OPTIMIZING REHABILITATION PLAN OF BRIDGE DECKS USING MULTIOBJECTIVE GENETIC ALGORITHM

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ABSTRACT: Most of the optimization problems in the infrastructure management have multiple objectives which are heterogeneous due to the changes of essential factors. However, in the previous research, attention was mainly paid to cost optimization by minimizing or maximizing a given objective function. Multiobjective optimization (MO) extends optimization theory by permitting multiple objectives to be optimized simultaneously. Although the solution methods of MO problems have undergone continual development over the past three decades, methods available to date are not particularly robust, and none of them performs well on the broad classes of MO problems. Because Genetic Algorithms (GA) work with a population of points, they can capture a number of solutions simultaneously, and easily incorporate the concept of Pareto optimal set in their optimization process. The rehabilitation plan of bridge decks represents a resource intensive activity, and has been paid special attention. In this paper, a simple Genetic Algorithm with two additional techniques are used to deal with the rehabilitation plan of bridge decks by minimizing the rehabilitation cost and deterioration degree simultaneously.

1. INTRODUCTION

The bridge deck is an important part of the bridge which is directly subjected to cyclic loading and harsh environmental conditions. Concrete decks are more widely built than steel decks. For instance, in Nagoya City, 269 of the 287 highway bridges which are over 15m in their length have concrete decks. The optimization of rehabilitation plan for concrete decks have been given special interest. In previous researches, one objective function, usually minimum cost, was considered. Multiobjective optimization approach is becoming a common approach among model developers or system analysts because it allows the decision maker to participate in the search process of an ideal solution after the formulation of the optimization problem. Traditional methods are handicapped in this aspect, since they are expected to find only one solution in one simulation run. In contrast with single objective optimization problems, there may not exist a single solution that is optimal with respect to all objectives because of their trade-off characteristics. There is a set of solutions which is superior to the rest of the solutions in the search space considering all objectives, and no solution in this set is absolutely better than the others. This solution set is defined as Pareto optimal set. Several methods for generating the Pareto optimal set have been proposed, such as weighting objectives, constraint approach, goal programming, and minimax approach. The basis of these methods is the transformation of the multiobjective optimization problem into a single objective optimization problem by combining multiple objectives into a single objective or transforming some objectives into constraints. Then, this single objective optimization problem is solved using some optimization technique. In those cases, the obtained optimal solution is highly sensitive to the input data of the problem. Actually, the multiobjective optimization methods available to date are not particularly robust, and none of them performs well on a broad class of problems (Adeli 1994).

The basic idea behind GAs is to generate a pool of solutions (population), represented by a string structure (coding structure). Then, in a manner similar to the natural genetic operators of selection, crossover and mutation, copying, swapping and modifying of partial strings are applied to improve these solutions. Since GAs work with a population of points, they can capture a number of solutions simultaneously and easily incorporate the concept of Pareto optimal set in their evolutionary process. The first practical GA for multiobjective optimization was developed by Schaffer, and is called Vector Evaluated Genetic Algorithm (VEGA) (Schaffer 1985). One of the problems with VEGA is its bias for some solutions at the extremities of the Pareto optimal set. Goldberg suggested a non-dominated sorting procedure to overcome this weakness (Goldberg 1989). He also suggested that this procedure should be used in conjunction with some technique for maintaining the Pareto optimal set distribution over a larger region. Fonseca and Fleming implemented these two suggestions with a simple GA and called the resulting algorithm a Multiobjective Genetic Algorithm (MOGA) (Fonseca and Fleming 1993). This approach was also examined through several examples of mathematical functions (Horn et al. 1994, Shinivas and Dels 1994). Because both of the above suggestions are related to the selection operator only, MOGA differs from simple GA only in the way the selection operator works. In this research, the simple GA operators and these two suggestions are implemented to set up and refine the Pareto optimal set for an engineering application, the rehabilitation plan of concrete decks. The optimization aims at minimizing the total rehabilitation cost and the average deterioration degree weighted by the bridge deck area.

