Allocating Highway Safety Funds

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Productivity in many governmental agencies can be greatly increased by the application of optimization techniques. As these techniques progress, it is important to keep those agencies who are using them up-to-date with the most recent innovations. Presented is an update of a highway safety application, progressing over 15 years, from the use of dynamic programming to a branch-and-bound technique. The branch-and-bound technique is faster, can handle larger sets of project data, and does not suffer from round-off errors as did the dynamic programming technique. These features have enabled the total available funds from categorical highway safety grants to be allocated to produce the maximum benefit in terms of estimated savings of lives, injuries, and property damage.

One of the primary functions of governmental authorities is the management of funds that are placed under their supervision. In order to ensure that maximum benefits are obtained from the application of limited funds, government agencies must make intelligent decisions as to which projects are to be funded and the degree of funding. This need is true whether the project area is medical research, housing for the underprivileged, or highway safety improvement. These decisions may be based on many factors such as public opinion, equity, and the mandates of higher authorities. However, all other things being equal, these decisions should be based on maximizing the total quantified benefit that can be produced from the expenditure of the available funds. Unlike other factors, economic comparisons of roadway improvement projects can be quantified for easy manipulation on the computer. Such projects range from simple warning sign upgrades to major rechannelizations and bridge repairs.

If accurate costs and benefits for each of these proposed projects are obtained, guaranteed optimal budget allocations can be generated. To obtain such accuracy, cost and benefit estimates must be made by individuals who are experienced with such projects for consistency if not perfect accuracy. Methods of assessing costs and benefits of projects have been developed and are available elsewhere (*1*). Early studies by Graham and Glennon (*2*) determined that the most important aspect of the cost assessment process is in the initial identification of high-accident locations. Many studies have determined the value of a cost-safety effectiveness approach to the allocation of funds including the works of Brown and Colson (*3*) and Bellamo et al. (*4*).

In a study by McFarland and Rollins (*5*), data from five states were used to compare three optimization techniques as applied to the allocation of highway funds. The three techniques were dynamic programming, integer programming, and incremental benefit-cost analysis. These were also compared with the simple benefit-cost method, which was demonstrated to produce less than optimal results. Budget allocations produced by the three optimization techniques were similar, and generally better than the simple benefit-cost method by 35 to 40 percent. Most important, a sensitivity analysis found that proportionate overestimation (or underestimation) of countermeasure effectiveness did not significantly affect project selection. This result is critical because relative accuracy is much easier to attain than absolute accuracy in estimating future highway safety costs and benefits.

Brown (*6*) and Brown and Colson (*3,7,8*) documented the state of Alabama Highway Department's support of the development of a software system known as Cost-Benefit Optimization for the Reduction of Roadway Environment Caused Tragedies (CORRECT). On the basis of a collection of standardized High Accident Location Investigation Forms (HALIForms), this system computes cost-benefit information regarding roadway improvement projects under consideration and derives potential budget allocations from this information. The optimization technique originally applied in CORRECT was dynamic programming, and the computer program for this algorithm is documented in the work by Brown (*9*).

Recently, a branch-and-bound algorithm was implemented to replace the dynamic programming module as the optimization portion of the CORRECT system. The branch-and-bound program is faster, can handle larger sets of nonhomogeneous data, and does not suffer from round-off errors as did the dynamic programming routine. Following is the definition of this problem and the mathematical and human-factors advantages of the branch-and-bound approach.

PROBLEM STATEMENT

Consideration will be restricted to those problems that can be addressed by roadway modifications, such as the installation of signs, lights, or the entire reconstruction of an intersection. The fact that most people are familiar with some part of the roadway system presents a unique problem in applying standard management techniques to allocating funds for safety improvements. Political expediency can have heavy influence because elected officials are in ultimate control of the public budgetary expenditures.

A perceived cause-effect mechanism influences the public and, hence, the politicians. Two catastrophic forces are currently perceived to motivate action in this arena: (a) an accident itself, and (b) legal action against public officials. The recurring question of why someone has to be killed at a location before corrective action is taken is well known.The perception is that the officials are acting only as a result of a given incident and not as a result of some comprehensive plan.

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Although this perception might be accurate in many political arenas, any comprehensive plan must begin with those locations that historically have proven to be hazardous. Public officials may well be so limited in funds that improving a location where an accident had not occurred would be incompetent on their part.

