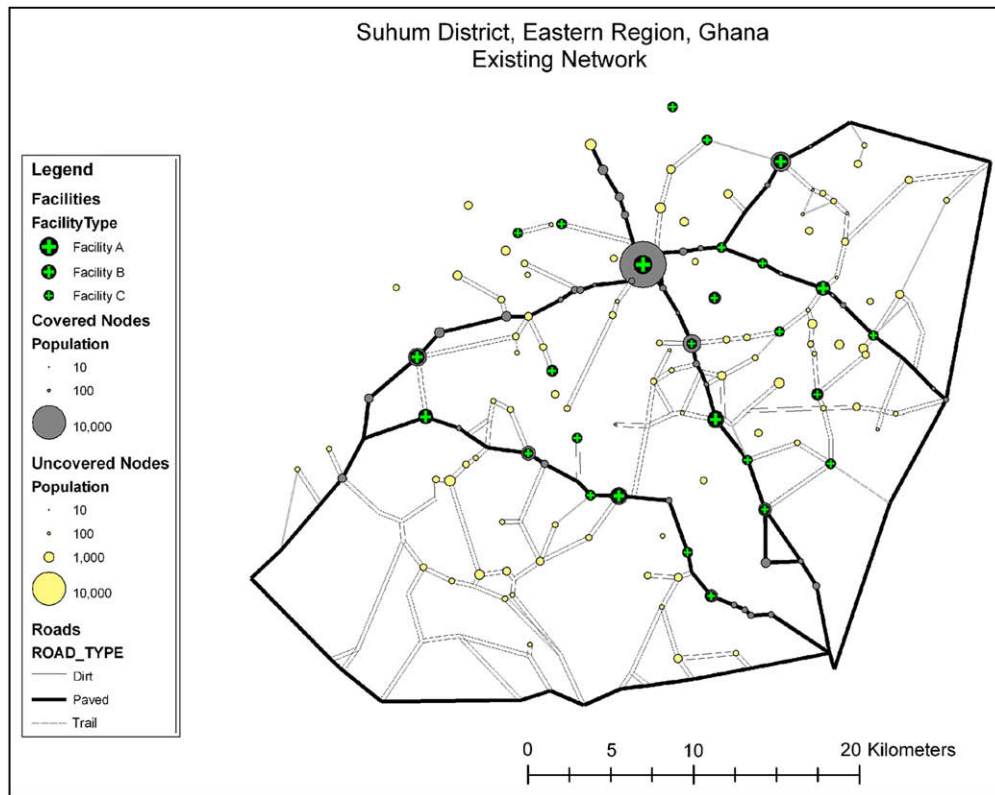


Fig. 1. Map of the Suhum District of Ghana. Health facilities are indicated with plus signs and roads are classified as trail, dirt, and paved.

live close to the road system. Unfortunately, network data is not complete enough to assess how these individuals may be provided service. Despite efforts to develop more road information, it was determined that this part of the population cannot be analyzed as a part of the model without doing a more extensive ground survey. Although it would have been desirable to have included this population in

the study, the main purpose was to demonstrate the value of the model and the ease with which it can be solved. There are 28,174 people (27%) who are associated with the existing road network and who do not have an all season route less than 7 km to an existing clinic. The MC-NIP model was then solved to maximize access for this group of people.

Table 1 presents results of the MC-NIP model in attempting to maximize access for the 28,174 people who are accessible to the network, but do not have all-season

Breakdown of Population in Suhum District, Ghana

Figures given for S-max = 7; Total population = 102,531

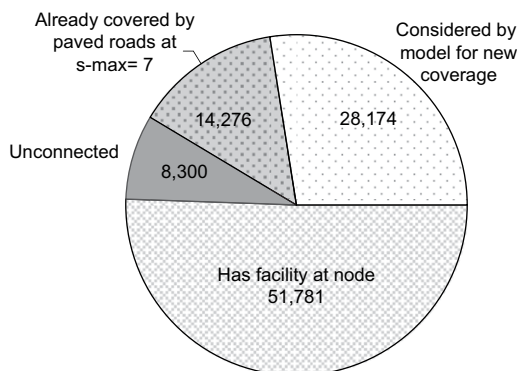


Fig. 2. Breakdown of population by type of accessibility to existing health facilities.

