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Multiobjective optimization for pavement maintenance and rehabilitation programming using genetic algorithms

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ABSTRACT

This paper develops a Genetic-Algorithm-based procedure for solving multi-objective project level pavement maintenance and rehabilitation programming problems. A two-objective optimization model which considered maximum pavement performance and minimum action costs as functions is put forward. It was found that the robust search characteristic and multi-solution handling capability of genetic- algorithms were suitable for multi-objective optimization analysis. Formulation and development of the solution algorithm were described and demonstrated with a numerical example in which a hypothetical project level pavement maintenance and rehabilitation analysis was performed for two-objective optimization. From the result calculated by the computer program, chromosome 31020212322222300100 represents the following 20years maintenance strategies: Overlay in year 1, 9, and 5; Crack sealing in year 2, 7, and 18; Do nothing in year 3, 5, 16, 17, 19, and 20; and Pothole patching in year 4, 6, 8, 10, 11, 12, 13, and 14. Based on the computing results, the Pareto optimal solutions of the two objective optimization functions are obtained. The optimal solutions of this two – objective optimization model can provide the decision makers the maintenance and rehabilitation planning with maximum pavement performance and minimum action costs.

Key words: Genetic Algorithms, optimal solutions, effective performance, minimum cost, multiobjective, decision maker.

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 requires only a reasonable low budget and use of resources. It will not create any significant adverse impacts on the environment, safe traffic operations social and economic activities [1]. The decision process in programming of pavement maintenance activities involves a multiobjective consideration that should address the competing requirements of different objectives [1].

Practically the pavement maintenance programming tools currently in use are based on single-objective optimization. The optimization techniques employed include linear programming [2], dynamic programming [3]. Integer programming [4], optimal control theory [5], non-linear programming and heuristic [6]. This work describes the development of a genetic–algorithm (GA) – based formulation for multiobjective programming of pavement management activities. Genetic Algorithms, which are a robust search technique formulated on the mechanics of natural selection and natural genetics [7], 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 [1].

MULTI-OBJECTIVE OPTIMIZATION

Increasing complexity of modern design problems often generate disagreeing objectives. Engineering design which aims to minimize cost, minimize weight, maximize reliability, maximize performance, etc, demonstrates such important but conflicting objectives [8]. Multiobjective optimization is therefore an optimization process that systematically and simultaneously optimizes a collection of objective functions [9]:

Find the vectors of decision variable $X = [x_1, x_2, \ldots, x_n]$
Subject to: $g_i\ X \geq 0,\ i = 1, 2, \ldots, b$
b inequality constraints
q equality constraints $h_i\ X = 0,\ i = 1, 2, \ldots, q$
and minimize m conflicting objective functions:

$$F = [f_1(x), f_2(x), \ldots f_m(x)]$$

Concept of Pareto Optimality

For multi-objective optimization, a Pareto set is usually identified. The Pareto set is a subset of the set of decision variable for which the performance of one objective cannot be improved without reducing the performance of at least one other [8].

There exists a family of optimal solutions that none of these solutions can be said to be superior or inferior to the other solutions. Each of these "non-dominated" solutions can be considered as optimal because no better solutions can be found. Therefore, for a multi-objective problem, there exists a family of optimal solution that are known as the Pareto optimal solution set [10]. Let $u = (u_1, \ldots, u_m)$, and $v = (v_1 \ldots, v_m) c R^m$ be two vectors of a MOP minimization problem, u is said to dominate v if $u_i \leq v_i$ for all $i = 1, \ldots, m$, and $u \neq v$. Generally, MOP can be roughly categorized into four main classes that reflect the decision-maker's preferences [9].

GENETIC ALGORITHMS FOR MULTI-OBJECTIVE OPTIMIZATION

Mechanics of Genetic Algorithms solution process

The Genetic Algorithms are formulated loosely based on the principles of Darwian evolution [7,10]. The problem – solving process of genetic algorithms begins with the identification of problem parameters and the genetic representation (i.e. coding) of these parameters. The search process of genetic algorithms 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 [1].

