Multiobjective Optimization for Pavement Maintenance Programming

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(Reviewed by the Highway Division)

Abstract: Pavement maintenance planning and programming requires optimization analysis involving multiobjective considerations. Traditionally single-objective optimization techniques have been employed by pavement researchers and practitioners because of the complexity involved in multiobjective analysis. This paper develops a genetic-algorithm-based procedure for solving multiobjective network level pavement maintenance programming problems. The concepts of Pareto optimal solution set and rank-based fitness evaluation, and two methods of selecting an optimal solution, were adopted. It was found that the robust search characteristics and multiple-solution handling capability of genetic-algorithms were well suited for multiobjective optimization analysis. Formulation and development of the solution algorithm were described and demonstrated with a numerical example problem in which a hypothetical network level pavement maintenance programming analysis was performed for two- and three-objective optimization, respectively. A comparison between the two- and three-objective solutions was made to highlight some practical considerations in applying multiobjective optimization to pavement maintenance management.

INTRODUCTION

An ideal pavement management program for a road network is one that would maintain all pavement sections at a sufficiently high level of service and structural conditions, but require only a reasonably low budget and use of resources, and not create any significant adverse impacts on the environment, safe traffic operations, and social and community activities. Unfortunately, many of these are conflicting requirements. For instance, more resources and budget are usually needed if the pavements are to be maintained at a higher level of serviceability; and a program with more pavement treatment activities would, in general, cause longer traffic delay, increased environmental pollution, more disruption of social activities, and inconvenience to the community. Therefore, the decision process in programming of pavement maintenance activities involves a multiobjective consideration that should address the competing requirements of different objectives.

Practically all the pavement maintenance programming tools currently in use are based on single-objective optimization. The optimization techniques employed include linear programming (Lytton 1985), dynamic programming (Li et al. 1995; Feighan et al. 1987), integer programming (Fwa et al. 1988), optimal control theory (Markow et al. 1987), nonlinear programming and heuristic methods (OECD 1987). In these single-objective analyses, those requirements not selected as the objective function are imposed as constraints in the formulation. This can be viewed as an interference of the optimization process by artificially setting limits on selected problem parameters. As a result, the solutions obtained from these single-objective analyses are suboptimal with respect to one derived from multiobjective considerations.

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This study describes the development of a genetic-algorithm (GA)-based formulation for multiobjective programming of pavement management activities. GAs, which are a robust search technique formulated on the mechanics of natural selection and natural genetics (Holland 1975), are employed to generate and identify better solutions until convergence is reached. The selection of good solutions is based on the so-called Pareto-based fitness evaluation procedure by comparing the relative strength of the generated solutions with respect to each of the adopted objectives. The application of the algorithm is demonstrated with a two- and three-objective optimization analysis of a numerical example.

GENETIC ALGORITHMS FOR MULTIOBJECTIVE OPTIMIZATION

Mechanics of GA Solution Process

The GAs are formulated loosely based on the principles of Darwinian evolution (Holland 1975; Goldberg 1989). They are different from traditional optimization techniques in a few important aspects. First, GAs operate by manipulating a pool of feasible solutions instead of one single solution each time. Working with a pool of solutions enables GAs to identify and explore properties simultaneously in different search directions. Second, GAs employ probabilistic transition rules to generate new solutions from the existing pool of solutions. This introduces perturbations to move out of local optima. Third, GAs select better solutions in each step by comparing directly the objective-function values of generated solutions. The search process is not gradient-based, and does not require any information on differentiability, convexity, or other auxiliary properties.

The problem-solving process of GAs begins with the identification of problem parameters and the genetic representation (i.e., coding) of these parameters. The search process of GAs for solution(s) that best satisfy the objective function involves generating an initial random pool of feasible solutions to form a parent solution pool, followed by obtaining new solutions and forming new parent pools through an iterative process. This iterative process consists of copying, exchanging, and modifying parts of the genetic representations in a fashion similar to natural genetic evolution.

Each solution in the parent pool is evaluated by means of the objective function. The fitness value of each solution, as by its objective function value, is used to determine its probable contribution in the generation of new solutions known as offspring. The next parent pool is then formed by selecting the fittest offspring based on their fitness (i.e., their objective function values). The entire process is repeated until a predetermined stopping criterion is reached, on the basis of either the number of iterations or the magnitude of improvement in the solutions.

Single- versus Multiobjective Optimization

In a single-objective optimization problem, the superiority of a solution to another can be easily determined by comparing the objective function values of the two solutions, and there exists a single identifiable optimal solution that gives the best objective function value. This is not the case for a multiobjective optimization problem. This is illustrated in Fig. 1 where there are five solutions with the rank of 1. None of the solutions can be said to be superior or inferior to the other four solutions. In other words, none of these five solutions is ''dominated'' by any of the other three solutions. One may, therefore, think of a family of solutions that are not dominated by any other solutions. Each of these nondominated solutions can be considered as optimal because no better solutions (i.e., dominating solutions) can be found. Therefore, for a multiobjective problem, there exists a family of optimal solutions that are known as the Pareto optimal solution set (Goldberg 1989).