Table 1

Results of the MC-NIP model applied to the Suhum District, Ghana using a maximal service distance $S = 7$.

S	Budget	Objective function value	Percent covered	Persons covered/unit cost	Solution time (s)
7	5.00	3711	13.2	742.2	0.12
7	10.00	5982	21.2	598.2	0.23
7	18.00	8707	30.9	483.7	0.20
7	25.00	10,803	38.3	432.1	0.32
7	40.00	14,373	51.0	359.3	0.49
7	50.00	16,265	57.7	325.3	0.60
7	65.00	18,484	65.6	284.4	0.63
7	75.00	19,722	70.0	263.0	0.91
7	85.00	20,677	73.4	243.3	0.39
7	100.00	21,374	75.9	213.7	0.18
7	117.68	21,445	76.1	182.2	0.02
7	125.00	21,445	76.1	171.6	0.04

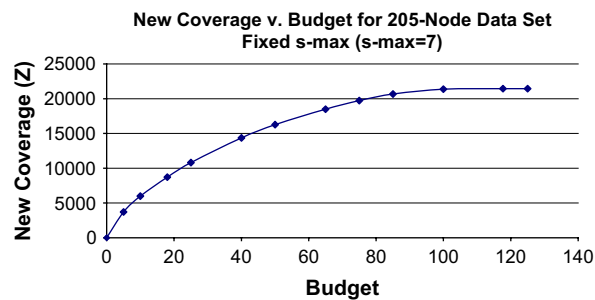


Fig. 3. Tradeoff curve depicting additional population covered associated with increases in road investment.

access coverage by a health clinic. The model was solved over a range of budget values of 5–125. All problems listed in Table 1 have the same model size since the MC-NIP model size is fixed for a given value of S ; for $S = 7$, the model has 1387 variables and 1684 constraints. Solution times for this set of parameters are all under 1 s. The solution information given in Table 1 shows that road improvement can have considerable impact on improving all season access coverage. For example, given a budget of 18 (the cost of updating 18 km (10.8 miles) of dirt road to pavement) access can be increased by 8707 people or 488 people per km of road improvements. Note that the limit on coverage is 21,445, as the remaining villagers are further than 7 km from their closest clinic. Thus, the reported objective function values range from 0 to 21,445, representing the new coverage added as a result of new pavement decisions, varying based on the allowed budget for road upgrades. It should be noted that the road expenditures do not always exhaust the allowed budget for a given solution. The last line of the table includes a solution that provides the same coverage as the solution given on the preceding line, even when the budget was higher. This is due to the fact that the added budget (i.e. going from 117.68 to 125) yielded no further increase in coverage. A closer examination indicated that the two solutions were the same as the additional budget was not allocated.

Fig. 3 depicts the trade-off curve of increasing new coverage versus increasing budget. These non-inferior points represent the range of decisions available to the

road planner. As shown, population coverage increases quite rapidly with increasing budget, and then begins to taper off gradually. With a budget of 50, less than half of the 117.68 it takes to cover the entire population, 76% of the “uncovered and eligible population” are provided coverage within a maximal service distance of $S = 7$ by making road improvements. With a budget of 85, the percentage covered jumps to 96%.

The model was also tested for varying values of maximum service distance, S , for a fixed budget of 50. Table 2 shows results of this analysis. Note that model sizes ranged from very small to 7081 variables and 8627 constraints. All problem instances were solved in less than 5 s. For $S = 0$, the objective function value is 0 but total coverage is 51,781, as this represents the number of people who live in a town with a clinic. When S is increased, access-coverage increases in two ways. First, access-coverage increases as some who have an existing paved route are now within the within the distance standard S . That is, some people that may not be considered covered for a given S may indeed have a paved route to a facility for a higher S value. Second, access-coverage is increased by virtue of the road investments made by the model. As one can observe from the results given in Table 2, access-coverage cannot be fully achieved without some type of improvement: additional clinics, improved roads, or a combination of both. Also observe that increasing the standard of service from 11 to 12 does not yield any increases in coverage. This is due to the proximity of clinics and villages and further increases in the service standard may well result in increases in coverage, however increasing the standard above $S = 12$ is probably not very meaningful.