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 criteria is reached, on the basis of either the number of iterations of the magnitude of improvement in the solutions [1].

Single – Versus Multi-Objective optimization

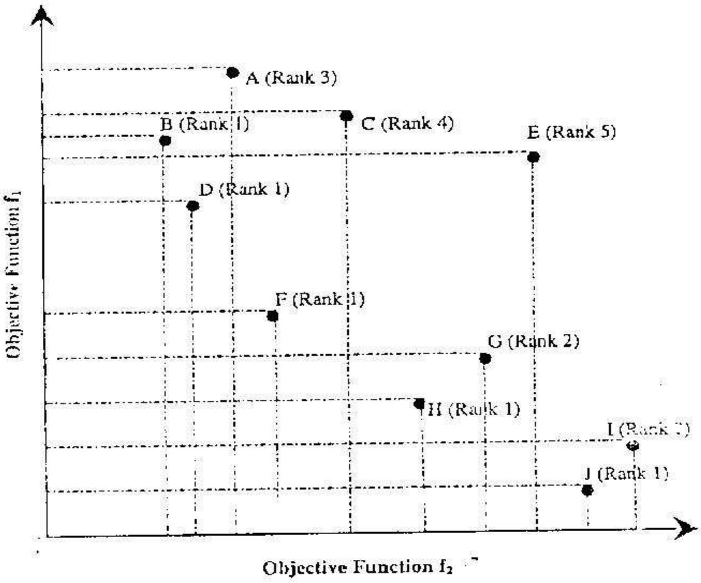

Fig. 1: Rank-Based Fitness Evaluation [1]

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 [1]. This is illustrated in figure 1 where there are five solutions with the ranks of 1. None of the solutions can be said to be superior or inferior to the other four solutions.

Genetic Algorithms Operation

Fwa et al. [11,12,13] demonstrated the application of genetic algorithms in single-objective optimization problems of pavement management. When applied to multi-objective problems, the general procedure of genetic algorithms operations and offspring generation remains unchanged. The main difference lies with the evaluation of fitness of each solution, which is the driving criterion of the search mechanism of genetic algorithms. The rank-based fitness evaluation technique and the concept of Pareto optimality are adopted in this work. Figure 2 shows the operations involved in the genetic algorithms operations. An important consideration of the optimization process is to produce representative solutions that are spread more on 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 figure 2 has been found to produce satisfactorily spread solutions on the Pareto for the problems analysed in this work.