Since GAs deal with a pool of solutions at a time, instead of one single solution, they can be adapted relatively easily to solve multiobjective problems. The ability of GAs to handle complex problems involving features such as discontinuities, multimodality, and disjointed spaces further enhances their effectiveness in multiobjective search and optimization (Fonseca and Fleming 1995). The probabilistic search mechanism of GAs is well suited to work in problems, including the network level pavement management programming problem, with intractably large, poorly understood solution spaces (Horn et al. 1994).

Rank-Based Fitness Evaluation

An important aspect of the multiobjective GA analysis is the definition of fitness of a solution. The fitness of a solution directly influences the probability of the solution being selected for reproduction to generate new offspring solutions. As explained earlier in connection with Fig. 1, solutions *B*, *D*, *F*, *H*, and *J* in the figure are considered equal in fitness in the sense of multiobjective optimization, because none of the solutions are superior in all attributes (or objective function values). Since the actual objective function values of these nondominated solutions are not equal, taking these values directly as measures of fitness would be inappropriate.

To overcome the aforementioned problem, Goldberg (1989) proposed a rank-based fitness assignment scheme where all nondominated solutions in a given pool of solutions are assigned a rank of 1. The method of determining fitness rank is illustrated in Fig. 1, which shows a pool of 10 solutions to a two-objective problem where the objective functions f_1 and f_2 are to be minimized. Solutions *B*, *D*, *F*, *H*, and *J* are nondominated solutions and thus are all assigned the same rank of 1. Solutions *I* and *G* each have the rank of 2 since they are dominated by *J* and *H*, respectively. Solution *A* is dominated by *B* and *D*, hence, assigned a rank of 3. By similar reasoning, solutions *C* and *E* can be shown to have ranks of 4 and 5, respectively.

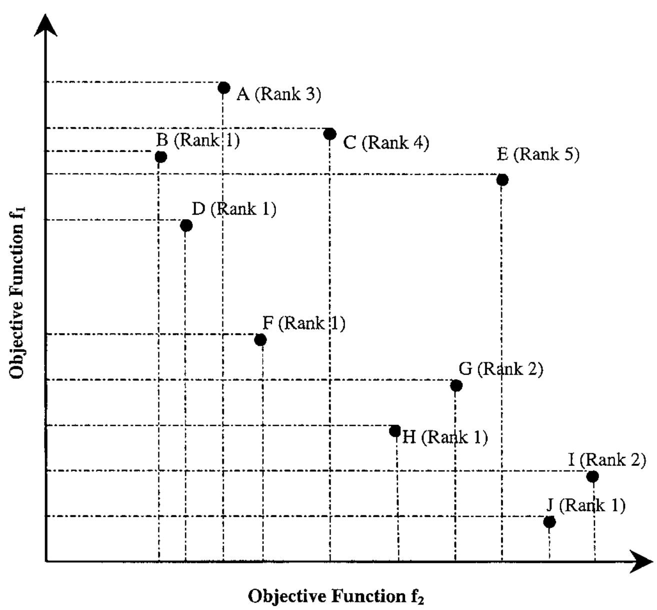

FIG. 1. Rank-Based Fitness Evaluation

Concept of Pareto Optimality

In the evaluation of a pool of solutions such as those in Fig. 1, one can identify a curve (for the case of two-objective problems), or a surface (for the case of three or higher multiobjective problems) that is composed of all nondominated solutions. This curve or surface is known as the Pareto frontier. The GA optimization process seeks to generate new solutions that would give an improved frontier that dominates the existing frontier. This process continues until, ideally, a set of globally nondominated solutions is found. These globally nondominated solutions, called the Pareto optimal set, define the Pareto optimal frontier.

GA Operations

Applications of GAs in single-objective optimization problems of pavement management have been demonstrated by Fwa et al. (1994a,b, 1996). When applied to multiobjective problems, the general procedure of GA operations and offspring generation remains largely unchanged. The main difference lies with the evaluation of fitness of each solution, which is the driving criterion of the search mechanism of GAs. The rank-based fitness evaluation technique and the concept of Pareto optimality are adopted in the present study as described in the preceding sections. Fig. 2 shows the operations involved in the GA optimization process.

An important consideration of the optimization process is to produce representative solutions that are spread more or less evenly along the Pareto frontier. This can be achieved by using an appropriate reproduction scheme to generate offspring solutions and to form a new pool of parent solutions. The procedure depicted in Fig. 2 has been found to produce satisfactorily spread solutions on the Pareto frontier for the problems analyzed in this study.