2. MULTIOBJECTIVE REHABILITATION PLAN OF BRIDGE DECKS

According to the results of inspection, the conditions of bridge decks are assessed to be one of five deterioration levels. At level I, deterioration is serious; at level II, deterioration is obvious, and detailed inspection may be needed; at level III, deterioration is aggravating, and further investigation is needed; at level IV, deterioration is minor, and at level V, the bridge deck is like new. Each deterioration level can be quantified by a range of the deterioration degree. For deterioration levels V, IV, III, II, and I, the ranges of deterioration degree are 0.0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, and 0.8–1.0 respectively (Liu et
al. 1997). For simplicity, rehabilitation is assumed to be the only possible maintenance method. Rehabilitation implies fairly major reconstruction of the deck and large maintenance effort, and sometimes closure of the bridge to traffic (Markow et al. 1994, Purvis et al. 1994, Silano 1993). Attaching additional longitudinal girders or steel plates, and increasing the cover thickness of the reinforcement are common rehabilitation techniques.

2.1 Deterioration Model of Concrete Bridge Decks

Deterioration models can be classified into three types: stochastic models, nonlinear deterioration models, and piecewise linear deterioration models. Although some stochastic models such as the Markovian chain method have been developed to represent the transition probability from one condition level to another, these models are difficult to be adopted for the time being due to the lack of inspection data. A nonlinear deterioration model on concrete decks is adopted in this research from Markow et al. (1994) and Purvis et al. (1994). There exist a large number of factors influencing the deterioration processes of concrete decks such as thickness of the deck, structural type, materials properties, drainage system, girder spacing, construction method, age, traffic volume, environmental factors, and so on. However, it is not easy to represent all these factors in the mathematical formulation. All these factors can be classified into two categories depending on whether they have a close relationship with the time or not. Two comprehensive parameters, \( \alpha \) \( \) \( \) and \( \beta \), representing these two categories for bridge \( i \) are used as follows:

\[
d(t,i) = \frac{1}{1 + e^{\alpha i + \beta t}}
\]

(1)

where \( d(t,i) \) is the predicted deck deterioration degree of bridge \( i \) at age \( t \). Because of the lack of inspection data, \( \alpha \) \( \) \( \) is determined by assuming a value for the initial deterioration \( d(0,i) \). The parameter \( \beta \) \( \) \( \) is related to the age of the bridge, and is calculated for each bridge using the inspection data. For deterioration levels I, II, III, IV, and V from the inspection data, the values of deterioration degrees are taken as 0.9, 0.7, 0.5, 0.3, and 0.1, respectively.

2.2 Objective Functions

Two objective functions, total rehabilitation cost and weighted average deterioration degree, are to be minimized. The yearly deck rehabilitation cost of a bridge is calculated using the deck area and the unit cost of the rehabilitation. The total cost \( C \) of a bridge system over the rehabilitation plan period is determined by:

\[
C = \sum_{i=1}^{N} \sum_{t=1}^{T} \left( (1+r)^{-t} \times c \times s(i) \times n(i,t) \right)
\]

(2)

where \( N \) is the number of bridges; \( T \) is the length of the plan period; \( r \) represents the discount rate that is assumed to be constant during the plan period; \( c \) is the unit area cost of rehabilitation; \( s(i) \) is the deck area of bridge \( i \); and the value of \( n(i,t) \) is 1 if a rehabilitation activity is performed on the deck of bridge \( i \) at year \( t \), or it is 0 for the case of no rehabilitation activity. The rehabilitation cost is calculated at the beginning of the plan period without considering the possible changes in unit costs due to inflation. The second objective function, average deterioration degree \( D \) over the plan period weighted by the deck area of each bridge, is formulated in Eq. (3). Here, \( S \) is the sum of deck areas of all bridges.

\[
D = \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} d(t,i) \times s(i)}{T \times S}
\]

