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Maintenance optimization of infrastructure networks using genetic algorithms

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Abstract

This paper presents an approach to determining the optimal set of maintenance alternatives for a network of infrastructure facilities using genetic algorithms. Optimal maintenance alternatives are those solutions that minimize the life-cycle cost of an infrastructure network while fulfilling reliability and functionality requirements over a given planning horizon. Genetic algorithms are applied to maintenance optimization because of their robust search capabilities that resolve the computational complexity of large-size optimization problems. In the proposed approach, Markov-chain models are used for predicting the performance of infrastructure facilities because of their ability to capture the time-dependence and uncertainty of the deterioration process, maintenance operations, and initial condition, as well as their practicality for network level analysis. Data obtained from the Ministére des Transports du Québec database are used to demonstrate the feasibility and capability of the proposed approach in programming the maintenance of concrete bridge decks.

Keywords: Maintenance optimization; Concrete deck; Markov chain; Genetic algorithm; Infrastructure management

1. Introduction

The life-cycle cost analysis is a decision-making approach that evaluates the total cost accrued over the entire life of an infrastructure facility from its construction to its replacement or final demolition [13]. For an existing facility, the life-cycle cost analysis is considered an efficient approach for comparing the long-term impacts of different maintenance strategies and identifying the optimal ones. Fig. 1 shows an example of the performance profile of an infrastructure facility when two different maintenance strategies that are technically acceptable (i.e. satisfy performance requirements) are implemented. Using the life-cycle cost approach allows the decision maker to compare the two strategies from the economic perspective and determine the most cost-effective one over a certain planning horizon. This is extremely important for most

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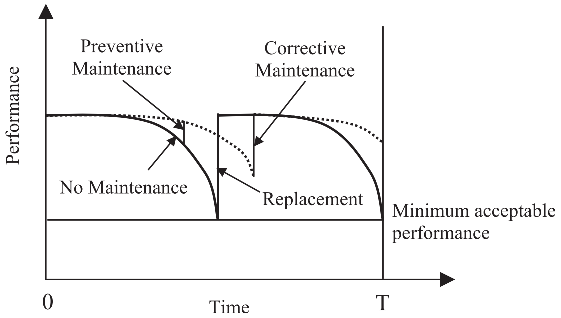

Fig. 1. Performance profiles of two different maintenance strategies.

facility managers because of the limitations on the availability of resources required to fulfill even urgent maintenance needs.

Infrastructure management systems have been developed to apply the life-cycle costing approach to optimize maintenance decisions at both network and project levels and achieving network/project performance requirements under financial constraints. Since the early 1980s, many optimization techniques have been adopted for this purpose, such as optimal control theory, linear and nonlinear programming, dynamic programming, and integer programming [10,14,19]. Although these optimization techniques have provided satisfactory results, many agencies still prefer using traditional methods of maintenance optimization in spite of their arbitrary nature and relatively low degree of accuracy. These methods are mostly heuristic and based on subjective ranking and priority rules developed by domain experts. The reason of this preference is due in-part to the mathematical complication of formulating a maintenance optimization problem using these techniques in addition to the computational complexity associated with large size networks.

Genetic Algorithms (GAs) are robust, practical, and general-purpose stochastic search-based optimization techniques that can provide a comparable level of accuracy while being more efficient than conventional optimization techniques. GAs were developed by Holland in the early 1970s based on the principles of natural selection and genetics [12]. Since the early 1990s, GAs have been extensively used by many researchers in civil engineering for solving global optimization problems, such as the design of structures and transportation networks [25,28]. Although the area of global optimization comprises several techniques, such as simulated annealing, and Tabu Search, GAs are highly recognized for their computational efficiency. This is mainly because other techniques select a single solution and randomly change it until it reaches the best solution, which requires several iterations. GAs, on the other hand, store multiple solutions to the problem (i.e. population) and use probabilistic rules to generate new and better populations, which is more efficient and increases the likelihood of finding optimal solutions in a timely fashion [11]. In addition, GAs use information on the objective function only and do not require any information on its gradients, which greatly simplifies the mathematics of the problem.