HYPOTHETICAL NUMERICAL EXAMPLES

For the purpose of illustrating the solution method and highlighting the considerations involved in multiobjective analysis of pavement maintenance programming, a relatively simple hypothetical numerical problem is selected. It is a hypothetical problem that has been solved by Fwa et al. (1988) using integer programming, and again by Fwa et al. (1994b) using single-objective GAs. This problem addresses maintenance budget needs, resources requirements (including manpower, equipment, and materials), and pavement distress conditions. For ease and clarity in presentation, this simpler example problem is preferred over a more elaborate example problem [e.g.,

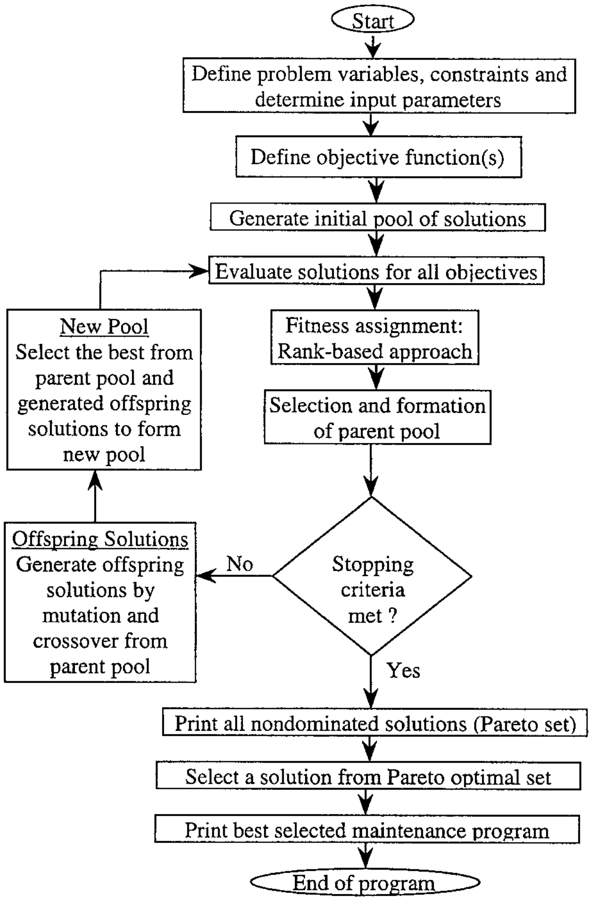

FIG. 2. Genetic Algorithm Analysis for Multiobjective Optimization

see solutions by Fwa et al. (1996)] that also addresses rates of pavement deterioration, rehabilitation projects, and effectiveness of repair. The procedures of applying the proposed multiobjective optimization methodology to the simpler and the more elaborate problems are similar.

Problem Description

On the basis of the framework of pavement management practice in Indiana, Fwa et al. (1988) formulated a hypothetical problem and solved the problem for an optimal pavement repair program at the network level for a given rehabilitation schedule and subjected it to five forms of resource and operation constraints. The five constraints were production requirements, budget constraint, manpower availability, equipment availability, and rehabilitation schedule constraints. The programming analysis addressed only maintenance treatments and not rehabilitation projects, but imposed the so-called rehabilitation constraints so that maintenance treatments would not be programmed for pavement sections that have been earmarked for rehabilitation or reconstruction.

The hypothetical problem considered four highway classes, four pavement defects, and three levels of maintenance-need urgency. Its objective was to select an optimal set of maintenance activities for an analysis period of 45 working days. Table 1 gives the maintenance production rate and unit cost data for each combination of pavement defect and urgency level. The requirements for four manpower types and six equipment types are listed in Table 2. Recorded in Table 3 are the pavement repair priority weighting factors that are functions of highway class, pavement repair activity type, and its need-urgency level.

The estimates of the amount of work required for each type of repair in terms of workdays are found in Table 4. The input for rehabilitation schedule constraint factors are given in Table 4. A zero value of the factor represents a case where is a complete interference from rehabilitation work, while a value of unity indicates no interference from rehabilitation. Other necessary input information, namely the analysis period, budget allocation, manpower availability, and equipment availability are shown in Table 5.