Fig. 4 depicts the tradeoff of increasing coverage as a function of increasing service distance S , while keeping the road investment budget at 50. As S is increased, the total coverage grows slowly when S is very small, then increases quickly until S is about 5 or 6 km, and then coverage gains slowly taper off as S becomes quite large. This aggregate total coverage is composed of nodes covered in one of three ways: (1) a fixed population already has facilities located at their village; (2) a village is covered by a route comprised of already-paved arcs within the maximum service distance; or (3) a village is provided coverage because existing roads have been upgraded to all-weather roads by the model.

Table 2

Results of the MC-NIP model applied to the Suhum District of Ghana for a fixed budget of 50.

S	Budget	MC-NIP objective function value	Covered by paved route	Total coverage	Percent of total population covered	Solution time	Variables	Constraints
0		0	0	51,781				
1	50	462	159	52,402	51	<0.01	154	16
2	50	2731	4069	58,581	57	<0.01	172	57
3	50	9600	6045	67,426	66	<0.01	256	208
4	50	13,174	9118	74,073	72	<0.01	362	366
5	50	15,371	10,831	77,983	76	0.05	576	661
6	50	16,774	11,809	80,364	78	0.12	895	1077
7	50	16,265	14,276	82,322	80	0.58	1387	1684
8	50	15,862	15,874	83,517	81	1.32	1983	2422
9	50	16,109	15,874	83,764	82	1.58	2846	3510
10	50	16,515	15,874	84,170	82	2.76	3991	4893
11	50	16,875	15,874	84,530	82	2.68	5366	6570
12	50	16,875	15,874	84,530	82	4.76	7081	8627

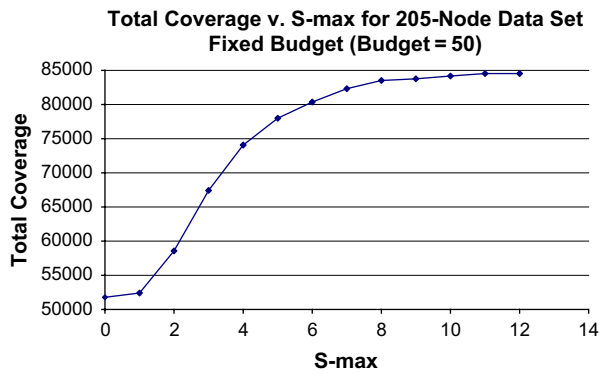


Fig. 4. Tradeoff curve of added coverage as a function of increasing maximal service distance S , while holding the budget fixed at 50.

Finally, Fig. 5 presents a solution for the MC-NIP model using $S = 7$ km and a budget of 50. The level of road investment for this solution is relatively modest, however, an additional 16,265 people are provided all season access within 7 km. If one compares the existing road system (Fig. 1) to the solution in Fig. 5, it is easy to see that road investments are scattered and often involve short links. This fact alone shows that small barriers to access exist and if eliminated with road improvements can have a significant impact on access to health facilities.

7. Summary and conclusions

Less developed regions often lack many basic elements of infrastructure which aids economic growth and supports

a high quality of life. Such elements include a safe and sustainable water supply, sewers and wastewater treatment, educational facilities, safe and efficient road system, and accessible health services. Past research has concentrated on the development of models to efficiently allocate resources in order to improve educational access, water supply, the road network, and access to health services. Virtually all of the past models involve improving one element of infrastructure independent of other elements. For example, a number of models have been developed for the purpose of locating health services. These models hold other elements of infrastructure fixed while optimizing health service access by the location of new health facilities (or the relocation of existing facilities). However, access to health facilities is also determined in part by the condition and location of the supporting road system. Further, many roads in developing countries are often impassable in the rainy season, and modeling access to health services must consider the impact of weather on access. Based upon this perspective we can define three important spatial optimization problems, related to improving health service access. They are: (1) determining optimal clinic and hospital locations assuming that the road system is fixed; (2) maximizing health facility access by making improvements to the road network; and (3) maximizing health services access by optimizing the location of health facilities as well as optimizing road network improvements. The existing literature has concentrated on developing models associated with health facility location. This paper has introduced a new model that can be used to maximize access to health facilities by making selected improvements to the road system. We have applied the

