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Optimization of Pavement Maintenance and Rehabilitation Activities Using Differential Evolution Algorithms

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Abstract—**A large number of publications have dealt with the computational efficiency of a novel evolutionary algorithm referred to as the differential evolution (DE) algorithm. The DE algorithm is able to optimally adjust the parameters in a dynamic and complex system such as a pavement management system. This study, which is based on real data, identifies maximization of pavement serviceability as the objective to efficiently optimize maintenance and rehabilitation (M&R) activities using the DE algorithm. It is clear that the DE algorithm is capable of searching based on the objective function under specified constraints for solving the optimization problem regarding pavement M&R activities.**

Keywords—**optimization, pavement, maintenance and rehabilitation, differential evolution**

I. Introduction

A pavement provides a steady, fast, and economic surface for road users. Good pavement conditions depend on effective collaboration among planning, design, construction, excavation management, and maintenance and rehabilitation (M&R) activities. Pavement conditions deteriorate with time owing to internal and external causes such as poor subgrades, defective drainage systems, unstable embankments, problematic quality control, traffic usage, material aging, and varying temperatures. Since pavement defects easily affect road users' safety, pavement engineers have to maintain pavement serviceability above an acceptable level by implementing timely and appropriate M&R activities [1]. If a pavement defect is not rapidly addressed, it can result in serious problems and significantly shorten the lifespan of the pavement. Hence, the optimization of M&R activities is very important. However, the resource allocation for M&R activities is usually performed by a ranking system (a prioritization method) or an optimization model (network optimization) [2] to search for optimal activities for maintaining pavements in a serviceable condition over a period of time. For prioritization methods, some priority-ranking criteria or a ranking matrix is used to prioritize M&R resource allocations to obtain alternative M&R activities. For network optimizations, a network optimization model with its objective functions and constraints is used to identify the optimal M&R activities, which is adopted in this study.

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The differential evolution (DE) algorithm is a population-based direct-search algorithm for global optimization [3]. The DE algorithm was initially proposed for unconstrained, continuous optimization problems. Its basic principle relies on the design of a simple mutation operator based on the linear combination of three different individuals and on a crossover step that mixes the initial and the mutated solutions. The mutation process included in a DE algorithm is not only simple but also important for efficiently obtaining optimal solutions. DE algorithms have been rarely used in pavement engineering and management application. In this study, a network optimization model based on the objective of maximizing pavement serviceability is proposed to identify optimal M&R activities via the DE algorithm. Real data from the Taiwan Area National Freeway Bureau (TANFB) were collected to conduct an empirical study to reveal and verify the feasibility of the model.

The remainder of this paper is organized as follows. The second section reviews prioritization and optimization in pavement management. The third section briefly reviews the DE algorithm. The fourth section elaborates the model development and conducts an empirical study by using the DE algorithm according to the actual situation in Taiwan. The analytical results are demonstrated and discussed. Finally, the conclusions are summarized in the fifth section.

II. Review of Optimization in Pavement Management

Pavement inspections are periodically performed via both man-made and automatic approaches to collect large amounts of pavement condition data. Based on this data, existing pavement conditions are represented using specified indexes such as present serviceability index (PSI), pavement condition index (PCI), and international roughness index (IRI) to assist in M&R resource allocations. A number of methodologies are commonly adopted to allocate M&R resources. They are generally categorized into prioritization methods and network optimizations [1, 4-6]:

- Prioritization models are used to categorize and rank the entire pavement sections by using simple priority-ranking criteria to establish the ranking of a pavement section without considering the future performance of the pavement. The common ranking factors include pavement type, pavement conditions, traffic volume, pavement age, roughness, friction, and structural capacity. The M&R resources are allocated according to the ranking and priority assigned to it. The

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prioritization model is suitable for project-level pavement management.

- Network optimization models identify network M&R activities. The objectives can be specified as maximizing the performance of a complete pavement network, minimizing the total network cost, and/or minimizing the total M&R cost subjected to constraints such as acceptable serviceability and budget limits [1]. The pavement condition data are used as inputs to the model while decision variables represent the application of feasible M&R activities to pavement sections. Further, resource limits act as constraints. A network optimization model is suitable for network-level pavement management that concentrates on the entire pavement network, which uses M&R performance as objective functions with budget limitations [7].

According to a review of a survey conducted in 1991 [8], the percentage of most U.S. state highway agencies that implement and plan to implement a prioritization model are 77% and 2%, respectively. This is shown in Table I. Meanwhile, the percentage of states that have and plan to implement a network optimization model are 28% and 19%, respectively. Note that the total percentage exceeds 100% as some states implement both a prioritization model and an optimization model. According to Table I, thirteen states use optimization models but just four techniques are used in the optimization models, as shown in Table II. Linear programming is the most common programming technique to allocate M&R resources. In addition, other programming techniques such as dynamic programming are also proposed [9-12].