Problem Formulation

GA formulation is a key step in the solution process in which a GA representation of the problem is established. This is achieved by representing the decision variables in a string structure similar to the chromosomes in natural evolution. For

TABLE 1. Production Rate and Unit Cost Data

	Production Rate				Unit Cost			
Need-urgency level (1)	Shallow patching (kg mix/day) (2)	Deep patching (kg mix/day) (3)	Premix leveling (kg mix/day) (4)	Crack sealing (km/day) (5)	Shallow patching ($/kg mix) (6)	Deep patching ($/kg mix) (7)	Premix leveling ($/kg mix) (8)	Crack sealing ($/km) (9)
High	6,537.6	17,978.4	10,896.0	10.1	0.0938	0.0852	0.0403	81.37
Medium	3,813.6	9,443.2	80,448.8	13.5	0.1311	0.1333	0.0420	70.19
Low	2,542.4	6,174.4	49,940.0	16.4	0.1751	0.1817	0.0467	63.98

TABLE 2. Manpower and Equipment Requirements

	Manpower Requirement (man-days/production day)				Equipment Requirement (equipment-days/production day)					
Repair activity (1)	Type 1 (2)	Type 2 (3)	Type 3 (4)	Type 4 (5)	Type 1 (6)	Type 2 (7)	Type 3 (8)	Type 4 (9)	Type 5 (10)	Type 6 (11)
1	0	2	4	0	1	0	1	0	0	0
2	1	1	5	1	1	1	0	0	0	1
3	1	3	5	2	3	1	1	1	0	1
4	1	2	2	4	2	1	0	1	0	0

Note: Manpower Types 1–4 represent supervisors, drivers, laborers, and equipment operators, respectively; equipment Types 1–6 represent dump trucks, pickup trucks, crew cabs, distributors, loaders, and rollers, respectively. Repair activities 1–4 refer to shallow patching, deep patching, premix leveling, and crack sealing, respectively.

TABLE 3. Pavement Repair Priority Weighting Factors

Highway class (1)	Need-urgency level (2)	Shallow patching (3)	Deep patching (4)	Premix leveling (5)	Crack sealing (6)
Urban interstate	High	90	100	70	50
	Medium	63	90	63	45
	Low	54	60	42	30
Urban arterial	High	72	80	56	40
	Medium	54	70	49	35
	Low	45	50	35	25
Rural interstate	High	76.5	85	59.5	42.5
	Medium	58.5	75	52.5	37.5
	Low	40.5	45	31.5	22.5
Rural primary	High	70.5	65	45.5	32.5
	Medium	36	40	28	20
	Low	18	20	14	10

TABLE 4. Repair-Needs Data and Constraints Information

Highway (1)	Need-urgency level (2)	Shallow patching (3)	Deep patching (4)	Premix leveling (5)	Crack sealing (6)
(a) Repair Work Requirements in Workdays					
Urban interstate	High	4	6	8	2
	Medium	6	4	2	3
	Low	3	25	13	18
Urban arterial	High	2	6	9	2
	Medium	2	10	8	8
	Low	4	20	15	15
Rural interstate	High	5	8	6	5
	Medium	5	2	10	10
	Low	5	15	15	10
Rural primary	High	3	4	8	4
	Medium	4	16	12	20
	Low	15	15	18	15
(b) Rehabilitation Constraint Factors					
Urban interstate	High	0.82	0.83	1.00	0.80
	Medium	0.70	0.90	0.90	1.00
	Low	1.00	1.00	1.00	1.00
Urban arterial	High	0.93	1.00	1.00	0.92
	Medium	0.84	1.00	1.00	0.96
	Low	0.81	1.00	1.00	0.90
Rural interstate	High	0.92	1.00	1.00	0.83
	Medium	0.78	1.00	1.00	0.91
	Low	0.80	1.00	1.00	0.96
Rural primary	High	1.00	1.00	1.00	1.00
	Medium	1.00	1.00	1.00	1.00
	Low	1.00	1.00	1.00	1.00

TABLE 5. Resource Constraints and Other Input Information

Parameter (1)	Value (2)
Analysis period	D = 45 working days
Budget allocation	b_1 = \$18,000, b_2 = \$20,000, b_3 = 13,000, b_4 = 9,000
Manpower availability	H_1 = 90 man-days, H_2 = 135 man-days, H_3 = 270 man-days, H_4 = 90 man-days
Equipment availability	Q_1 = 135 equipment days, Q_2 = 45 equipment days, Q_3 = 45 equipment days, Q_4 = 45 equipment days, Q_5 = 45 equipment days, Q_6 = 45 equipment days

the example problem, the decision variables are the respective amounts of maintenance work, measured in workdays, assigned to each of the 48 maintenance treatment types. The 48 treatment types refer to maintenance repairs arising from four distress forms of three maintenance-need urgency levels on four highway classes. The coded string structure of GA representation would thus consist of 48 cells as shown in Fig. 3. Each cell can assume an integer value of workdays from 0 to 45.

Selection of Objective Functions

The earlier single-objective analyses performed by Fwa et al. (1988, 1994b) offered solutions that maximized the work production in total workday units. In the present study, in addition to maximizing work production, the following two additional objective functions were considered: (1) Minimization of the total maintenance cost; and (2) maximization of overall network pavement condition. For the purpose of this study to illustrate the flexibility of GAs in handling multiobjective problems, a two- and three-objective problem, as depicted in Table 6, were analyzed.