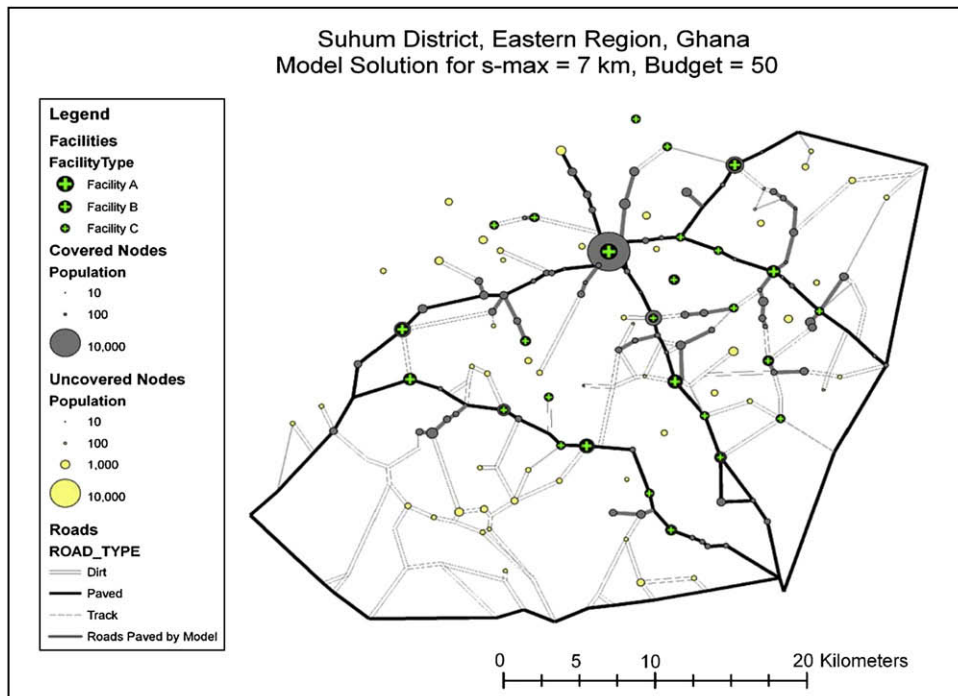


Fig. 5. MC-NIP solution for a budget of 50 and a maximal service distance $S = 7$.

model to the Suhum District of Ghana. Our application shows that significant increases to all season health services access can be obtained by a modest level of road investment. Although road network expansion is often modeled for the purpose of supporting commerce and increasing efficiency in travel and freight transport, the role of the road network in providing basic services like access to health and education services is often overlooked. Given the results of this paper, it seems appropriate that future network investment models need to be developed to consider not only impacts to commerce and access to markets, but access to services like health and education. Future research is also needed to develop a combined model of road and health facility investment, so that the appropriate tradeoff can be struck between clinic and hospital investment and infrastructure investment to improve access to such services. Finally, the nature of the investment decision might also be expanded to consider any economies to scale that might accrue to identifying larger contiguous projects as compared to a number of smaller disjoint projects.

Acknowledgements

We first want to dedicate this paper to the memory of Prof. Charles ReVelle. His writings, lectures, and encouragement were instrumental in inspiring and guiding this work. He will be missed by all who knew him. We also wish to acknowledge the helpful comments of Joseph Oppong and his willingness to share his data concerning the Suhum District. Finally, we thank Anna Carla Lopez for providing regional maps of the Suhum District.