TABLE I. METHODOLOGIES FOR M&R ACTIVITIES USED IN THE U.S.

Prioritization/Optimization	Number	Percentage
no methodologies adopted	4	0
prioritization model	36	77
plans for prioritization model	1	2
optimization model	13	28
plans for optimization model	9	19

TABLE II. TECHNIQUES USED IN OPTIMIZATION MODELS

Technique	Number	Percentage
linear programming	7	55
integer programming	2	15
incremental benefit-cost	2	15
marginal cost-effectiveness	2	15

All M&R activities cannot be funded and implemented within one or even within a few years due to resource constraints. The decision-making task of M&R activities has to identify specific objectives and constraints. The programming methodology searches for feasible solutions to decision variables that optimally satisfy specific objective functions and constraints. The common objective functions and constraints are summarized in Tables III and IV, respectively. Note that the total percentage in Table III exceeds 100% as some optimization models have more than one objective function.

TABLE III. OBJECTIVE FUNCTION USED IN OPTIMIZATION MODELS

Objective Function	Number	Percentage
minimize cost	8	62
maximize area under performance curve	5	39
minimize disutility	1	8
maximize maintenance effectiveness	1	8

TABLE IV. CONSTRAINTS USED IN OPTIMIZATION MODELS

Constraint	Number	Percentage
budget	13	100
minimal pavement condition requirement	5	39
resources	2	15
other	5	39

This study takes network-level pavement management into account to identify one objective function, namely maximizing pavement serviceability, to determine the optimal M&R activities via the DE algorithm.

III. Differential Evolution (DE) Algorithm

The DE algorithm computes the optimal solution based on the characteristic of a swarm, which strengthens the searching ability in both local and global domains. The DE algorithm has the same mutation, crossover, and selection operations as a genetic algorithm (GA); it also has the same randomly-searching mechanism as a particle swarm optimization (PSO) algorithm. Compared to a GA, the DE algorithm bears the advantages of setting fewer parameters and easy of operations; meanwhile, compared to a PSO, the DE algorithm can obtain more diverse solutions.

The operations of a standard DE algorithm (as shown in Fig. 1) includes five stages, namely initialization, mutation, crossover, selection, and stopping condition verification. Suppose that one would like to minimize a cost objective function $f(X)$, the number of decision variables is D. Each of the stages are elaborated in Fig. 1 [13, 14].

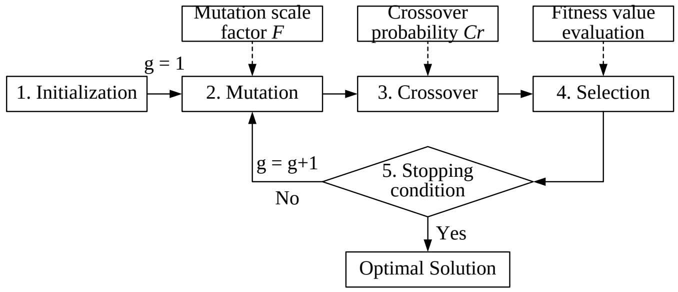

Figure 1. Differential evolution algorithm [14].

- Initialization: the DE algorithm commences the search operation by randomly generating an NP number of D -dimensional parameter vectors $X_{i,g}$, where $i = 1, 2, \ldots, NP$ and g represents the current generation. In the DE algorithm, NP does not change during the optimization process [15]. In addition, the

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initial population, $g=0$, is randomly generated to cover the entire search space.

- Mutation: A vector in the current population is referred to as a target vector. For each target vector, a mutant vector is produced through the following equation [15]:

$$V_{i,g+1}=X_{r_1,g}+F\cdot\left(X_{r_2,g}-X_{r_3,g}\right)$$

where r_1, r_2, and r_3 are three random indices and $r_1,r_2,r_3\in[1,NP]$, are integers and are mutually different and $r_1\neq r_2\neq r_3\neq i$. F is a real number ($F>0$) and a mutant scale factor that controls the amplification of the differential variation $\left(X_{r_2,g}-X_{r_3,g}\right)$. Meanwhile, $V_{i,g+1}$ represents the newly created mutant vector.

