Evolutionary Multiobjective Optimization in Engineering Management: An Empirical Study on Bridge Deck Rehabilitation

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Abstract

There exist multiple objectives in engineering management such as minimum cost and maximum service capacity. Although solution methods of multiobjective optimization problems have undergone continual development over the past several decades, the methods available to date are not particularly robust, and none of them performs well on the broad classes. Because genetic algorithms 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. In this paper, a genetic algorithm is modified to deal with the rehabilitation planning of bridge decks at a network level by minimizing the rehabilitation cost and deterioration degree simultaneously.

1. Introduction

The bridge deck is the physical extension of the roadway across the obstruction to be bridged. It is an important part of a bridge that is directly subjected to cyclic loading and harsh environmental conditions. In much previous research, the optimization of maintenance planning for bridge decks has been given special interest [1], [2]. Multiobjective optimization (MO) approach is becoming a common phenomenon because it allows decision makers to participate in the search process of an ideal solution after the formulation of the optimization problem [3], [4], [5], [6]. The basis of the conventional solution 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. Generally speaking, the multiobjective optimization methods available to date are not particularly robust, and none of them performs equally well on a broad class of problems [7], [8].

The basic idea behind genetic algorithms (GAs) is to generate a pool of solutions that are represented by a string 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. The first practical GA for multiobjective optimization was developed by Schaffer, and is called Vector Evaluated Genetic Algorithm (VEGA) [9]. One problem with VEGA is its bias for some solutions at the extremities of Pareto optimal set. Goldberg suggested a non-dominated sorting procedure to overcome this weakness [10]. It is 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 and called a simple GA with these two suggestions a multiobjective genetic algorithm (MOGA) [11]. Although there are increasing interests to apply genetic algorithms for multiobjective optimization in engineering management, optimizing the long-term plan of a network-level infrastructure system is still challenging researchers [12], [13], [14]. In this research, the simple GA operators and these two suggestions are implemented to set up and refine the Pareto optimal set for an empirical study on optimizing the rehabilitation planning of concrete decks of six real bridges. The optimization aims at minimizing the total rehabilitation cost and the average deterioration degree weighted by the bridge deck area.

2. Multiobjective rehabilitation planning of bridge decks

According to the results of inspection, the conditions of bridge decks are normally assessed to be one of five deterioration levels. At level I, deterioration is serious; at level II, deterioration is obvious, and...
determined by: system over the rehabilitation plan period is cost of the rehabilitation. The total cost of the bridge is calculated using the deck area and the unit cost per square foot. The yearly deck rehabilitation cost of a bridge is assumed to be constant during the plan period, and is calculated for each bridge using the inspection data. 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. The maintenance method is then selected and performed. For simplicity, rehabilitation is assumed to be the only possible maintenance method in this research. Rehabilitation implies fairly major reconstruction of the deck and large maintenance effort, and sometimes causes closure of the bridge to traffic [15].

A nonlinear deterioration model on concrete decks is adopted from [2]. There exist a large number of factors influencing the deterioration process 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, \( a_i \) and \( \beta_i \), representing these two categories of bridge \( i \), are used as follows:

\[
d(t, i) = \frac{1}{1 + e^{a_i t - \beta_i s}}
\]

(1)

where \( d(t, i) \) is the predicted deck deterioration degree of bridge \( i \) at age \( t \). Because of the lack of inspection data, \( a_i \) is determined by assuming a value for the initial deterioration \( d(0, i) \). The parameter \( \beta_i \) 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.

Two objective functions, the total rehabilitation cost in US dollars and weighted average deterioration degree with no unit, are to be minimized simultaneously. 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 planning 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.

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

(3)

3. Optimization process of bridge deck rehabilitation

Figure 1 illustrates the multiobjective genetic algorithm implemented in optimization progress the present study. The program starts from generation 0. After comparing the objective functions of all individuals, the initial Pareto optimal set is generated. For each generation, the multiobjective genetic algorithm 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, the multiobjective genetic algorithm 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 the research presented in this paper, the rehabilitation actions are used directly to code the GA strings. In Figure 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.
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 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 Figure 2.

The superscripts $i$ of a solution $S^i_j$ 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 $fit(i)$ 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) $num(i)$:

$$fit(i) = \frac{1}{rank(i) \times num(i)}$$  \hspace{1cm} (4)

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 new population individuals of the next generation, while other rehabilitation plans will be eliminated. 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 [1].

4. An empirical study

A numerical example with six bridges in practice is studied to examine the developed optimization approach by multiobjective genetic algorithm and demonstrate its capability in optimizing the rehabilitation plan of bridge decks. Their lengths, widths, construction years, deterioration degrees at the inspection year are shown in Table 1. According to Eq. (1), the parameter $\alpha_i$ 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. Since the lack of data, a constant value of 0.02 is used as the deterioration degrees of all bridge decks for the purpose of simplicity. From this assumption, the parameter $\alpha_i$ of all bridge decks becomes 3.892 as shown in Table 1. The deterioration degree of each bridge deck at the inspection year is used to determine the parameter $\beta_i$, 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.
Table 1. Bridge deck data

<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>27.0</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>$\alpha_i$</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>$\beta_i$</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>

It is assumed that the rehabilitation can extend the service life of a bridge deck by 10 years [15], and its cost is assumed to be $200/m^2$ US$. The planning period of deck rehabilitation is taken as 5 years, which is in accordance with the rehabilitation plan of most infrastructures in a country. 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.

The optimization process developed in multiobjective genetic algorithm 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 Figure 3.

![Figure 3. Population distributions with multiobjective optimization progress](image)

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. One ideal rehabilitation plan can be selected from the Pareto optimal set at the final generation (generation 50) 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 about 1.9 Million US$ 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 about 0.9 Million US$ and a moderate deterioration degree of 0.16 can also be found from the above Pareto optimal set.

Further studies have been carried out to check the effects of Pareto optimal ranking and fitness sharing on the optimization results. It is found that each of these two assumptions obviously influences the optimization process and the final optimal set, especially its distribution of solutions.

5. Conclusions

This paper demonstrated the multiobjective optimization approach for network-level bridge deck rehabilitation planning. Pareto optimal ranking and fitness sharing were two necessary techniques to modify the fitness function of each population individual, by which an even distribution of the population individuals evolved with the increase of the generation number. 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.

References