The use of GAs in maintenance optimization has been introduced by Fwa et al. [7] in an investigation that led to the development of a computer model, known as PAVENET, for maintenance planning of pavement networks. Updated versions of this model were developed to demonstrate the use of GAs in solving the trade-off between maintenance and rehabilitation activities and resolving the complexity of multiobjective problems [5,6]. Liu et al. [15] and Miyamoto et al. [22] also developed GA-based models for the determination of optimal long-term maintenance strategies of bridge deck networks. In all these investigations, linear and nonlinear deterministic models were used for predicting the future condition of a pavement section or a bridge deck as a function of its initial condition, governing deterioration parameters, and impact of maintenance alternatives. This is because of the simplicity and computational efficiency of deterministic deterioration models. However, these models neglect the uncertainty due to the stochastic nature of infrastructure deterioration and presence of unobserved variables and measurement errors.

State-of-the art infrastructure management systems, such as Pontis, BRIDGIT, and MicroPAVER, use stochastic Markov chains for predicting the future condition of infrastructure components, systems, and networks [9,27]. A Markov chain is a special case of the Markov process whose development can be treated as a series of transitions between certain states. A stochastic process is considered as a Markov process if the probability of a future state in the process depends only on the present state and not on how it was attained [24]. Markov-chains are used as performance prediction models for infrastructure by defining discrete condition states and accumulating the probability of transition from one condition state to another over multiple discrete time intervals [1]. These stochastic models have two main advantages over deterministic models. First, they are able to capture the considerable randomness that affects the performance of structures due to uncertainties in initial condition, applied stresses, condition assessment, and inherent uncertainty of the deterioration process [16]. Second, they are incremental models that account for the current condition in predicting the future condition [18]. Moreover, Markov-chain models are practical in dealing with large-sized networks due to their computational efficiency and simplicity of use.

The objective of this paper is to present an approach that uses genetic algorithms in conjunction with Markov-chain models for programming maintenance alternatives. The proposed approach is expected to enhance the capability and efficiency of the optimization module in the existing infrastructure management systems. The first section presents the proposed formulation of the maintenance optimization problem. The second section presents the solution of this problem using a genetic algorithm. The last section demonstrates the feasibility of the proposed approach using an application example on concrete bridge decks.

2. Problem formulation

From a review of the literature, the only maintenance optimization model that combines the use of Markov-chain models and genetic algorithms is the pavement management optimization model proposed by Ferreira et al. [4]. This model is a segment-linked model that identifies the segments of the road network where maintenance actions should be applied every year in the planning horizon. The decision variables in this model represent the instruments that can be applied to change the state of each segment. This is practical when there is a small number of segments, however, it is computationally inefficient for a network with a large number of segments, which is the case of most infrastructure networks. To address this problem, the proposed formulation of the maintenance optimization problem classifies infrastructure facilities into groups according to some explanatory variables, such as type, material properties, operating loads, and environmental conditions, which govern the facility performance. In this formulation, all facilities of the same group are assumed to have the same performance characteristics and should be analyzed in a similar manner. The objectives of such a classification are threefold: (i) achieve reliable performance modeling; (ii) reduce the computational complexity of the optimization problem; and (iii) provide the decision maker with the flexibility to select the specific facility that will be treated in every year according to some other intangible factors (e.g. social, environmental, political, etc.) that cannot be easily considered in the formulation. The parameters of the proposed formulation are defined as follows:

G=number of facility groups;
T=number of years in the planning horizon;
S=number of condition states in the adopted rating system;
Q_g=total quantity of facilities in group g (number of units, length, or area);
M_g=number of possible maintenance alternatives for facilities in group g;
$\boldsymbol{D}_{gt}$=condition vector ($1\times S$) of group g at the beginning of year t;

$$\boldsymbol{D}_{gt} = \left| d_{gt}^{1} \quad d_{gt}^{2} \quad \ldots \quad d_{gt}^{s} \right| \tag{1}$$

where, d_{gt}^{s}=percentage of facilities from group g in condition state s at year t. $\mathbf{P}_{gm}$=transition probability matrix ($S\times S$) of group g when the maintenance alternative m is implemented;