(3)

3. OPTIMIZATION OF CONCRETE DECK REHABILITATION USING MOGA

Fig. 1 illustrates the multiobjective genetic algorithm (MOGA) implemented in the present study. The program starts from the initial generation (generation 0). After comparing the objective functions of all individuals, the initial Pareto optimal set is generated. For each generation, MOGA first determines the fitness functions of individuals in the previous generation using two techniques, Pareto optimal ranking and fitness sharing. Then, two strings at the present generation are selected on the basis of their fitness, and reproduced as two individuals of the next generation by crossover and mutation until the whole population is recreated. Finally, MOGA decodes and evaluates the strings of this new generation,
and revises the Pareto optimal set. This procedure is repeated many times until one of the following termination criteria is satisfied: (1) the maximum generation number is reached; and (2) the convergence index is sufficiently small. In this research, the rehabilitation actions are used directly to code the GA strings. In Fig. 1, the string bits 0 and 1 represent "doing nothing" and "undertaking rehabilitation action", respectively. The string of a rehabilitation plan consists of many sub-strings representing the rehabilitation strategies of bridges in a given order. The string length is the sum of all sub-strings’ lengths. In a sub-string, every string bit from left to right represents the rehabilitation action at one year from the beginning to the end of the plan period.

3.1 GA Operators

The fitness function of each rehabilitation plan is taken into consideration the selection criterion. Pareto optimal ranking and fitness sharing are adopted to revise the original fitness function obtained by decoding each string. Pareto optimal ranking suggested by Goldberg (1989) is a ranking method based on the original fitness functions which take into consideration all optimization objectives. To illustrate this method, an example of a ranked population of 20 rehabilitation plans, plotted according to rehabilitation cost versus average deterioration degree, is shown in Fig. 2. The superscript $i$ of a solution $S^i$ is the rank number, and the subscript $j$ represents the ordered number of an individual in rank $i$. First, all individuals in the current population are compared, and the non-dominated individuals are identified and assigned rank 1, which is also the Pareto optimal set of this population. Then, these individuals are set apart, and the remaining individuals are compared to select a new non-dominated set with rank 2. This process continues until the entire population is ranked.

Fitness sharing aims to divide the population into several sub-populations according to the objective functions of all individuals. It is proposed to stabilize the multiple sub-populations that arise along with the Pareto optimal set and preventing excessive competition among distant population members. For the present research, the rehabilitation cost is divided into several intervals. Each rehabilitation plan is assigned to an interval, thus forming several sub-populations (classes) of solutions. The fitness function $f(i)$ of each individual $i$ is assigned according to its rank number $rank(i)$ and the number of rehabilitation plans belonging to its sub-population (class) $num(i)$:

$$f(i) = \frac{1}{rank(i) \times num(i)}$$

(4)

In this research, the rehabilitation plans with fitness function values that are equal to or greater than the average fitness function in the population will survive and be selected to generate the new population individuals of the next generation, while the rehabilitation plans with smaller values will be eliminated in the selection procedure. There is a need for developing efficient crossover and mutation operators that are suitable for the presented coding structure. Crossover is introduced within every sub-string corresponding to one bridge, and the number of the crossover points is same as the number of bridges. This multipoint crossover affects every bridge with the same probability and accelerates the optimization process. Similarly, the bit-wise complement mutation operator changes one value to the opposite within every sub-string (Liu et al. 1997).

3.2 Performance Measure

Performance measure aims to quantify the distribution of population individuals for any one generation. Srinivas and Deb (1994) used the chi-square like deviation measure, which represents the fitness function (phenotypic measure). Collins and Jefferson (1991) described another method of performance measure, which focused on the distributions of the genotype alleles (genotypic measure). In this study, the performance measure at each generation is calculated following the former method as:

$$\text{performance measure} = \frac{\sum_{i=1}^{q} \left( \frac{m(i) - \mu}{\mu} \right)^2}{\mu}$$

(5)

where $m(i)$ is the actual number of solutions in class $i$, and $\mu$ is the average number of rehabilitation plans in each class; and $q$ is the number of classes. The smaller is the performance measure, the more uniform is the population distribution in which there exists a higher possibility for bridge engineers to find a solution locating a given range of objective functions.