The second perceived motivator is litigation. Although some lawsuits against public officials serve the long-term good, near term they are devastating. Both the defense and the settlement are generally paid from public funds, reducing the ability of the governmental unit to use that money for improvements. Further, a paranoia develops analogous to the gun-shy dog. In the absence of a dependable method for allocating safety funds, the lawsuit-shy officials often retreat from every form of quantification. There have been cases occurring outside of Alabama where needed improvements were intentionally not made after an accident because the improvement would infer that the political unit was negligent in not making the improvement prior to the accident.

Given the legal and economic constraints under which public officials must function, how are they to approach the difficult task of budget allocation? The solution is in using the most advanced tools available. The decision maker should not turn the entire decision-making process over to a computer—this would show a misunderstanding of the capabilities and limitations of computerized tools. The process cannot be so quantified that human judgment is completely removed. The objective of the proposed approach is to provide the decision maker with the knowledge of the theoretically optimal solution, so that when compromises are made from that solution, they can be done in an intelligent manner, maximizing the overall good of the public.

Public funds should be expended in a way that maximizes the total benefit to society produced by these expenditures. The real problem lies in formulating a quantitative method of assessing the amount of benefit produced by a given set of expenditures. When a public official takes the initiative and establishes a procedure whose objective is to reach this goal, the criticism is shifted from the official to the procedure. Because allocations are not being made according to political favoritism, criticism along these lines can be easily rebutted. Critics are now duty-bound to devise a better procedure. This is unlikely, because public officials will continually improve their procedures if they are indeed striving for the overall public good. Of course, it is contingent on their communicating their processes to their constituency.

It therefore behooves public officials to use an optimization technique to allocate available funds in this sensitive area of the public sector. Heuristic approaches have the danger of omitting a needed project in favor of an inferior one, which could be legally devastating to a public official. Further, it is to their benefit, from a political and legal standpoint, to publicize the technique and allow it to be subjected to public scrutiny and criticism. Because the applied technique returns the maximum benefit, critics might be challenged to devise a solution (i.e., a set of roadway projects) that would return a higher total benefit.

Given the presence of an optimization technique, there are two major problems involved in the allocation of highway safety funds. The first is the large number of locations (intersections, bridges, etc.) to which improvements could be made. The second is the production of estimates of the cost and the benefit for each of the improvements that might be proposed once a location becomes a candidate for improvement.

Clearly all locations pose some potential hazard that could be mitigated given the availability of funds. Imminently dangerous situations require immediate action, e.g., the detour of traffic around a hazardous work zone. The objective here is to identify and evaluate those locations that are not imminently dangerous, but have reasonable potential for safety improvement.

Brown (*10*) provides the details for selecting the most hazardous locations and obtaining a cost and a benefit for each potential improvement. The procedure begins by a computer search of accident records over the last several years to provide a list of candidate locations. The data are then summarized and sent to the divisional investigation team, where engineers familiar with the location generate possible alternatives to remedy the problems. The engineers are also encouraged to add locations to the list that may not have yet had enough accidents to be included, but are considered to be potentially hazardous. An investigation of each site is conducted and standardized forms are completed that include costs as well as expected results for each alternative improvement proposed. The forms are sent to the central office for accuracy and consistency checks, and then processed by an algorithm, which generates cost and benefit data for each alternative at each candidate location.

This process, while not perfect, is defendable in that it places the key judgments involving future countermeasure effectiveness upon the local investigation experts, who are most capable of making these decisions. The similarity of projects between investigation teams assures against bias, because patterns of overestimation and underestimation can readily be detected centrally. Further, the comparison of raw data from similar projects throughout the state ensures consistency, which is the critical element in obtaining an optimal set of projects to undertake. In those cases where one local investigating team is out of line with the majority of others, corrective action is taken by the central administrator by reviewing all source data from the field. The central administrator has the authority to overrule those estimates that deviate significantly from estimates based on past experience and documented evaluations. However, in most cases the cause of the deviation is determined, and the parties negotiate estimates while being as consistent as possible with other similar projects.

At this point, the problem is to take these sets of costs and benefits for each improvement and find the set of improvements and locations (i.e., policy) that returns the maximum total benefit. Although this might seem straightforward, the sheer number of alternatives leads to combinatorial explosion. For example, if there were only 30 locations with two alternatives at each location there would be 2^{30} possible budget allocations to be considered. If 1 million allocations per second were examined by computer, it would take about 20 min to enumerate them all. However, if the number of locations were doubled, resulting in 2^{60} allocations, the same computer would take more than 365 centuries. Because a typical problem faced by the state agency would have hundreds of locations, the complexity of the problem is enormous.