$$\boldsymbol{P}_{gm} = \begin{vmatrix} p_{gm}^{1,1} & p_{gm}^{1,2} & \ldots & p_{gm}^{1,S} \\ p_{gm}^{2,1} & p_{gm}^{2,2} & \ldots & p_{gm}^{2,S} \\ & & \ldots & \\ & & \ldots & \\ p_{gm}^{S,1} & p_{gm}^{S,2} & \ldots & p_{gm}^{S,S} \end{vmatrix} \tag{2}$$

where, $p_{gm}^{i,j}$=transition probability of group g from condition state i to condition state j during 1 year when the maintenance alternative m is implemented.

Transition probabilities are obtained either from accumulated condition data or by using an expert judgment elicitation procedure, which requires the participation of domain experts [26].

$\boldsymbol{X}_{gmt}$=maintenance vector ($1\times S$) of group g for maintenance alternative m during year t;

$$\boldsymbol{X}_{gmt} = |\, x_{gmt}^{1} \quad x_{gmt}^{2} \quad \dots \quad x_{gmt}^{S} \,| \tag{3}$$

where, x_{gmt}^{s}=percentage of facilities in group g and condition state s that had the maintenance alternative m during year t.

$\boldsymbol{C}_{gm}$=cost vector ($S\times 1$) of group g and maintenance alternative m.

$$\boldsymbol{C}_{gm} = \begin{vmatrix} c_{gm}^{1} \\ c_{gm}^{2} \\ \cdot \\ \cdot \\ c_{gm}^{S} \end{vmatrix} \tag{4}$$

where, c_{gm}^{s}=unit cost of implementing maintenance alternative m on the facilities in group g and condition state s (these unit costs have to be adjusted for inflation when long planning horizons are used).

The condition of facilities from group g at year t can be predicted using the initial condition vector at year ($t-1$) and the transition probability matrices corresponding to the maintenance alternatives taken during this year multiplied by the maintenance vectors of this year as follows:

$$D_{gt} = \sum_{m=1}^{m=M_g} D_{g(t-1)}\left(\boldsymbol{I}\boldsymbol{X}_{gm(t-1)}\right)\mathbf{P}_{gm} \tag{5}$$

where, $\boldsymbol{I}$ is a unit vector ($S\times 1$)

This equation corresponds to the Chapman–Kolmogorov equations that define the multi-step transitions for any values of the time t that is greater than or equal to 1 and less than or equal to T. The present value of the total cost of maintenance alternatives implemented on facilities from group g over the entire planning horizon T, denoted PV_g^T, assuming a discount rate r, can be calculated as follows:

$$PV_g^T = Q_g \sum_{t=1}^{t=T} \sum_{m=1}^{m=M_g} \frac{\boldsymbol{D}_{gt}\left(\boldsymbol{I}\boldsymbol{X}_{gmt}\right)\boldsymbol{C}_{gm}}{(1+r)^t} \tag{6}$$

The users' costs and failure costs can be discounted and added to the above maintenance cost to obtain the total cost when adequate data become available. Considering the maintenance costs only, the objective is to minimize the sum of the present value of the maintenance costs of all facility groups while keeping the condition of every group at any time above a predefined threshold value. The optimization problem can be formulated as follows:

$$\text{Minimize} \quad \sum_{g=1}^{g=G} PV_g^T \tag{7a}$$

$$\text{Subject to:}\ \boldsymbol{D}_{gt}^{\mathrm{Cum}} \geqslant \boldsymbol{D}_{g}^{\mathrm{Thr}} \tag{7b}$$

