

# I - A 400      Multi-objective Optimization of Bridge Deck Rehabilitation Using Genetic Algorithm

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## 1. Introduction

Most of the optimization problems in infrastructure maintenance have multiple objectives, which are possibly conflicting objectives, such as minimum cost and minimum risk. In multi-objective optimization (*MO*), there may not exist one solution that is best with respect to all objectives. Instead, there is a set of solutions in which any solution 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 others in the same set. This set is called Pareto optimal set. The solution methods of *MO* have undergone continual development over the past three decades. However, the methods available to date are not particularly robust, and no one algorithm performs uniformly well on broad classes of problems (Adeli 1994). Genetic Algorithms (*GAs*) have been proved to be one of the most effective and robust optimization techniques for single objective optimization problems. Because *GAs* work with a population of points, they can capture a number of solutions simultaneously and can easily incorporate the concept of Pareto optimal set in their evolutionary process. In this research, *GA* is implemented to set up and refine the Pareto optimal set of the rehabilitation plan of bridge decks aiming to minimize the total rehabilitation cost and the average deterioration degree.

## 2. Multi-objective Rehabilitation Planning of Bridge Decks

The objective functions, total rehabilitation cost and average deterioration degree of all bridge decks over the planning period, are to be minimized. The formulations of these two objective functions are explained in the following sub-sections.

**2.1 Deterioration Factors and Model:** There exist a large number of factors influencing the deterioration process of a concrete bridge deck. Several factors have been recognized, such as thickness of the deck, structural type, materials properties, drainage system, distance between girders, construction method, age, traffic volume, environmental factors, and so on. However, it is not easy to represent all these factors in the form of mathematical formulation. All these factors can be classified into two categories depending whether they have a close relation with the service age of the bridge. Two comprehensive parameters,  $\alpha$  and  $\beta$ , representing these two categories, respectively, are used to construct a nonlinear deterioration model as shown in Eq. (1) (Markow et al. 1994). In this equation,  $D_t$  is the predicted deterioration degree at age  $t$ .  $\alpha$  is determined by giving a value representing the initial deterioration ( $D_0$ ) according to design and construction conditions.  $\beta$  is related to the service parameters and is calculated for each bridge using inspection data.

**2.2 Cost Analysis:** 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 maintenance planning period is determined by Eq. (2), where,  $N$  is the number of bridges;  $T$  is the length of the planning period;  $r$  represents the discount rate;  $c$  is the unit cost of the rehabilitation;  $n(i, t)$  equals 1 or 0 corresponding to rehabilitation or no rehabilitation for the deck of bridge  $i$  at year  $t$ , respectively; and  $L(i)$  and  $W(i)$  indicate the length and width of bridge  $i$ , respectively. The maintenance cost is calculated at the beginning of the planning period.

$$D_t = \frac{1}{1 + e^{\alpha - \beta \times t}} \quad (1) \quad C = \sum_{i=1}^N \sum_{t=1}^T ((1+r)^{-t} \times c \times n(i, t) \times L(i) \times W(i)) \quad (2)$$

## 3. Rehabilitation Optimization of Bridge Decks Using MOGA

**3.1 Optimization Process:** Multi-objective Optimization Genetic Algorithms (*MOGAs*) differ from simple *GAs* only in the way the selection operator works. Goldberg (1989) suggested a non-dominated sorting procedure (Pareto-optimality ranking) for *MOGA* in conjunction with the fitness sharing, which are applied in this research.

**Pareto-optimality Ranking:** First, all individuals in the current population are compared and the non-dominated individuals are identified and assigned a rank of 1, which is also the Pareto optimal set of this population. Then, these points are removed from the population and the remaining individuals are compared, and a new set of non-dominated individuals is identified and assigned a rank of 2. This process continues until the entire population is ranked. Finally, the fitness function value of each individual is assigned according to its rank as shown in Eq. (3). Here,  $fit(i)$  and  $rank(i)$  are the fitness function and the rank number of element  $i$ , respectively.