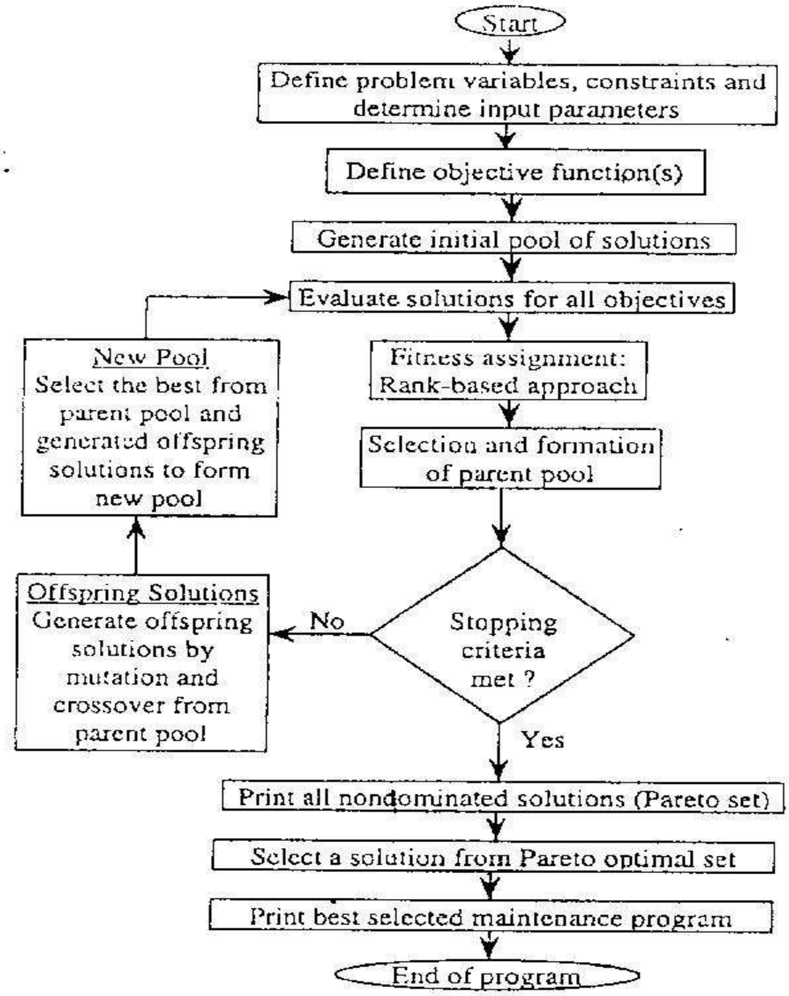

Fig. 2: Genetic Algorithm Analysis for Multiobjective Optimization (PROGRAM-R)

METHODS

An optimization problem for pavement activities programming at the project level is characterized by a user – define objective function subject to operational and resource constraints.

A hypothetical problem of a road project level of 1km pavement segments is analysed in the work to highlight the main features of genetic algorithms formulation in Program-R and to illustrate the proposed applications of genetic algorithms.

The multi-objective functions adopted are to minimize the maintenance cost action and maximize the pavement performance condition.

The major problem parameters are summarized in Table 1

Table 1: Problem Parameters for Hypothetical Example

Parameter (category (1)	Parameter adopted (2)
Project parameters:	
Section length	1km
Section width	15m
Planning period	20 years
Traffic parameters:	
Traffic loading	Constant 50,000 passes of equivalent 80KN single axle per year
Annual average daily traffic	4,500 (Veh/day)
Warning levels:	
Cracking	0.8m^2 of cracks per km per lane
Rutting	20mm rut depth
Potholing	50 potholes per km per lane
Surface disintegration	20% of wheel-path area affected
Structural damage	Present serviceability index = 2.5

For simplicity only four main pavement distress types are considered. They are cracking, rutting, disintegration of pavement surface materials and potholing. From a review of distress determination functions [4] reported in literature [15,16,17,18] the following deterioration models are assumed for this work.

Cracking $C = 21{,}600(N)(SN)^{-SN}C = 21{,}600(N)\,(SN)^{-SN}$ (1)

Rutting $R = 4.98\,(Y)^{0.166}(SN)^{-0.5}(N)^{0.13}$ (2)

Surface disintegration $S = 80(e^{2.2677N} - 1)$ (3)

Potholing $P = 0.54\,(1 + 10N)$ (4)

Where

C = total area cracked in m^2/Km/lane

N = traffic loading in million passes of equivalent 80KN single axle

R = rut depth in mm

Y = age of pavement in years

S = total surface disintegrated in m^2/km/lane

P_i = additional number of potholes per kilometer derived from distress type i

For the case of structural damage requiring rehabilitation, the decision to trigger overlay construction is dependent on the value of present serviceability index (PSI). The optimization model is designed to maximize the average PSI value of the whole motorway. The knowledge of the pavement deterioration curve is very important to the optimal planning pavement maintenance activities. It is decided to define pavement condition using PSI values.