where $\boldsymbol{D}_{\mathrm{gt}}^{\mathrm{Cum}}$ is the cumulative condition vector of group g at the beginning of year t, which contains the percentages of facilities whose condition is equal to or higher than a given condition state. $\boldsymbol{D}_{\mathrm{g}}^{\mathrm{Thr}}$ is the threshold condition vector ($1\times S$) of group g, which represents the minimum acceptable conditions that will be compared with the cumulative condition vector in every year. The threshold conditions are determined by the facility managers or domain experts based on their condition requirements and budget availability (i.e. user defined). The threshold condition vectors represent the constraints of the cost minimization problem that differ also from one group to another. This is because the definition of facility groups considers governing deterioration parameters that implicitly represent the importance and vulnerability of the infrastructure and, consequently, control the determination of the minimum acceptable condition. For instance, bridge decks on express highways with high traffic volume are more important than those on collector highways with low traffic volume. Therefore, the minimum acceptable condition of bridge decks on an express highway is higher than that of bridge decks on a collector highway. Other constraints, such as non-negativity constraints, are applied to this optimization model in order to guarantee the feasibility of the solutions obtained.

The previous optimization problem is based on cost minimization. However, in some cases where there are constraints on the maintenance budget available for every year in the planning horizon, the optimization problem can be formulated differently as a quality maximization problem. In this case, the objective function tends to maximize the average network condition given the annual budget constraints. The maintenance optimization problem can be formulated as follows:

$$\text{Maximize} \quad \frac{\sum_{s=1}^{s=S} S \sum_{t=1}^{t=T} \sum_{g=1}^{g=G} d_{gt}^{s}}{TG} \tag{8a}$$

$$\text{Subject to}: \quad \sum_{g=1}^{g=G} Q_g \sum_{m=1}^{m=M_g} \boldsymbol{D}_{gt} \boldsymbol{I} \boldsymbol{X}_{gmt} \boldsymbol{C}_{gm} \leqslant B_t \tag{8b}$$

where, B_t is the maintenance budget available for year t. The following section demonstrates the use of GA optimization techniques to solve the cost minimization problem presented in Eqs. (7a) and (7b). However, the same procedures can be applied to solve the quality maximization problems presented in Eqs. (8a) and (8b).

3. Maintenance optimization using Genetic Algorithms

Fig. 2 shows a simplified flow chart of the process of problem-solving using GAs. This process starts with identifying the parameters that describe the solutions of the given problem and determining its objective function and constraints (which were presented in the problem formulation). The following step is encoding the problem solutions into genetic representation (i.e. chromosomes). In this representation, each solution contains several genes that can be manipulated by the genetic operators described later. These genes are represented by a string of symbols that can be obtained using different encoding methods [8]. A binary encoding method is used for the current problem because it allows fast computation and easy manipulation of genes [22]. Three issues have to be considered when encoding and decoding between chromosomes and solutions: feasibility, legality, and uniqueness of mapping. Feasibility means that the decoded solutions lie in the feasible region of the given problem, which is determined by the problem constraints. Legality refers to whether decoding chromosomes results in meaningful solutions. Uniqueness of mapping means that each chromosome can be decoded into a single solution. The one-to-one mapping is considered the best mapping method since it allows easy and fast decoding. However, this method may yield a number of illegal chromosomes having lethal genes, which decreases the efficiency of calculation. Therefore, a trade-off between the simplicity of mapping and legality of solutions is required for a good genetic representation.

Fig. 3 shows the genetic representation of an individual solution for the current problem. This solution identifies the percentages of facilities in each group (g) and condition state (s) that are subjected to each maintenance alternative (m) in every year (t). For each maintenance alternative, a 5-bit binary code is used to express 32 different values. The values corresponding to different maintenance alternatives are divided by their total sum to calculate the percentages of facilities that are subjected to each maintenance alternative. Fig. 4 shows an example for the binary code of three maintenance alternatives. The percentages of facilities subjected to each alternative are 50%, 21%, and 29% based on the ratio of the decoded value relative to the sum of all decoded values. Although this is considered to be an indirect and complicated mapping method, it eliminates the presence of lethal genes that negatively affects the computational efficiency of the GA.