- Crossover: In order to increase the diversity of the current population, the crossover stage is conducted by exchanging components of the target vector and the mutant vector. In this stage, a new vector named the trial vector, is created. The trial vector is also referred to as the offspring. The following trail vector $U_{j,i,g+1}$ is adopted:

$$U_{j,i,g+1}=\left(U_{1,i,g},U_{2,i,g},\ldots,U_{D,i,g}\right)^{I}$$

$$U_{j,i,g+1}=\begin{cases}V_{j,i,g+1}, & if\ rand_j\leq Cr\ or\ j=rnb(i)\\ X_{j,i,g}, & if\ rand_j>Cr\ and\ j\neq rnb(i)\end{cases}$$

where j denotes the element index for any vector and $rand_j\in[0,1]$ is a uniform random number. Cr is a user-defined crossover rate, and F and Cr are both generally in the range $[0.5,1.0]$. Meanwhile, $rnb(i)$ is a randomly chosen index from $[1,D]$ which guarantees that at least one parameter from the mutant vector $\left(V_{j,i,g+1}\right)$ is copied to the trial vector $\left(U_{j,i,g+1}\right)$.

- Selection: In order to decide whether the new vector U shall become a population member at generation $g+1$, it is compared to $X_{i,g}$. If vector U yields a smaller objective function value than $X_{i,g}$, $X_{i,g+1}$ is set to U, otherwise the old value $X_{i,g}$ is retained. The selection operator is expressed as follows:

$$X_{i,g+1}=\begin{cases}U_{i,g} & if\ f\left(U_{i,g}\right)\leq f\left(X_{i,g}\right)\\ X_{i,g} & if\ f\left(U_{i,g}\right)>f\left(X_{i,g}\right)\end{cases}$$

- Stopping condition verification: The optimization process terminates when the stopping criterion is met. The stopping criterion can be assigned by a user. In general, maximum generation $\left(G_{\max}\right)$ or maximum number of function evaluations can be adopted as the stopping criterion. When the optimization process terminates, the final optimal solution is obtained.

IV. Empirical Study: The Optimization of Pavement M&R Activities via the DE Algorithm

Since defects on pavements are easily perceived by road users, pavement engineers are responsible for maintaining desired levels of serviceability by implementing appropriate and timely M&R activities.

A. *Analytical Model*

M&R activities are implemented to improve pavement serviceability. Therefore, based on the actual situation in Taiwan (annual M&R budget must be completely exhausted every year, that is, any surplus cannot be carried over to the following year), this study identifies one objective, namely maximization of pavement serviceability, for the analytical model. The optimal solution can be obtained via the DE algorithm by optimizing the objective.

The literature states that surface roughness and surface distress are the two principal factors that are commonly considered for the optimization of pavement M&R activities. Pavement surface roughness is one of the most important pavement performance measures in pavement construction quality control [16]. Surface roughness may occur as a result of the construction process, road use, or in some cases a combination of both factors [17]. Roughness represents the longitudinal evenness and is indexed by using the International Roughness Index (IRI). The smaller the IRI, the more even the pavement surface is; in other words, the higher the pavement serviceability. This empirical study uses the IRI data collected on a freeway which mainly provides an even pavement for road users. Hence, it is reasonable to use IRI as the factor for optimizing M&R activities. Note that the objective should present "maximizing pavement serviceability", but since a smaller IRI represents better pavement serviceability, this objective function is minimized. The optimization model and relevant notations are expressed as follows:

$$Min \qquad f=\sum_{i=1}^{I}\sum_{j=1}^{J}\left(X_i\cdot M_j\right)\cdot IRI_{ij}$$

subject to

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\left(X_i\cdot M_j\right)\cdot C_j\cdot A_i\leq B$$

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\left(X_i\cdot M_j\right)\leq D$$

$$\sum_{j=1}^{J}\left(X_i\cdot M_j\right)\leq 1 \quad \forall i=1,2,\cdots,I$$

where

I : total number of pavement sections

J : total number of M&R activities (frequently implemented M&R activities in Taiwan are 1.5 cm milling and overlay, direct overlay, and localized repair, which are denoted as j=1, 2, *and* 3, respectively. Meanwhile, j=4 indicates that no M&R activity is required)

i : candidate sections, $i \in \{1, 2, \cdots, I\}$

j : applicable M&R activities, $j \in \{1, 2, \cdots, 4\}$

$X_i \cdot M_j$: M&R activity j implemented on section i

C_j : unit cost of M&R activity j

IRI_{ij} : the roughness of section i implementing M&R activity j

A_i : M&R area of section i

B : allowable annual budget

D : the number of M&R projects that a road agency can handle

B. *Analytical Data*

The flexible pavements on the third National Freeway in Taiwan are selected as the analytical network, and the analytical data are obtained from the TANFB. The entire length of the network is 67.968 km (from 042k+000 to 109k+698). In the network, the length of a 6-lane section is 35.258 km, the length of a 7-lane section is 20.454 km, and the length of an 8-lane section is 11.462 km. The lane-km and integer mileage are used to divide the network into analytical units. For example, a 1-kilometer section (from 042k+000 to 043k+000) is subdivided into four analytical units since it has four lanes. Based on this principle, the entire network is subdivided into 387 analytical units for the analytical model.

