Multi-Objective Decision Making on Roadway Maintenance Engineering Considering $\varepsilon$-dominance

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Abstract. As an important part of state-owned assets, roads and other transportation infrastructure are an important foundation for the sustained and healthy development of the national economy. It is extremely important to increase the service life of roadways. Aiming at the highly restricted multi-objective optimization problem of roadway maintenance, this paper considers the three dimensions of construction schedule, cost and quality, and proposes an elitist evolutionary multi-objective optimization algorithm based on the concept of $\varepsilon$-dominance, called $\varepsilon$-multi-objective genetic algorithm variable ($\varepsilon$v-MOGA) to solve roadway maintenance problems. Experimental results show that the algorithm can help decision makers choose the most suitable solution among a large number of feasible solutions.

Keywords: Roadway Maintenance Engineering; Multi-objective Optimization; $\varepsilon$v-MOGA.

1. Introduction

In terms of roadway maintenance management decision-making, it develops from two directions: aggregation and heuristic. The former focuses on the centralized optimization of the problem, while the latter focuses on the idea of successive approximation. At present, each country has established a roadway management system involving system construction, maintenance planning, and cost optimization. Singapore designed the pavement maintenance decision system with genetic algorithm [1]. Fallah-Fini S et al. [2] employing the simulation technology, conducted a study on the dynamic decision-making concerning roadway maintenance based on system dynamics. Gendreau and Soriano [3] analyzed the Pavement Management System. They emphatically focus on the cost-benefit analysis and repair strategies based on different pavement structure of the computer system. Ziarati et al. [4] studied the problem of project planning to determine resource constraints in an environment. They applied three kinds of bee colony algorithm respectively to solve the equilibrium solution of the model, and compared the effectiveness of the algorithm. Azaron et al. [5] established multi-stage and multi-objectives equilibrium optimization model of schedule, cost and quality under stochastic environment. In the respect of roadway performance evaluation and prediction, the evaluation index generally adopts separate evaluation index and synthetic evaluation index. There are different evaluation models and prediction models. The most widely used and promoted in China at present is CPMS (China Pavement Management System).

Roadway management is essential to maintain the performance of the roadway and meet the expectations of related benefits, but the budget is often insufficient to meet all the maintenance needs of
Due to factors such as the environment and traffic load, some roadways have experienced "sub-health" phenomena with short service life and serious early damage. With the rapid development of high-grade roadway, a series of problems need to be solved urgently, such as how to maintain the good performance of the roadway, extend the service life of the roadway, and reduce the maintenance cost of the roadway overhaul. It is particularly important to establish a suitable new roadway management system that runs through the entire life cycle of the roadway. Based on this target positioning, pay more attention to the conservation of maintenance funds, the coordination of the environment and the sustainable development, service life and the maintenance costs, the matching of service functions during the operation period; in terms of innovative methods, more attention is paid to system optimization, service optimization, cost optimization, consentrate on the guiding role of asset management concepts; in the application of new technologies, pay more attention to the integrated application of new materials, new technologies, and new processes, and consentrate on the application of scientific management methods.

These requires decision-making to determine the priority of different maintenance programs in order to optimize the limited budget to achieve multiple expected goals of the stakeholders. The main problems of roadway management are project schedule, cost and quality, which can be solved and obtain an optimal solution under complex and variable constraints by establishing multi-objective equation and then using multi-objective algorithm.

Herrero et al. in Ref. [6] first applied \( \varepsilon \)-MOGA based on the concept of epsilon dominance (\( \varepsilon \) dominance) to solve the non-linear robust identification of greenhouse mode [7]. Ehsan Afzalan et al. [8] proposed \( \varepsilon \)-MOGA to solve the frequency multi-objective economic load dispatch (ELD) problem. This method obtains an \( \varepsilon \)-Pareto set, which is used in the Pareto optimal set when dividing behaviors, while using limited memory resources. In addition, \( \varepsilon \)-MOGA can dynamically adapt to the limit of the Pareto front, thereby avoiding the loss in the process of solving and fitting. The most important feature of \( \varepsilon \)-MOGA is the \( \varepsilon \) dominance relationship. The introduction of \( \varepsilon \) dominance can maintain a representative subset of non-dominated individuals. The value of \( \varepsilon \) can adjust the density of the approximate set. Using \( \varepsilon \)-dominance to select a representative subset of the non-dominated set and save it in the archives throughout the generation, \( \varepsilon \)-MOGA shows good convergence and diversity. Based on \( \varepsilon \)-MOGA, this paper aims to design the roadway maintenance quality-cost-time-oriented multi-objective control system.

## 2. Methods

### 2.1. Roadway Evaluation Model

The roadway requirement analysis consists of two major steps: firstly, detect the roadway and collect the basic information based on the detected roadway. Then, evaluate and predict through the roadway performance evaluation method and prediction model. The roadway requirement analysis is the most fundamental basis of maintenance priority, funds distribution and final maintenance program determination. As for long-term maintenance planning, due to the uncertainty of performance prediction and maintenance program, this paper aims at the roadway performance maintenance of a given year. However, the roadway performance prediction value is only as a reference. In effect, it is the actual data based on the roadway detection in the previous year applied to the evaluation and maintenance requirement analysis.