Adopted for this study are the following PSI deterioration functions modeled after relationships developed by the American Association of State Highway Officials (AASHO) road test and Rauhut et al (1982).

$$PSI = 5.10 - 1.9\log(SV) - 0.01C^{0.5} - 0.0021R^2 \qquad (5a)$$

Modified PSI for this work

$$PSI = 5.10 - 1.9\log(SV) - 0.01(C + P)^{0.5} - 0.0021R^2 \qquad (5b)$$

Where

$$SV = 68.5\,\frac{(N^{*}10^{6})^{\beta}}{\rho} + 1.83 \qquad (5c)$$

$$\log\rho = 9.36\log(SN + 1) - 0.20 \qquad (5d)$$

$$\beta = \frac{0.4 + 1{,}094}{(SN + 1)^{5.19}}$$

$\beta = 0.4 + 1{,}094/(SN+1)^{5.19}$

The problem can be represented mathematically as follows [14]:

Maximize performance

$$= f_1(X) = \sum_{i=1}^{T} \sum_{j=1}^{A} X_{jt}\left[\left(PCI_{jt} - PCI_{min}\right) x\, L_x\, AADT_t\, x\, D\right] \quad (6)$$

Minimize cost =

$$f_2(X) \;=\; \sum_{i=1}^{T} \sum_{j=1}^{A} X_{jt}\, x\, c_j\, x\, L\, x\, D\, x\, (1+R)^{-1} \quad (7)$$

Subject to:

$$X_{jt} \quad = \begin{cases} 1 \text{ if treatement j is selected for section in year t} \\ 0 \quad\quad\quad\quad\quad \text{otherwise} \end{cases} \quad (8)$$

$$\sum_{j=1}^{A_j} X_{jt} \;\le 1 \quad (9)$$

Where

PCI_{jt} is pavement condition index for j treatment option in year t
PCI_{min} is minimum acceptable level of PCI of the section
$AADT_j$ is annual average daily traffic carried on section in year t
X_{jt} is a binary variable for section with j treatment option in year t
D is the width of pavement section
L is the length of pavement section
c_j is the actual unit cost of j treatment alternative options in initial year
R is discount rate for calculating present value of future cost
T is analysis period

A is treatment alternative options in analysis period

In order to gain the Pareto optimal solutions of multi-objective optimization functions by Genetic Algorithms (GA) a computer program coded using Matlab version 7.9.0 (R2009b) is employed in this work and a case study is introduced to the program. The basic information of pavement section is shown in table 1. Four maintenance measures are selected as part of input data for the analysis: No action, crack sealing, pothole patching and overlay (Rehabilitation).

In the first step of program, the parameters are necessary to be identified. Through a lot of trial calculation by the computer program, the reasonable parameters are acquired. These parameters are; population size = 150, chromosome length = 20; maximum generation = 100; crossover probability 0.5 and mutation probability = 0.01. And then inputing these parameters into the computer program, the results of the solutions are acquired in tables and figures.

RESULTS AND DISCUSSION

The results of the work carried out are displayed in table and figures.

Table 2: optimal maintenance and rehabilitation strategies in the Analysis Period

Action Cost (₦)X10³	User benefits (₦)	Maintenance and Rehabilitation strategies analysis period (years)																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
880,040	1,518,700	3	1	0	2	0	2	1	2	3	2	2	2	2	2	3	0	0	1	0	0
529,750	1,518,700	2	0	1	3	0	1	2	3	2	3	1	1	2	3	2	2	1	1	1	0
529,750	1,508,600	2	2	0	3	3	1	2	2	1	1	1	1	2	2	2	1	2	2	0	2
483,410	1,508,600	2	2	2	3	3	2	1	3	2	0	0	3	2	3	3	3	1	2	1	2
422,230	1,508,600	2	2	0	2	0	1	0	0	1	1	2	2	2	1	1	2	1	1	2	0
63673	1,508,600	1	2	1	2	2	2	0	3	0	1	1	0	1	1	3	0	3	3	1	1

'O' represents No action
'I' represents Crack Sealing
'2' represents Pothole Patching
'3' represents Overlay (Rehabilitation)

From the results calculated by the computer program, a set of Pareto optimal solutions of multi-objective optimization by Genetic Algorithms is obtained which consists of performance and action costs. Rehabilitation options are represented using allele values with each of these genes representing a possible maintenance action. As shown in table 2, chromosomes 31020212322222300100 could represent the following 20 years maintenance strategy: Overlay in year 1, crack sealing in years 2, 7, and 18, do nothing in year 3,5,16, 17, 19 and 20 and pothole patching in years 4, 6,8,9,10,11,12 and 13.