Then, the GA randomly selects an initial pool of solutions, referred to as the parent pool or population, with a predefined size. The individuals of this population are evaluated using the so-called “fitness function”, which is determined based on the objective function and the constraints presented earlier. For cost minimization problems, the fitter individual is the one with lower present value of the total maintenance costs. Since the maintenance programming is a constraint optimization problem, the penalty method is used to account for the constraints and ensure the feasibility of the obtained solutions. If an individual does not satisfy the condition constraint (i.e. facility condition is less than the threshold values), a penalty is applied in the form of extra maintenance cost. This reduces the fitness value of the individual and decreases its probability of being selected in the next generation. Performance prediction models and cost models are necessary inputs to the evaluation of candidate solutions.

Two processes are implemented on the parent pool to generate a new pool of solutions, referred to as the offspring pool. Selection is the first process and is considered the driving force of the GA since its selects

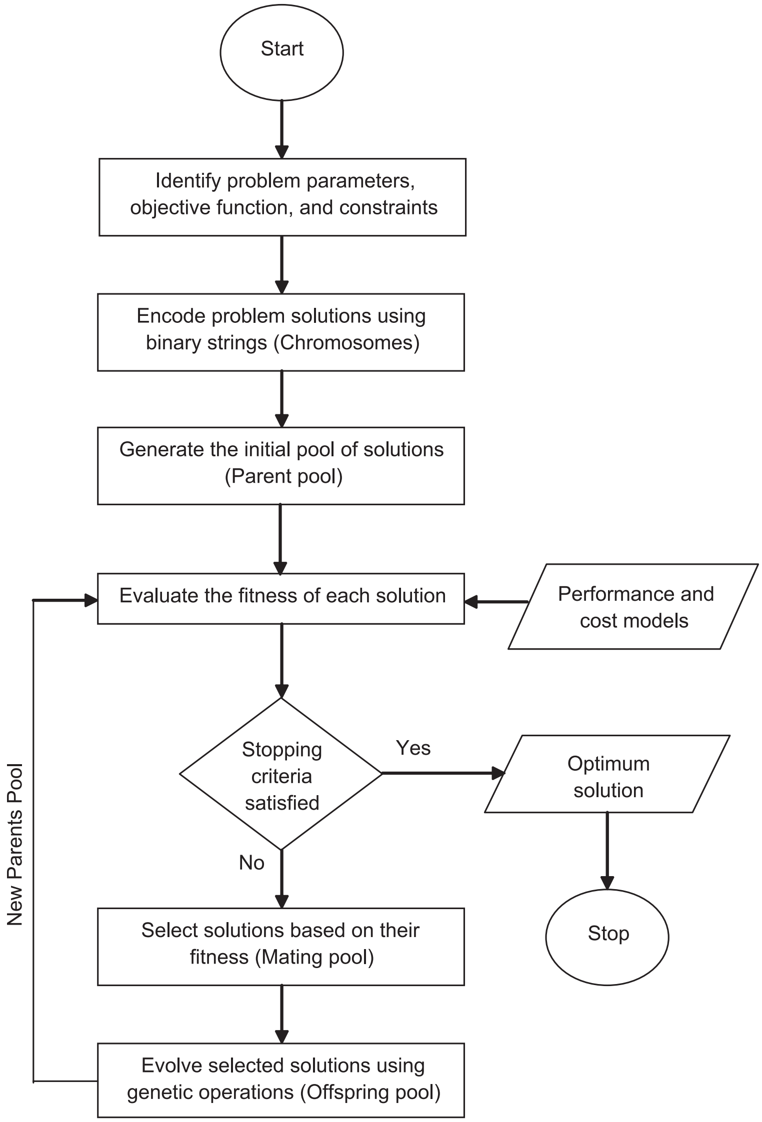

Fig. 2. Flow chart of problem solving using genetic algorithm.

the most promising chromosomes from the parent pool and generates a mating pool that has the same number of chromosomes. Several selection schemes, such as roulette-wheel, tournament selection, and linear and exponential ranking selection, can be adopted [3]. For the current problem, the roulette-wheel scheme was used, which is a common stochastic procedure that correlates the probability of selection for each chromosome to its fitness value calculated earlier. Evolution is the second process in which the chromosomes of the mating pool are manipulated by two genetic operations, crossover and mutation, in order to produce a new offspring pool. In the crossover operation, pairs of parent chromosomes are randomly selected with probability (p_c) and each pair exchanges the genes of the two chromosomes at a crossing site randomly selected to accelerate the search. This operation produces off-spring solutions that have combined features from the parent solutions, which is known as "exploitation". A