The maintenance work production is measured in terms of the total sum of workdays equivalent of maintenance repair activities performed. The total maintenance cost is computed based on the unit cost data given in Table 1. The network pavement condition is expressed as an index in direct relation to the distresses repaired, with weighting factors of 5, 3, and 1 assigned to severe, medium, and light distress severity, respectively. The index is measured on a scale of 0–100, with higher values assigned to better network pavement conditions. The total manpower requirement is assessed directly based on the total number of man-days needed.

Method of Solution

The steps of solution have been explained earlier as depicted in Fig. 2. Having defined the decision variables and objective functions in the preceding subsections, and adopted the solution string structure as shown in Fig. 3, the initial pool of solutions was generated by randomly assigning admissible values to each decision variables. A parent pool size of 200 and an offspring pool size of 160 were adopted. The GA crossover and operators were employed to generate offspring solutions. The mutation rate adopted was 10%.

Each solution was evaluated by computing its values of the individual objective functions, and these values were, in turn, used in determining its rank according to the rules demonstrated in Fig. 1. The selection of solutions to form the parent pool was based on the ranks (i.e., fitness) of the solutions. For the present study, the stopping criterion was chosen to be 500 iterations. This was chosen to facilitate the examination of the convergence pattern of the solutions.

ANALYSIS OF SOLUTIONS TO NUMERICAL EXAMPLES

Two-Objective Optimization

For each solution run of the problem, it took less than 2 s CPU time on a Silicon Graphics Workstation IMPACT R10000. It is of interest to examine how a multiobjective analysis approaches the optimal Pareto frontier. Fig. 4(a) shows the trend of convergence of the Pareto frontier with the number of iterations. Fig. 4(b) indicates that, for the present example, the Pareto optimal frontier was reached after about 200 iterations.

A common problem faced by users (such as pavement maintenance engineers and planners) is the choice of a particular solution on the Pareto optimal frontier for implementation. Many ways exist where the subjective judgment of the user can be exercised to select a solution from the optimal frontier. For example, as depicted in Fig. 5, if the maintenance allocated becomes available after the analysis, then it would be a relatively simple matter to look for the solution with maintenance cost equal or nearest to (say within ±1%) the available budget.

Where,

W_{ijk} = workload units for highway class I, maintenance treatment type j and maintenance need urgency level k for i = 1,2,3,4; j = 1,2,3,4; k = 1,2,3

$W_{ijk} \in [0,1,2,3, \ldots\ldots\ldots\ldots\ldots\ldots,45]$

FIG. 3. Coding for Genetic Representation of Example Problem

TABLE 6. Objective Functions Considered in Analysis of Numerical Example

Analysis (1)	Number of objectives (2)	Description of objectives (3)
A	2	• Minimization of total maintenance cost • Maximization of maintenance work production
B	3	• Minimization of total maintenance cost • Maximization of maintenance work production • Maximization of network pavement condition

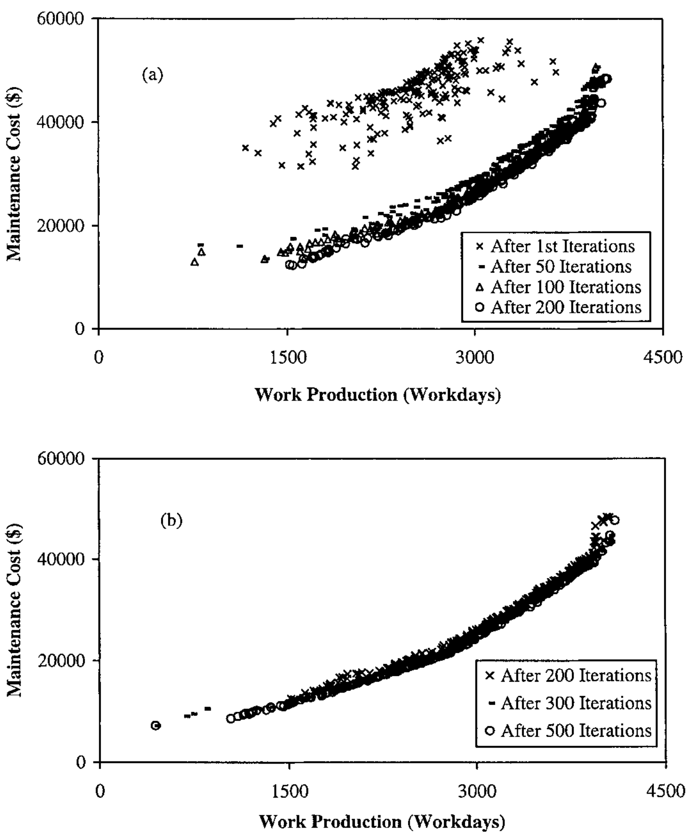

FIG. 4. Convergence of Pareto Frontier in GA Solutions

When there does not exist any guiding constraints in the selection of the solution for implementation, a possible method is shown in Fig. 6. First the optimal solutions *I* and *J* are identified. Solution *I* is the optimal solution with the lowest maintenance cost and production, while solution *J* is the one with the highest work production and maintenance cost. These two solutions could also be obtained by means of single-objective optimization analysis using minimization of maintenance cost and maximization of work production, respectively, as the objective function. The point K in Fig. 6(a) can thus be defined. This point represents the theoretical best possible optimal solution when the best possible values of both objective functions are reached simultaneously. For the problem analyzed, the values of point K is given by \$13.026 of maintenance cost and 4,026 workdays of work production.