The information represented in Table 2 and figure 3 is of great value to decision maker. The pavement manager can learn how much the maximum performance is under a certain budget constraint. For example, if the fund to invest the pavement management during the analysis period is N9x10^8 a maximum performance of 1,518,700 would be produced under this fund level. The pavement manager can also learn about how much maximum performance the road user desired. For instance, if the decision maker want to keep the maximum performance of this section not below 1,508,600, the total cost they should invest in they should invest in the analysis period is not less than N6.4x10^7

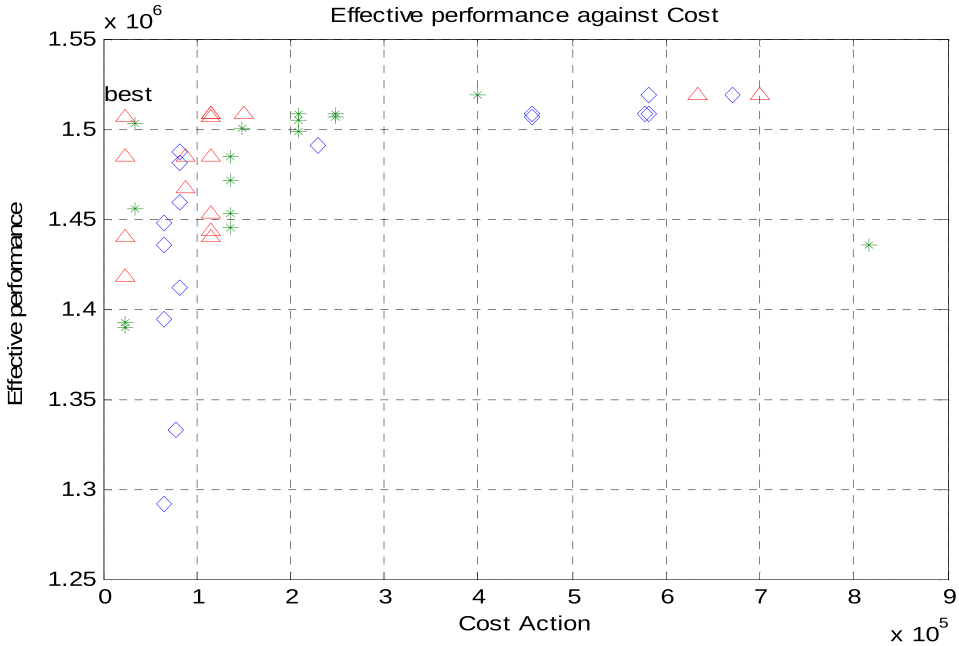

Figure 3: Pareto Optimal Solution of the two-objective Optimization function

Figure 3 displays the Pareto optimal solution of the two objective optimization functions.

It can be seen from figure 3 that there is not a great deal of variance in performance for higher cost solutions, the variance increases considerably as the cost decreases. This is a consequence of the fact that with a large amount of maintenance being carried out at all times during the analysis period, little deterioration is allowed to develop and hence the variability in final performance is minimal.

CONCLUSION

A tradeoff problem between fund investment performance production in pavement management at project level is discussed in this work. A two –objective optimization model which considers maximum pavement performance and minimum action costs as function is put forward. From the result calculated by the computer program, chromosome 31020212322222300100 represents the following 20years maintenance strategies: Overlay in year 1, 9, and 5; Crack sealing in year 2, 7, and 18; Do nothing in year 3, 5, 16, 17, 19, and 20; and Pothole patching in year 4, 6, 8, 10, 11, 12, 13, and 14. Based on the computing results, the Pareto optimal solutions of the two objective optimization functions are obtained. The optimal solutions of this two – objective optimization model can provide the decision makers the maintenance and rehabilitation planning with maximum pavement performance and minimum action costs

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