Group (*g*)	1								… G							
Year (*t*)	1				… T				1				… T			
State (*s*)	1		… S		1		… S		1		… S		1		… S	
Maintenance (*m*)	1	… M	1	… M	1	… M	1	… M	1	… M	1	… M	1	… M	1	… M
String	0	1	1	1	0	1	1	0	1	1	0	0	1	0	1	0
	1	0	1	1	1	1	1	0	1	0	0	0	1	0	0	1
	0	0	1	0	0	0	0	0	0	1	1	0	1	1	0	1
	1	1	1	1	0	0	1	1	0	0	0	0	1	1	0	0
	0	0	0	1	0	0	1	0	0	0	0	0	1	1	1	0

Fig. 3. Genetic encoding of problem solutions.

high crossover probability allows the generation of promising solution quite fast. In the mutation operation, parent chromosomes are selected and their genes are changed randomly from 0 to 1, or vice versa, and with probability (p_{m}) to conduct a random search. This operation introduces random changes into a small fraction of solutions to try potential solutions that have never been selected while it avoids being trapped in a local optima, which is known as "exploration". A very low mutation probability reduces the possibility of exploring new solutions, while a very high mutation probability may seriously affect the convergence of solutions.

The resulting population is then evaluated using the fitness function and used as a new parent population. The selection and evolution processes are repeated iteratively until a predefined stopping criterion is satisfied. This criterion may specify the maximum number of iterations, minimum improvement in the average fitness, or both. The optimum solution is determined as the solution that has the highest fitness in these iterations.

	Maintenance Alternatives 1	2	3	
	1	1	0	
	0	1	1	
	0	1	0	
	0	0	1	
	1	0	0	
Value	17	7	10	34
Percentage	50%	21%	29%	100%

Fig. 4. Example for decoding a solution.

4. Application

Highway bridges are considered the most critical and vital links in any transportation network because the full or partial failure of these links affects significantly the overall performance of the network and may lead to catastrophes and serious economic impacts. Concrete bridge decks are the weakest links and the most expensive elements of most bridge systems in North America and Europe, from durability point of view [2]. This is mainly due to the effects of the corrosion of reinforcing steel because of using deicing chemicals in winter, freezing and thawing cycles, and direct exposure to traffic loads [17]. Concrete bridge decks are selected as a "proof of concept" application of the proposed approach, however, the same procedures can be applied to other infrastructure facilities.

The data required for developing Markov-chain models of concrete bridge decks are obtained from the Ministére des Transports du Québec (MTQ) database, which is part of a comprehensive system for managing highway structures in Québec. This database includes inventory data, which consists of bridge identification, description, environment, and geometry; condition data, which contains the results of the detailed visual inspections carried out on all bridges approximately every 3 years; and maintenance data, which includes the estimated costs and expected times for recommended maintenance and rehabilitation activities. The condition data comprises two condition ratings [20]: (i) material condition rating (MCR), which represents the condition of an element based on the severity and extent of observed defects, and (ii) performance condition rating (PCR), which describes the condition of an element based on its ability to perform the intended function in the structure. Both the MCR and

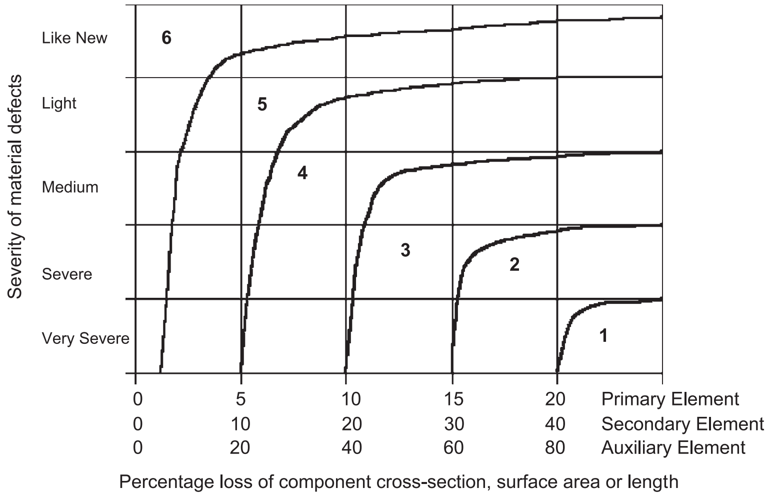

Fig. 5. Material condition rating system used by MTQ (MTQ 1995).