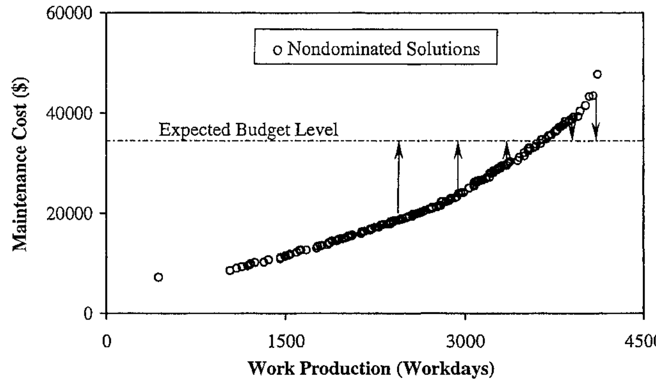

FIG. 5. Selection of Solution Based on Desired Budget Level

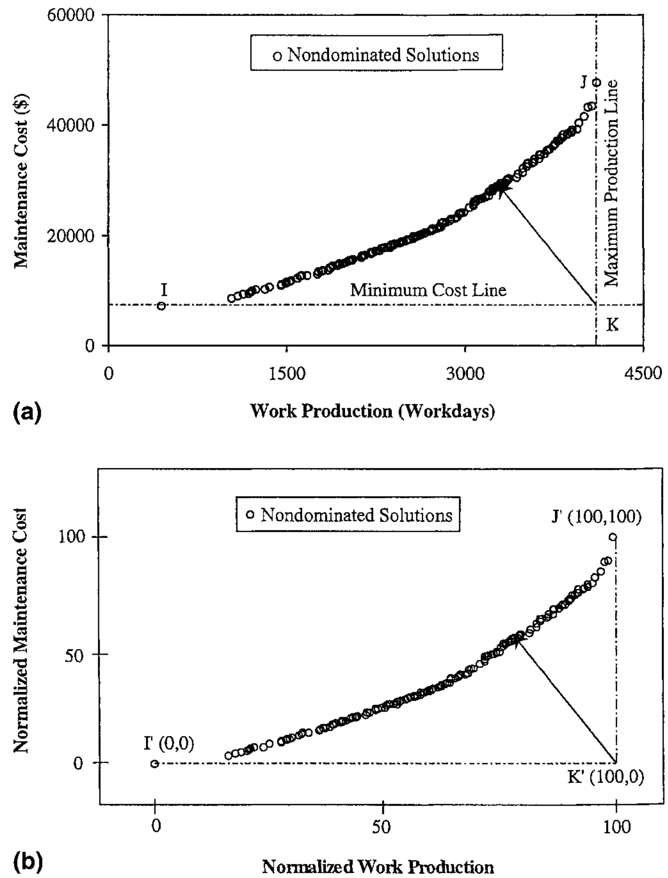

FIG. 6. Selection of Solution Based on Shortest Normalized Distance: (a) Establishing of Reference Points; (b) Normalized Plot Using Normalized Scales

The solution to be used for implementation is the one that is nearest to point K in terms of normalized distance. The normalized distance is computed on the basis of normalized parameter objective function values. A normalized objective function value is computed over a scale of 0–100 for each objective parameter according to the following transformation rules:

$$O^*(1, x) = \left(\frac{O(1, x) - O(1, \min)}{O(1, \max) - O(1, \min)}\right) \times 100 \qquad (1)$$

where $O^*(i, x)$ is the normalized parameter value of a solution X; $O(i, X)$ is the actual parameter value of objective i for solution X; and $O(i, \max)$ and $O(i, \min)$ are, respectively, the maximum and minimum parameter values of objective i for solution X. For the problem analyzed, $O(1, \min)$ = \$13,028 and $O(1, \max)$ = \$45,285 for the objective of minimizing maintenance cost; $O(2, \min)$ = 1,195 workdays; and $O(2, \max)$ = 4,026 workdays for the objective of maximizing work production.