**Fitness Sharing:** Fitness sharing aims to force individuals to share available resources by dividing the population into sub-populations of similar individuals. In a *MO* problem, fitness sharing is useful in stabilizing the multiple sub-populations that arise along with the Pareto optimal set. Therefore, this prevents excessive competition among distant population members. At the present research, the cost, one objective function, is divided into several intervals characterized by their bounds. Each individual is assigned to one interval, thus forming sub-populations (classes) of solutions having a value within specified limits. The *shared fitness function* of an individual is determined as its fitness function divided by the number of individuals belonging to its class as shown in Eq. (4). In this equation,  $share\_fit(i)$  is the shared fitness function of individual  $i$ , and  $N(i)$  is the number of individuals in the class to which individual  $i$  belongs. The shared fitness function of each individual replaces its fitness function as the selection criterion.

$$fit(i) = \frac{1}{rank(i)} \quad (3) \quad share\_fit(i) = \frac{fit(i)}{N(i)} \quad (4)$$

**3.2 Case Study:** To illustrate the multi-objective rehabilitation decision process, an example is formulated and solved using six bridges in Nagoya city. The data of these six bridges are shown in Table 1. It is assumed the initial deterioration value,  $D_0$ , is a constant value for all bridges ( $D_0 = 0.02$ ). Because the data of only one inspection are available, these data are used to generate the  $\beta$  value of each bridge deck. It is also assumed that rehabilitation can reduce the age of a bridge deck by 10 years and its cost is 20000 Yen/ $m^2$ . The planning period is 5 years. According to the calculation results, most of the solutions are near the Pareto optimal set and their values of cost and deterioration degree become less with the increase of the generation number. In Fig. 1, the Pareto optimal set of the final generation (generation 100) shows the trade-off between the cost and the average deterioration degree. The decision maker can select one rehabilitation plan from this set according to his particular requirements.

Table 1: Bridge Deck Data used in the Case Study

|                    | Bridge Number |       |       |       |       |       |
|--------------------|---------------|-------|-------|-------|-------|-------|
|                    | 1             | 2     | 3     | 4     | 5     | 6     |
| Length             | 39.3          | 27.8  | 18.4  | 87.4  | 26.2  | 27.0  |
| Width              | 23.7          | 8.50  | 7.0   | 26.0  | 7.0   | 12.0  |
| Constructeion Year | 1957          | 1961  | 1968  | 1971  | 1979  | 1982  |
| Condition at 1992  | 0.5           | 0.5   | 0.3   | 0.3   | 0.1   | 0.1   |
| $\alpha$           | 3.892         | 3.892 | 3.892 | 3.892 | 3.892 | 3.892 |
| $\beta$            | 0.111         | 0.126 | 0.127 | 0.145 | 0.130 | 0.169 |

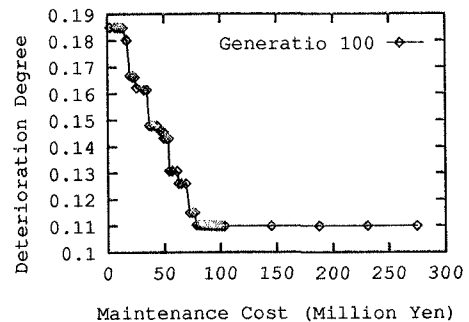


FIG. 1. Pareto optimal set of Generation 100

#### 4. Conclusions

Although there exist a number of classical multi-objective optimization techniques, they require the priori problem information. Because *GAs* use a population of points, they are able to find multiple Pareto optimal solutions simultaneously. In this research, a *MOGA* was used to solve the rehabilitation optimization problem. The results suggested that *MOGA* can be successfully used to find the Pareto optimal set, satisfying the minimum cost and minimum deterioration degree of bridge decks.

- References:** 1) Adeli, H. (1994). "Advances in Design Optimization." Chapman & Hall, London, UK.  
 2) Goldberg, D. E. (1989). "Genetic Algorithms in Search, Optimization, and Machine Learning." Addison-Wesley Inc., U.S.A.  
 3) Markow, M. J., Madanat, S. M., and Gurenich, D. I. (1994). "Optimal Rehabilitation Times for Concrete Bridge Decks." *Transportation Research Record 1392*, TRB, National Research Council, Washington, D.C., 79-89.