4. NUMERICAL EXAMPLE

A numerical example with six bridges is used to examine the MOGA optimization approach and demonstrate the capability of MOGA in optimizing the rehabilitation plan of bridge decks. Their lengths, widths, construction years, deterioration degrees at the inspection year (1992) are shown in Table 1. According to Eq. (1), the parameter $\alpha$ is determined according to the deterioration degree of bridge $i$ at age 0. Estimating this degree is difficult, and it should be different for each bridge deck. Because of the lack of data, a constant value of 0.02 is used as the deterioration degrees of all bridge decks. From this assumption, the parameter $\alpha$ of all bridge decks becomes 3.892 as shown in Table 1. The deterioration degree of each bridge deck at 1992 is used to determine the parameter $\beta$ and the results are shown in Table 1. These parameters' values can be adjusted when more inspection data are available. According to the present values of these parameters, the deterioration degrees of most bridge decks will reach 0.98 at an average age of about 60 years, which is the design service life of most bridges. It is also assumed that the rehabilitation can extend the service life of a bridge deck by 10 years (Silano 1993), and its cost is 20,000 Yervm$^2$ (about 200/m$^2$ US$). The plan period of deck

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rehabilitation is taken as 5 years in accordance with the rehabilitation plan of other infrastructures in Japan. The discount rate is assumed to be 1.75% per year during the plan period. A moderate population size of 300, a high crossover probability of 80%, and a low mutation probability of 1% are adopted. In order to compare several approaches, only the maximum generation number is used as the terminating condition.

<table>
<thead>
<tr>
<th>Bridge Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length (m)</td>
<td>39.3</td>
<td>27.8</td>
<td>18.0</td>
<td>87.0</td>
<td>27.2</td>
<td>27.0</td>
</tr>
<tr>
<td>Width (m)</td>
<td>24.7</td>
<td>8.50</td>
<td>7.0</td>
<td>7.0</td>
<td>7.0</td>
<td>13.0</td>
</tr>
<tr>
<td>Deterioration degree</td>
<td>0.5</td>
<td>0.5</td>
<td>0.3</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>α_1</td>
<td>3.892</td>
<td>3.892</td>
<td>3.892</td>
<td>3.892</td>
<td>3.892</td>
<td>3.892</td>
</tr>
<tr>
<td>β_1</td>
<td>0.111</td>
<td>0.126</td>
<td>0.127</td>
<td>0.145</td>
<td>0.130</td>
<td>0.169</td>
</tr>
</tbody>
</table>

4.1 Optimization Process of MOGA

The MOGA optimization process has been programmed in Fortran. The execution time per run on a SUN SPARC Station II is only a few minutes. This example is solved by several runs of the program. Although the specific results are not completely identical because of the randomness involved in GA, these results are very similar. Given the number of classes as 5, the population distributions of one run at generations 0, 10, 30 and 50 are shown in Fig. 3. It is found that with the increase of the generation number, the rehabilitation cost and deterioration degree of most solutions decrease, and most solutions approach the Pareto optimal solutions.

![Population Distribution of MOGA with Fitness Sharing](image)

Fig. 3 Population Distribution of MOGA with Fitness Sharing

One ideal rehabilitation plan can be selected from the Pareto optimal set at the final generation according to particular requirements. For example, if a large budget for the deck rehabilitation of these bridges is available, a suggested solution is with a rehabilitation cost of 193.5 Million Yen and an average deterioration degree of 0.06. This is because the reduction of deterioration degree is very small with the increase of the rehabilitation budget if a larger amount is invested. On the other hand, the average deterioration degree is about 0.42 if no rehabilitation action is taken. A solution with a moderate rehabilitation cost of 88.06 Million Yen and a moderate deterioration degree of 0.16 can also be found from the above Pareto optimal set. Furthermore, the bridge engineer can also apply other multiobjective optimization method to decide one satisfactory solution from the final Pareto optimal set by considering other available information.