PCR are represented in an ordinal rating scale that ranges from 1 to 6, where 6 represents the condition of a new and undamaged element. Because MCR is the governing parameter in most of MTQ maintenance decisions, transition probability matrices are developed for MCR only. Fig. 5 shows how the MCR of an element is determined given the type of element (i.e., primary, secondary, or auxiliary), percentage of the material defects in the element cross-section, surface area, or length, and the severity of these defects (i.e. very low, low, medium, severe, and very severe).

The MTQ data are screened by filtering out the records with missing or inconsistent condition data, which resulted in data for 9181 concrete bridge decks. Each deck consists of seven elements that are evaluated in every inspection: wearing surface, drain-

	6	5	4	3	2	1
6	0.98	0.02	0	0	0	0
5	0	0.96	0.04	0	0	0
4	0	0	0.93	0.07	0	0
3	0	0	0	0.84	0.16	0.0
2	0	0	0	0	0.92	0.08
1	0	0	0	0	0	1.00

Benign environment

	6	5	4	3	2	1
6	0.93	0.07	0	0	0	0
5	0	0.93	0.07	0	0	0
4	0	0	0.94	0.06	0	0
3	0	0	0	0.94	0.06	0
2	0	0	0	0	0.90	0.10
1	0	0	0	0	0	1.00

Low environment

	6	5	4	3	2	1
6	0.83	0.17	0	0	0	0
5	0	0.86	0.14	0	0	0
4	0	0	0.95	0.05	0	0
3	0	0	0	0.91	0.09	0.0
2	0	0	0	0	0.84	0.16
1	0	0	0	0	0.0	1.00

Moderate environment

	6	5	4	3	2	1
6	0.77	0.23	0	0	0	0
5	0	0.81	0.19	0	0	0
4	0	0	0.87	0.13	0	0
3	0	0	0	0.93	0.07	0
2	0	0	0	0	0.88	0.12
1	0	0	0	0	0.0	1.00

Severe environment

Fig. 6. Transition probability matrices of concrete bridge decks with AC overlay for “do-nothing” maintenance alternative.

Table 1
Maintenance alternatives and unit costs for bridge decks with AC overlay

Condition state	Alternative 1: "Do-nothing"		Alternative 2: "Repair"		Alternative 3: "Replace"	
	Description	Unit cost ($\$/m^2$)	Description	Unit cost ($\$/m^2$)	Description	Unit cost ($\$/m^2$)
6	Do Nothing	0	N/A	N/A	N/A	N/A
5	Do Nothing	0	Minor repair	40	N/A	N/A
4	Do Nothing	0	Major repair	60	Replace overlay and repair substrate	160
3	Do Nothing	0	Rehabilitate	80	Replace overlay and repair substrate	160
2	Do Nothing	0	Replace overlay and repair substrate	160	Replace deck	300
1	Do Nothing	0	Replace overlay and repair substrate	180	Replace deck	300

age system, two exterior faces, two end portions, and the middle portion. The overall condition of the bridge deck (MCR) is calculated as the aggregation of the MCRs of the seven elements using the balancing factors defined by bridge experts in the MTQ bridge management system [21]. Fig. 6 shows the transition probability matrices developed for concrete bridge decks protected with asphaltic concrete (AC) overlay in four environmental categories (benign, low, moderate, and severe). These environmental categories were determined for bridge decks in an earlier study based on the values of four deterioration parameters: highway class, region, average daily traffic and percentage of truck traffic [23]. Since the proposed approach of maintenance optimization is applied to groups of facilities and not to individual facilities, concrete bridge decks are classified into four groups that correspond to the four environmental categories determined earlier.