It’s worth pointing out that, each roadway shows its particularity when analyzing the maintenance requirement. Therefore, the investigation and analysis are necessary, which includes technical index like mileage, roadway types, the number of lanes and operational index like operation time, traffic volume, the importance of the section among road network, social and economic influence need to be considered. Regulations like ‘Asphalt pavement maintenance technical specifications’, ‘Roadway maintenance quality inspection and evaluation method’ and ‘Roadway technical condition evaluation standard’ constitute a set of corresponding roadway performance evaluation standard. Currently, the roadway management department has fundamentally established roadway evaluation system. There is a roadway evaluation model base in the system, which can be adaptively improved according to the actual situation in specific implementation. According to the relevant standard specification of roadway, the roadway
basic data that needs to be detected includes international roughness index (IRI), damage rate (DR), pavement deflection, and sideways force coefficient (SFC). On the basis of pavement current condition data, we need to respectively compute the riding quality index (RQI), pavement condition index (PCI), skidding resistance index (SRI), pavement structure strength index (PSSI) of each line and section. The Table 1 shows Roadway Evaluation Indexes and Models.

| Index | Model |
|-------|-------|
| RQI   | \[ RQI = \frac{100}{1 + \alpha_0 e^{\varepsilon R}} \] |
| PCI   | \[ PCI = 100 - \alpha_{PCIDR} \] |
| IRI   | \[ IRI = 100 + 0.0185 e^{\varepsilon IRI} \] |
| DR    | \[ DR = 100 - 15DR^{0.41} \] |
| SRI   | \[ SRI = \frac{100 - SRI_{min}}{1 + \alpha_{SRI} e^{\varepsilon SRI}} + SRI_{min} \] |
| SFC, SRI_{min} | \[ SFC = \frac{100 - SRI_{min}}{1 + 266 e^{\varepsilon SRI}} + SRI_{min} \] |
| PSSI  | \[ PSSI = \frac{100}{1 + \alpha_{PSSI} e^{\varepsilon PSSI}} \] |
| SSI, l_s, l_0 | \[ SSI = \frac{l_s}{l_0} \] |

Ps: \( \alpha_0, \alpha_1 \) are preset parameters. \( l_s \) is Design value of Pavement Deflection. \( l_0 \) is real Pavement Deflection

2.2. Multi-Objective Optimization Model

Preventive maintenance decision is actually a combination of a set of nonlinear multi-objective optimization problems. Evolutionary algorithm search simulates the natural evolution of probability. It pioneered a new approach and idea for multi-objective optimization problem. The evolutionary algorithm do not have to be limited strictly be the mathematical conditions compared to the traditional algorithm. Besides, it is rather more global and multi-directional when it searches for Pareto solutions. In order to solve dynamic multi-objective optimization problems, multiple sets of multi-objective optimization evolutionary algorithm have been developed, such as MOGA, SPEA, PAES, NSGA, PSO, IA, etc. The MO problem can be formulated as follows:

\[
\min O(\theta) = \min [O_i(\theta), O_2(\theta), \ldots O_s(\theta)]
\]

\[
\left\{ \begin{array}{l}
  f_i(\theta) \leq 0, (1 \leq x \leq m) \\
  g_i(\theta) = 0, (1 \leq y \leq n) \\
  \theta_0 \leq \theta_i \leq \theta_u, (1 \leq i \leq L)
\end{array} \right.
\]

Where \( O_i(\theta) \), \( i \in B := [1 \ldots s] \) shown in equation(1) are the objectives to be optimized, \( \theta \) is a solution inside the L-dimensional solution space \( D \), \( f_i(\theta) \) and \( g_i(\theta) \) shown in equation(2) are each of the m inequality and n equality problem constraints respectively and \( \theta_0 \) and \( \theta_u \) are the lower and upper constraints which defined the solution space \( D \). The \( \varepsilon \)-MOGA variable \[ [9] \] is an elite multi-objective evolutionary algorithm \[ [10] \] based on the \( \varepsilon \)-dominant concept \[ [7] \]. It is used to control the contents of the archive \( A(t) \) that stores the results of the optimization problem. \( \varepsilon \)-MOGA tries to ensure that \( A(t) \) converges toward the \( \varepsilon \)-Pareto set \( \varepsilon P \) in an intelligently distributed manner along the Pareto frontier \( O(\theta P) \), but the memory resources are limited. It can also dynamically adjust the limits of the Pareto front and prevent the loss of solutions belonging to the front. Therefore, the objective space is divided into a fixed number of boxes. For each dimension \( i \in B \), \( box_i \) cells of \( \varepsilon_i \) width are created where.