This transformation according to (1) is to express the two-objective parameters on a common scale. By (1), Fig. 6(a) can be transformed into Fig. 6(b). The selection procedure is, thus, to identify the solution that has the smallest normalized distance, d_k, defined as follows:

$$d_k = \sqrt{[O^*(1, x) - O^*(1, \min)]^2 + [O^*(2, x) - O^*(2, \max)]^2} \qquad (2)$$

Note that by the definition of (1), $O^*(1, \min) = 0$ and $O^*(2, \max) = 100$. The optimal solutions selected on the basis of the two proposed methods of selection are presented in Tables 7 and 8. In general, the solutions in this table depict the expected trend that as budget level decreases, the total work production and pavement condition would also fall. The optimal solution based on the shortest normalized distance results in a maintenance cost of \$21,594 and a work production of 2,796 workdays, selected from the Pareto optimal solution set within the range of 13,028–\$45,285 for maintenance cost, and 1,195–4,026 workdays for work production.

Three-Objective Optimization

Analysis B for a three-objective problem as defined in Table 6 was performed using the GA program and the selected optimal solutions are presented in Table 9. The solutions selected based on the indicated budget levels are simply those solutions with their total maintenance costs nearest to the respective desired budgets. For the solutions obtained based on the shortest normalized distance, the normalized distance, d_k, from the theoretical best possible optimal solution to a solution X is computed by the following expressions:

$$d_k = \sqrt{\{[(O^*(1, x) - O^*(1, \min)]^2 + [(O^*(2, x) - O^*(2, \max)]^2 + [(O^*(3, x) - O^*(3, \max)]^2} \qquad (3)$$

where $O^*(1, \min) = 0$, $O^*(2, \max) = 100$; and $O^*(3, \max) = 100$. The values of the theoretical best possible optimal solution K in this case is given by \$13.026 of maintenance cost, 4,026 workdays of work production, and a pavement condition index of 29.80.

Comparison of Two- and Three-Objective Solutions

Tables 9 and 10 show the optimal solutions selected based on the two proposed methods. Again, from Table 9 one observes the expected falling trend of work production and pavement condition with a decrease in budget level. In Table 10, the optimal solution based on the shortest normalized distance yields a maintenance cost of \$29,910, a work production of 3,244 workdays, and a pavement condition index of 26.36, against the Pareto optimal frontier range of \$13,028–\$45,285 for maintenance cost, 1,195–4,026 workdays for work production, and 13.23–29.80 for pavement condition index.

Fig. 7 presents the Pareto optimal frontiers of the two- and three-objective optimization solutions in the same 2D plot of maintenance cost versus work production for comparison purposes. It can be seen that although the two Pareto frontiers are very close to each other, the Pareto frontier of the two-objective solutions appear to marginally dominate the frontier of the

TABLE 7. Selected Optimal Solutions for Two-Objective Problem Based on Desired Budget Level

Budget level (1)	Work production (workdays) (2)	Cost (\$) (3)	Pavement condition index (4)	Manpower need (man-days) (5)	Budget used (%) (6)	Manpower used (%) (7)	Equipment used (%) (8)
40,000	3,958.0	40,448.0	27.30	512	67.41	87.52	73.88
35,000	3,670.0	34,984.0	26.05	482	58.15	82.39	71.38
25,000	3,034.0	25,108.0	22.09	430	41.84	73.50	65.27
20,000	2,601.0	19,939.0	19.90	376	33.23	64.27	58.89

TABLE 8. Selected Optimal Solutions for Two-Objective Problem Based on Shortest Normalized Distance

Work production (workdays) (1)	Cost (\$) (2)	Pavement condition index (3)	Manpower need (man-days) (4)	Budget used (%) (5)	Manpower used (%) (6)	Equipment used (%) (7)
2,796	21,594.0	20.94	410	35.99	70.0	63.85

TABLE 9. Selected Optimal Solutions for Three-Objective Problem Based on Desired Budget Level

Budget level (1)	Work production (workdays) (2)	Cost (\$) (3)	Pavement condition index (4)	Manpower need (man-days) (5)	Budget used (%) (6)	Manpower used (%) (7)	Equipment used (%) (8)
40,000	3,753.0	40,080.0	28.97	523	66.80	89.40	76.67
35,000	3,643.0	34,944.0	27.09	507	58.24	86.67	75.56
25,000	2,953.0	24,928.0	22.92	439	42.55	75.04	67.50
20,000	2,456.0	19,958.0	20.21	397	33.10	67.86	63.61

TABLE 10. Selected Optimal Solutions for Three-Objective Problem Based on Shortest Normalized Distance

Work production (workdays) (1)	Cost ($) (2)	Pavement condition index (3)	Manpower need (man-days) (4)	Budget used (%) (5)	Manpower used (%) (6)	Equipment used (%) (7)
3,244.0	29,910.0	26.36	488	49.55	83.42	74.17