4.2 Effects of Pareto Optimal Ranking and Fitness Sharing

In order to check the effect of Pareto optimal ranking, the above MOGA results are compared with results from VEGA. In VEGA, the selection is performed by considering the rehabilitation cost only, one of the two objective functions. Fig. 4 shows the population distributions according to VEGA at the generations 0, 10, 30 and 50. By visual comparison of Figs. 3 and 4, MOGA gives better distribution of population individuals than VEGA. For instance, in the Pareto optimal set of VEGA, there is no plan whose rehabilitation cost is greater than 230 Million Yen. However, MOGA can provide a lot of rehabilitation plans satisfying this requirement.
The effect of fitness sharing on the optimization results is also studied by comparing the results at generations 0, 10, 30 and 50 with and without fitness sharing, as shown in Fig. 3 and Fig. 5, respectively. In the case without fitness sharing, only one class is available. From this comparison, the case with fitness sharing gives better distribution than the case without fitness sharing. In the Pareto optimal set of Generation 50 in Fig. 5, no rehabilitation plan can be found whose cost is greater than 250 Million Yen. However, MOGA can provide a lot of rehabilitation plans satisfying this requirement together with a relatively low average deterioration degree.

The comparison of above three methods can further be done using the performance measure, as shown in Fig. 6. Initially, all approaches start with a high performance measure because the initial population is spread over the search space with fewer individuals in some sub-populations. VEGA's increasing performance measure with the increase of the generation number indicates its poor distributing ability. The initial decrease is due to the convergence of population towards the non-dominated region. Up to generation 50, the performance measure of MOGA with numbers of class 5 is better than the performance measures of VEGA (without Pareto optimal ranking) and MOGA without fitness sharing. This means that MOGA can provide the decision maker with a greater number of alternative solutions at each generation, and the Pareto optimal ranking and fitness sharing are two necessary techniques to modify the population individuals.
4.3 Further Application in Network-Level Bridges

The above optimization approach is further applied to the rehabilitation plan of the whole bridge system of Nagoya city. Because of the lack of data, only 152 of the 259 bridges with concrete decks are studied. These bridges have the following characteristics: their concrete decks, their ages are less than 50 years, their lengths vary from 15.1m to 531.8m, and their widths vary from 5m to 49.2m. These decks were constructed or replaced between 1944 and 1991. The initial deterioration levels are assessed as level III (11 bridges), level IV (9 bridges), and level V (132 bridges). Fig. 7 shows the population distributions at several generations. It is clear that the solutions are improved with the increase of the generation number. The Pareto optimal set at generation 100 shows the trade-off between the rehabilitation cost and the deterioration degree. This trade-off shows the possible rehabilitation plans. One satisfactory solution can be selected by comparing all solutions in the Pareto optimal set according to some additional information. For example, if the rehabilitation budget is 4,000 or 5,000 Million Yen, the possible minimum average deterioration degree is 0.09 or 0.07, respectively.

5. CONCLUSIONS

The following conclusions can be stated: (1) MOGA was successful in optimizing bridge deck rehabilitation plan. It was found that this approach could find a satisfactory Pareto optimal set within a short calculation time; (2) Pareto optimal ranking and fitness sharing were two necessary techniques to modify the fitness function of each population individual, so that an even distribution of the population individuals evolved with the increase of the generation number; and (3) The Pareto optimal set at the final generation illustrated the trade-off between the rehabilitation cost and the deterioration degree. This trade-off provided the decision maker with a wide variety of candidate solutions. This research can be further extended in the following ways: (1) Further investigation is needed on determining the fitness function of each population individual; and (2) More advanced GAs operators should be examined for the multiobjective optimization problems.

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