This grid retains the diversity of \( O(\theta P) \), because each box can only be occupied by one solution in \( A(t) \), and at the same time generates intelligent distribution. The algorithm for dynamically adjusting the width \( \varepsilon_i \) is composed of three populations:

\[
\varepsilon_i = (O_i^{max} - O_i^{min}) / box_i
\]
\[ O_{\text{max}}^{\text{max}} = \max_{\theta \in \mathcal{P}_e} O_i(\theta) \] (4)

\[ O_{\text{min}}^{\text{min}} = \min_{\theta \in \mathcal{P}_e} O_i(\theta) \] (5)

Main population \( P(t) \) explores the searching space \( D \) during the algorithm iterations \( t \). Archive \( A(t) \) stores the solution \( \mathcal{S}_{P_0} \). Auxiliary population \( G(t) \).

This article establishes the S-C-Q objective function group with the goals of the shortest schedule, the smallest cost, and the best quality. The multi-objective optimization model is shown in equation (6).

\[
\begin{align*}
\min S &= \max \left\{ \sum_{i,j} d_{ij} \right\} \\
\min C &= \sum_{i,j} \left[ c_i^o + \alpha_i (d_i^m - d_i) + c_i^n - c_i^o + c_i^o (d_i^m - d_i) \right] \\
\max Q &= \left( \frac{100}{1 + 0.0185e^{-0.315R_{IRI}}} \right) + \frac{100 - SRI_{\text{min}}}{1 + 0.0185e^{-0.315R_{IRI}}} + \frac{SRI_{\text{max}}}{1 + 15.7e^{-0.315R_{IRI}}} \\
\end{align*}
\] (6)

In equation (6), \( d_{ij} \) means the duration between adjacent steps, \( c_i^o \) is direct cost, \( c_i^o \) is indirect cost, \( d_i^m \) is continuous duration, \( d_i^o \) is possible minimum duration, \( c_i^n \) and \( c_i^o \) are corresponding indirect cost. \( IRI \in [1.4, 1.5] \), the unit is m/km, \( SFC \in [40, 50] \), \( DR \in [0.001, 0.0015] \), \( l_k, l_0 \in [0.01, 0.012] \), the unit is mm, \( \alpha_i \) is a marginal increase factor, \( \in (0, 1) \).

Where schedule is measured in months, cost is in thousand, and quality is a dimensionless quantity. In this paper, \( \theta \) in ev-MOGA algorithm is a kind of hybrid multi-attribute parameters. Where \( d \) is set to \( \theta_1 \), \( c \) to \( \theta_2 \), \( IRI \) to \( \theta_3 \), \( DR \) to \( \theta_4 \), \( SRI \) to \( \theta_5 \), \( SFC \) to \( \theta_6 \), \( l_k \) to \( \theta_7 \). Since there is a complete set of technical reference standards for roadway maintenance program and the management of tendering and bidding is strict, thus, for the parameter \( \theta_2 - \theta_6 \), fine tuning is allowed within the error range of roadway maintenance standard. The major variable factors are \( c \) (cost) and \( d \) (duration).

3. Case Study

The primary issue revolves around the S-C-Q performance generated by the flexible variable factors in the engineering, such as the schedule arrangement of the engineering.

Figure 1. Flexible schedule arrangement.

As Figure 1 illustrated, it is supposed that steps of \( A, B \) and \( C \) start operating separately at \( t_i, t_j \) and \( t_k \), and the schedule corresponds to \( T_i, T_j, T_k \). Appropriate changes are available. Parameter settings: the searching space is three dimensional space. The crossover probability is 0.1–0.25. The aberrance scale is 20. The aberrance probability is 0.1. The Pareto set account reserved in each cycle is 100, the number of iterations is 100. After simulation, the Pareto front, set and the optimal solution were generated. The optimal solution of single objective satisfies the Pareto conditions, but the optimal solution of multi-objective is uncertain (Figure 2). This case chooses the optimal solution of single objective as the optimal ideal point and the shortest distance as a global multi-objective optimal solution through standard Euclidean distance calculations.
By setting ideal pointing (Figure 2), the multi-objective optimal value of roadway maintenance by calculating the distance is (11.7641, 1.50992, -11.5182). Compared with the ideal point, it is found out that the schedule stress does not achieve the optimized multi-objective and it is unrealistic to reduce cost. However, the construction is able to remain a pretty high level with punctual duration and controllable cost. The calculation results are much effective with the εv-MOGA algorithm due to the box setting of the optimized searching range, which is capable of handling the sudden emergency such as the weather and traffic in the roadway maintenance multi-objective decision.

4. Conclusion
Roadway maintenance not only needs to improve the overall service capacity of the road, but also tends to use detailed special road condition indicators as the selection criteria for maintenance measures, so as to integrate the achieved effects and choose economical and reasonable maintenance measures. This paper considers the roadway maintenance decision-making from the three goal systems of minimizing project schedule, minimizing cost and maximizing quality, establishes a multi-objective optimization model, and then uses the εv-MOGA to solve the multi-objective decision-making of roadway maintenance planning. The case analysis finally got an ideal solution, which shows that εv-MOGA is an effective algorithm for solving multi-objective optimization problems, which assists decision-makers to make optimal decisions.

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