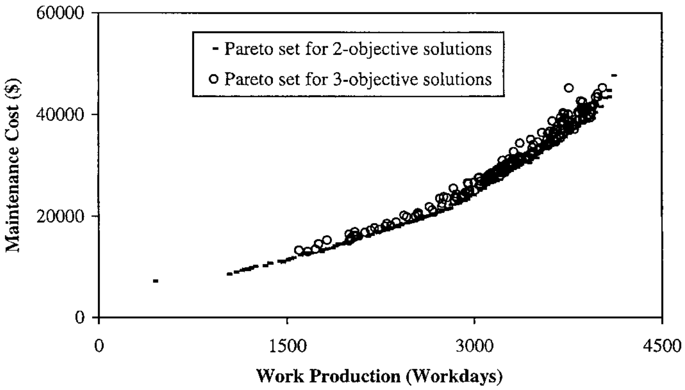

FIG. 7. Convergence of Pareto Frontiers for Two- and Three-Objective Solutions

three-objective solutions in terms of maintenance cost and work production. This is believed to be the effect of introducing a third objective (i.e., maximizing pavement condition) in the three-objective problem. This is evident by examining the values of pavement condition indices of the two sets of solutions as explained in the next paragraph.

Fig. 8(a) presents the distribution of pavement condition indices obtained from the 200 solutions on the Pareto optimal frontier of the two-objective optimization analysis, and Fig. 8(b) presents the corresponding distribution for the three-objective optimization analysis. The effect of considering maximizing pavement condition in the three-objective analysis can be seen from two significant differences between the two distributions. First, the lowest value of pavement condition index in the three-objective solutions is 13.23, while the lowest value in the two-objective solutions is as low as 2.29. Second, as clearly depicted in Fig. 8, the magnitudes of pavement condition indices of the three-objective solutions are, in general, considerably higher than those of the two-objective solutions. The means of the two distributions of pavement condition indices are 24.84 and 19.71, respectively. On the whole, it might be said that while improved pavement condition is achieved in the three-objective solutions, the respective values of the first two objective functions are slightly compromised as compared against the two-objective solutions.

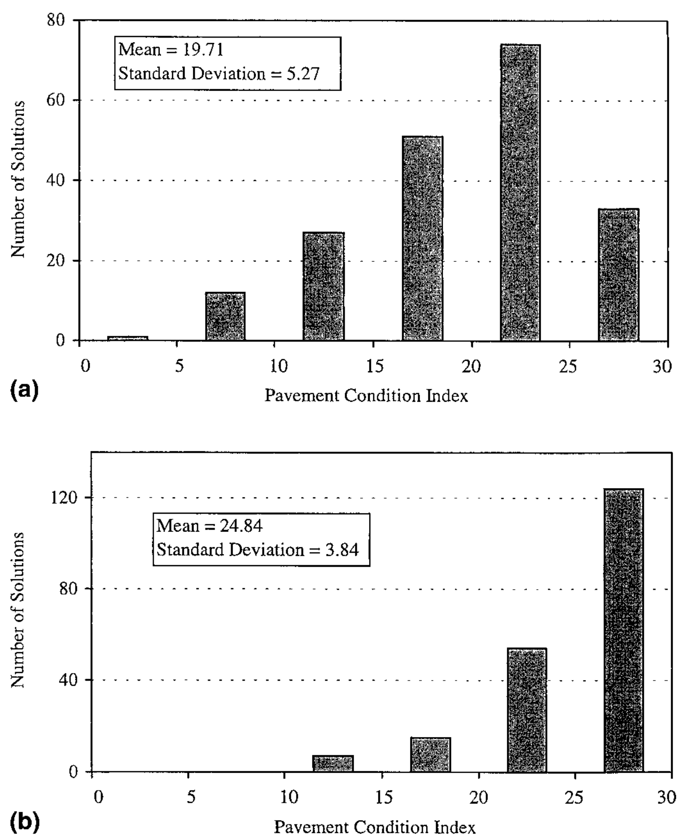

FIG. 8. Comparison of Distributions of Pavement Condition Indices for: (a) Two-Objective Solutions; (b) Three-Objective Solutions

CONCLUSIONS

This paper has developed a GA-based procedure to solve multiobjective network level pavement maintenance programming problems. The robust search characteristics and multiple-solution handling ability of GAs are well suited for multiobjective optimization analysis. The concepts of Pareto frontier and rank-based fitness evaluation, and two methods of selecting the optimal solution from the Pareto frontier were adopted in the proposed optimization algorithm. An application of the algorithm developed is demonstrated with a two- and three-objective optimization analysis of an example problem. The proposed algorithm was able to produce a set of optimal solutions that were well spread on the Pareto frontier. The optimization algorithm and the two methods of selecting an optimal solution are applicable to multiobjective analysis with any specified number of objectives.

APPENDIX. REFERENCES

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