References

- [1] Antunes A, Seco A, Pinto N. An accessibility-maximization approach to road network planning. *Computer-Aided Civil and Infrastructure Engineering* 2003;18:224–40.
- [2] Appiah-Kubi K. Access and utilisation of safe motherhood services of expecting mothers in Ghana. *Policy and Politics* 2004;32(3):387–407.
- [3] Barnes-Josiah D, Myntti C, Augustin A. The “three delays” as a framework for examining maternal mortality in Haiti. *Social Science and Medicine* 1998;46(8):981–93.
- [4] Boffey B, Narula SC. Models for multi-path covering-routing problems. *Annals of Operations Research* 1998;82:331–42.
- [5] Buor D. Analysing the primacy of distance in the utilization of health services in the Ahafo-Ano south district, Ghana. *The International Journal of Health Planning and Management* 2003;18(4):293–311.
- [6] Current JR, Pirkul H, Rolland E. Efficient algorithm for solving the shortest covering path problem. *Transportation Science* 1994;28:317–27.
- [7] Current JR, ReVelle CS, Cohon JL. The shortest covering path problem: an application of locational constraints to network design. *Journal of Regional Science* 1984;24:161–83.
- [8] Current JR, ReVelle CS, Cohon JL. The maximum covering/shortest path problem: a multiobjective network design and routing formulation. *European Journal of Operational Research* 1985;21:189–99.
- [9] Eaton DJ, Church RL, Bennett VL, Hamon BL, Valencia-Lopez LG. On deployment of health resources in rural Valle del Cauca, Colombia. *TIMS Studies in the Management Sciences* 1981;17:331–59.
- [10] Eaton DJ, Sanchez HM, Lantigua RR, Morgan J. Determining ambulance deployment in Santo Domingo, Dominican Republic. *Journal of the Operational Research Society* 1986;37(2):113–26.
- [11] Fawcus S, Mbizvo M, Lindmark G, Nystrom L. A community-based investigation of avoidable factors for maternal mortality in Zimbabwe. *Studies in Family Planning* 1996;27(6):319–27.
- [12] Kumar A, Tillotson HT. Planning model for rural roads. *Transportation Research Record* 1991;1291:171–81.
- [13] Leipziger D, Fay M, Wodon Q, Yepes T. Achieving the millennium development goals: the role of infrastructure. *World Bank Policy Research Working Paper* 2003:3163.
- [14] Matisziw TC, Murray AT, Kim C. Strategic route extension in transit networks. *European Journal of Operational Research* 2006;171(2):661–73.
- [15] Mehretu A, Wittick RI, Pigozzi BW. Spatial design for basic needs in eastern Upper Volta. *Journal of Developing Areas* 1983;17(3):383–94.
- [16] Okafor FC. The spatial dimensions of accessibility to general hospitals in rural Nigeria. *Socio-economic Planning Sciences* 1990;24(4):295–306.
- [17] Oppong JR. Accommodating the rainy season in third world location-allocation applications. *Socio-economic Planning Sciences* 1996;30(2):121–37.
- [18] Perry B, Gesler W. Physical access to primary health care in Andean Bolivia. *Social Science and Medicine* 2000;50(9):1177–88.
- [19] Rahman S, Smith DK. Deployment of rural health facilities in a developing country. *Journal of the Operational Research Society* 1999;50(9):892–902.
- [20] Rahman S, Smith DK. Use of location-allocation models in health service development planning in developing nations. *European Journal of Operational Research* 2000;123(3):437–52.
- [21] Scaparra MP, Church RL. A grasp and path-relinking heuristic for rural road network development. *Journal of Heuristics* 2005;11:89–108.
- [22] Stock R. Distance and the utilization of health facilities in rural Nigeria. *Social Science and Medicine* 1983;17(9):563–70.

Lisa Murawski is a legislative analyst with the California State Legislature. At the time this paper was written she was a transportation planner with the Santa Barbara County Association of Governments in the Traffic Solutions Section. She earned a B.S. in Industrial Engineering from the State University of New York at Buffalo and an M.S. in Geography from the University of California, Santa Barbara. As a student she specialized in transportation modeling, operations research techniques, and geographical information systems.

Richard L. Church is a Professor of Geography at the University of California, Santa Barbara. He earned a B.S. degree with majors in Mathematics and Chemistry from Lewis and Clark College and a Ph.D. in Environmental Engineering from The Johns Hopkins University. His research interests include urban systems modeling, location and transportation modeling, and geographical information science. He has published more than 180 papers and manuscripts on a range of topics in journals such as *Water Resources Research*, *Papers in Regional Science*, *International Journal of Geographic Information Science*, *Computers and Operations Research*, *Transportation Science*, *Geographical Analysis*, *Transportation Research*, *Biological Conservation*, and *Annals of the AAG* among others.