To formalize this problem somewhat, let the total budget to be allocated be B. At location $j = 1, 2, \ldots, N$, let $i = 1, 2, \ldots, M_j$ denote the mutally exclusive alternatives available. Define C_{ij} to be the cost of alternative i at location j, and b_{ij} its benefit. A policy is defined to be a statement of which alternative is to be implemented at each location. Let d_{ij} be equal to 1 if alternative i at location j is funded, and 0 otherwise. Only one value of d_{ij} will equal 1 at any location j. The objective is to find the values of the d_{ij}s that produce the maximum sum of the returns. Thus, the optimal value of the total return Z is obtained by maximizing

$$Z = \sum_{j=1}^{N} \sum_{i=1}^{M_j} b_{ij}\, d_{ij} \tag{1}$$

This objective function is subject to a total budget constraint given by

$$\sum_{j=1}^{N} \sum_{i=1}^{M_j} C_{ij}\, d_{ij} \leq B \tag{2}$$

No more than one alternative chosen at each location is enforced by

$$\sum_{i=1}^{M_j} d_{ij} \leq 1 \qquad \text{for all } j. \tag{3}$$

Finally,

$$d_{ij} = \text{binary}, i = 1,2, \ldots, M_j; j = 1,2, \ldots, N. \tag{4}$$

This model has the form of a multiple-choice knapsack problem (MCKP) defined in the work by Sinha and Zoltners (*11*). The knapsack problem is a special case of the MCKP, and any algorithm that can solve the MCKP can also solve the knapsack problem. Because Karp (*12*) has determined that knapsack is NP-complete, so is MCKP. Being NP-complete implies that if an algorithm is more efficient than the enumerative methods that exist for MCKP, this same algorithm can be easily modified to solve the traveling salesman problem, the job shop scheduling problem, and most other problems of interest to decision makers. Because people have searched for efficient algorithms for these problems for several centuries, it seems unlikely that they exist. Therefore, enumerative methods such as dynamic programming, branch-and-bound, or heuristic algorithms are appropriate ways to solve the problem.

EXISTING SOLUTION PROCEDURE—DYNAMIC PROGRAMMING

Dynamic programming (DP) has been successfully used to allocate highway safety funds in Alabama for the past 15 years. It has returned millions of dollars in additional benefits as demonstrated in several reports (*3,6–8*). However, the well-known curse of dimensionality affects this algorithm in the same way as it does other DP algorithms. If there are n potential projects (stages) and the budget to be allocated is B, then there must be at least nB storage locations available in the DP algorithm. The best solution must be stored for each possible value of the budget B for each of the n stages. For a typical problem with a budget of $7 million and about 60 projects, over 420 million words of computer memory would be needed. Clearly this amount is beyond the capability of the most advanced computer. Auxiliary storage such as disks could be used, but the degradation of execution time makes this solution unattractive.

Generally, it is possible to partition the budget to reduce the storage problem. If all project costs are in the tens of thousands, all costs and the budget can be divided by 10,000 to reduce the required storage. For the example previously mentioned, 4.2 million storage locations would still be needed. This is assuming that the thousands, hundreds, and tens digits are not significant. Substantial rounding error may result when large budgets are allocated between alternatives that differ significantly in their values (e.g., a signing project versus a major reconstruction of an intersection).

In order to further alleviate the storage problem, the DP algorithm was implemented iteratively. The total problem was decomposed into a number of subproblems, each containing alternatives with relatively homogeneous costs. The number of subproblems was chosen so that each budget was of manageable size. This telescoping technique yielded a range of potential budget allocations and returns for each of the subproblems. These were, in turn, used as input to a summary DP run to determine the size of each of the subbudgets (*13*).

There are two basic difficulties with this procedure. First, the results were no longer guaranteed to be optimal, because subsets of the original problem were optimized. This was not a severe practical problem because tests of the algorithm on actual data showed the results to be close to the optimal. However, the mere fact that there could be a better solution poses an ethical issue, especially in the area of safety. Second, manual intervention was required, which not only cost valuable professional time, but also introduced the possibility of handling errors. For these reasons, alternative techniques were explored for producing optimal solutions.