C. *Tools and Parameter Settings for the DE Algorithm*

The EvA2 (an Evolutionary Algorithms framework, revised version 2) [18], as shown in Fig. 2 and Fig. 3, is used to solve the analytical model. EvA2 is a comprehensive heuristic optimization framework with emphasis on evolutionary algorithms implemented in Java. EvA2 integrates several derivation free optimization methods including the DE algorithm.

The relevant parameters using the DE algorithm are listed in Tables V. For each test, the total number of iterations equal to 500 is employed as the stopping criterion when a population of $P = 50$ is used. The result is averaged over 10 random runs.

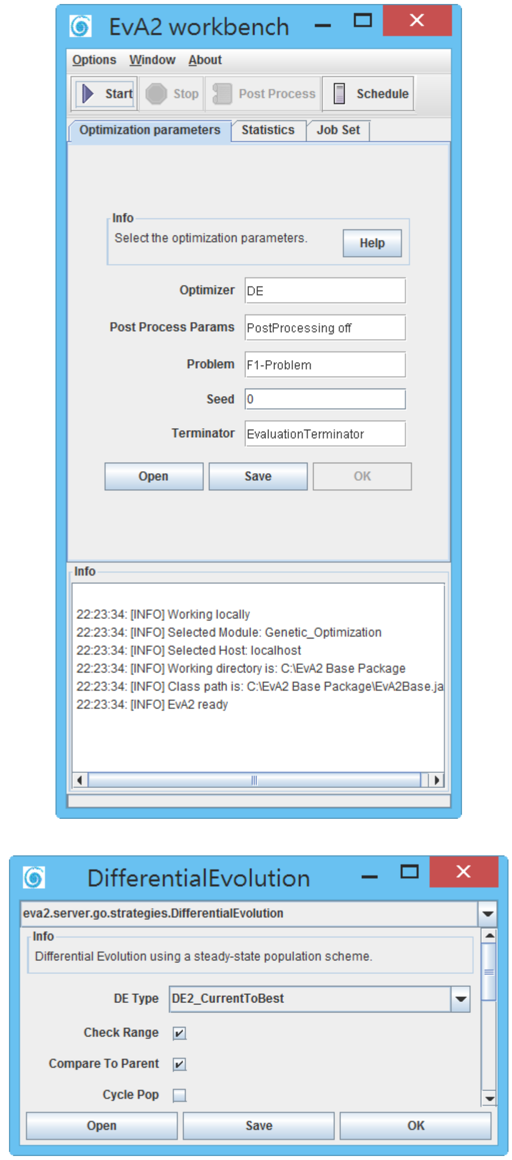

Figure 2. EvA2 base package [18].

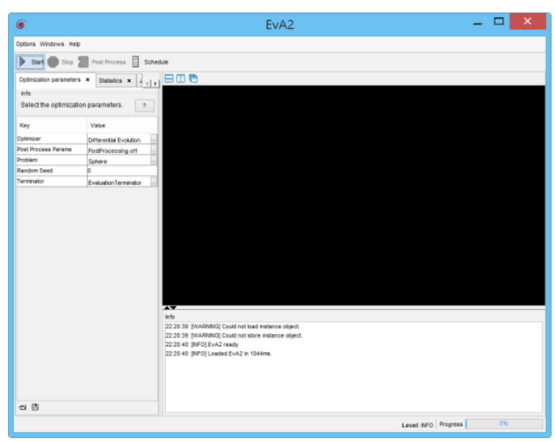

Figure 3. Development build [18].

TABLE V. EXPERIMENTAL PARAMETERS USING THE DE ALGORITHM.

Parameter	Description	Range
Cr	crossover rate	0.9
F	mutant factor	0.5
g	total number of iterations	500
P	population size	50

D. Results and Discussion

EvA2 is used to solve the analytical model. The results are obtained while satisfying the objective under the constraints. The maximization of pavement serviceability (387 analytical units) is 19,658,235. It is assumed that the annual budget is US$ 160,000 (NT$ 5 million), the road agency can handle twelve projects per year, and every project costs around US$ 13,000 (NT$ 420,000).

V. Conclusions

The DE algorithm searches for the optimal solution based on the characteristics of a swarm. Compared to a GA, the DE algorithm bears the advantages of fewer parameter settings and easy of operations; meanwhile, compared to a PSO, the DE algorithm can yield more diverse solutions. This paper considers the relevant literature and actual M&R activities in Taiwan, and identifies maximization of pavement serviceability as the objective to efficiently optimize M&R activities via the DE algorithm. It is clear that the DE algorithm is capable of searching based on the objective function under the specified constraints to solve the optimization problem of pavement M&R activities. Research is currently underway for selecting proper parameters for the DE algorithm in order to yield a more adequate optimal values more efficiently.

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