NEW SOLUTION PROCEDURE

Because of the drawbacks of the current DP approach, a branch-and-bound procedure was used. This was motivated by encouraging computational results reported both for knapsack problems (*14*) and for multiple-choice knapsack problems (*11*).

The branch-and-bound procedure was based on the same algorithm used to solve the knapsack problem presented by Bulfin et al. (*14*). Relatively straightforward modifications of this algorithm were made for node selection, branching rules, and generating an initial solution. Bounds were obtained by solving the linear programming relaxation of MCKP using the method discussed in the work by Sinha and Zoltners (*11*). These bounds were strengthened by Tomlin-type penalties (*15*), comparable to penalties used by Bulfin et al. (*14*). A further modification was made to force all other members of a mutually exclusive set to zero when a variable in the set was fixed at one. Details of similar algorithms are given by Bulfin (*16*) and Bulfin and Liu (*17*). Previous computational studies (*14,16,17*) indicate that budgeting 2,000-location problems with five alternatives (i.e., 10,000 variables) can be solved with relative ease. These studies also show that the solution approach is insensitive to the problem data, as long as it does not require double precision arithmetic on the computer.

The implementation of the branch-and-bound algorithm went smoothly. There was no hesitation in using the model

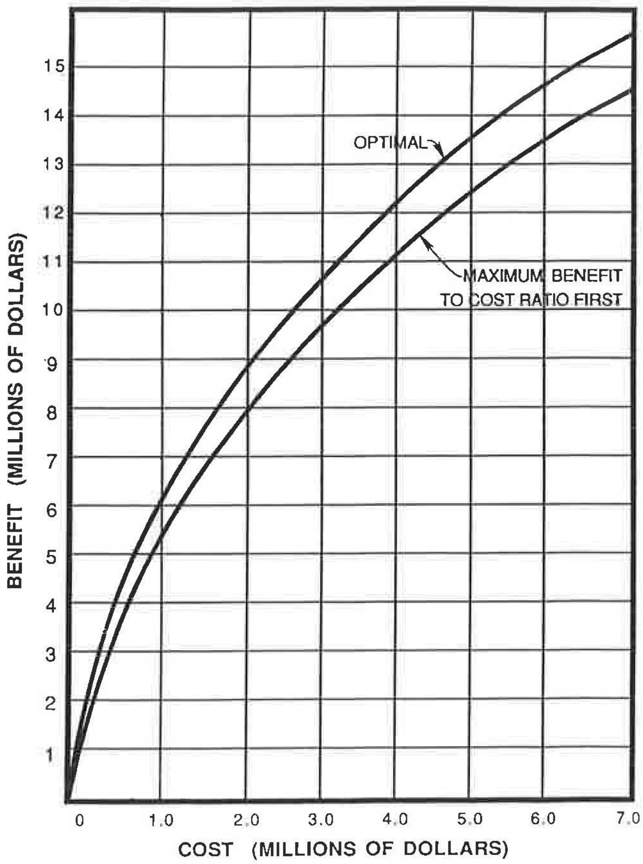

FIGURE 1 Cost-benefit curve, Section 209—Phase II.

because a similar one had been successfully used for years. The raw costs and benefits were fed directly into the computerized routine, eliminating the need for manual intervention. A comparison between the DP and the branch-and-bound solutions showed insignificant differences, confirming that the round-off errors did not cause practical problems for the highway data. The new technique was well received because of the time savings it produced in professional personnel. This amounted to approximately one person-day per run. Because some allocations required several runs, this saving was substantial. As an added benefit, a novice could use the new system as easily as the experienced user.

DISCUSSION OF RESULTS

Figure 1 shows the results obtained using the branch-and-bound technique for the first time. The optimal line shows the total benefit obtained from implementing the optimal policy obtained for each of the corresponding budgets. For comparison, another good policy (i.e., maximum benefit-cost first) is plotted for comparison. The term good is relative—it is not arbitrary and it has intuitive appeal. The original studies in Alabama determined that this policy was far superior to the unquantified policies previously employed.

Assuming that a maximum benefit-to-cost ratio first (or worse) is employed without optimization, there are significant returns at all reasonable budget levels. For example, a $4 million budget has an additional return of $1 million. This is attained at no additional cost to the taxpayer.

In conclusion, the use of optimization techniques for budget allocation has been established. It is essential that those techniques be applied that not only produce optimal results, but also are easy and efficient to invoke. In this application, the branch-and-bound technique not only guaranteed optimality, but also enabled this solution to be obtained at a great time savings.

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