Transition probability matrices are developed for 1-year transition period when the "do-nothing" maintenance alternative is implemented and assuming an undamaged initial state. For simplicity purposes, the cells of the matrices shown in Fig. 6 are considered zeros except for the diagonal line and the line above it assuming that a bridge deck can change by, at most, one condition state in a year. Additionally, only three possible maintenance alternatives are considered for each bridge deck: (i) "do-nothing"; (ii) "repair"; or (iii) "replace". The description of each alternative, its applicability to concrete bridge decks in different condition states, and its estimated unit cost are listed in Table 1. Actual unit costs may differ from the listed ones, however, the unit costs of each alternative relative to other alternatives are almost similar. Fig. 7 shows the transition probability matrices when the "repair" and "replace" alternatives are implemented on bridge decks in any of the four environmental categories. These matrices represent the impact of each maintenance alternative on the condition of concrete bridge decks and are determined based on expert judgment.

$$
\begin{array}{c|cccccc|}
 & 6 & 5 & 4 & 3 & 2 & 1 \\
6 & 1 & 0 & 0 & 0 & 0 & 0 \\
5 & 1 & 0 & 0 & 0 & 0 & 0 \\
4 & 0 & 1 & 0 & 0 & 0 & 0 \\
3 & 0 & 1 & 0 & 0 & 0 & 0 \\
2 & 0 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 & 0 & 0 & 0
\end{array}
\qquad
\begin{array}{c|cccccc|}
 & 6 & 5 & 4 & 3 & 2 & 1 \\
6 & 1 & 0 & 0 & 0 & 0 & 0 \\
5 & 1 & 0 & 0 & 0 & 0 & 0 \\
4 & 1 & 0 & 0 & 0 & 0 & 0 \\
3 & 1 & 0 & 0 & 0 & 0 & 0 \\
2 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0
\end{array}
$$

Alternative 2 **Alternative 3**

Fig. 7. Transition probability matrices of concrete bridge decks with AC overlay for maintenance alternatives 2 and 3.

Table 2
Size and threshold condition vector for the investigated bridge deck groups

Bridge deck group	Size (m^2)	Threshold condition vector (cumulative conditions)					
		6	5	4	3	2	1
Group 1	48,744	0.50	0.90	0.98	1.00	1.00	1.00
Group 2	50,090	0.40	0.90	0.95	0.98	1.00	1.00
Group 3	179,821	0.15	0.50	0.80	0.90	0.95	1.00
Group 4	9570	0.10	0.40	0.70	0.80	0.90	1.00

Table 2 shows the size of the bridge deck network in each group (represented by the total deck surface area) along with the threshold condition vector that is defined as annual constraints on the network condition for that group. These constraints are considered in the optimization model using a penalty method that adds a unit cost of \$500 to the present value of the solution that violates the condition constraints. For simplification purposes, the bridge decks of each group are assumed to have an undamaged initial condition (D_{g0}=[1 0 0 0 0 0]). This condition changes annually over the 15-year planning horizon using the transition probability matrices shown in Figs. 6 and 7 based on the chosen maintenance alternative every year. A discount rate of 5% is used to calculate the total present value of maintenance costs.

In the proposed GA model, a population size of 50 individuals and a crossover probability of 50% were estimated based on the values recommended by the adopted GA simulator and those used earlier in the literature for similar applications [15]. The crossover method used was the single point method that has a randomly chosen cut point to divide the selected chromosomes. A mutation probability of 1% was initially estimated and then adjusted automatically by the GA simulator based on the model performance (i.e. convergence) during iterations. In addition, the simulator was used to test different types of crossover (e.g. standard, arithmetic, and heuristic) and mutation (e.g. standard, boundary, and non-uniform) operators to find the optimal combination for the given problem. Fig. 8 shows the progress graph of GA iterations that plots the number of iterations versus the average and best fitness values of each population while searching for optimal solutions. A maximum number of 10,000 iterations is chosen as the stopping criterion because

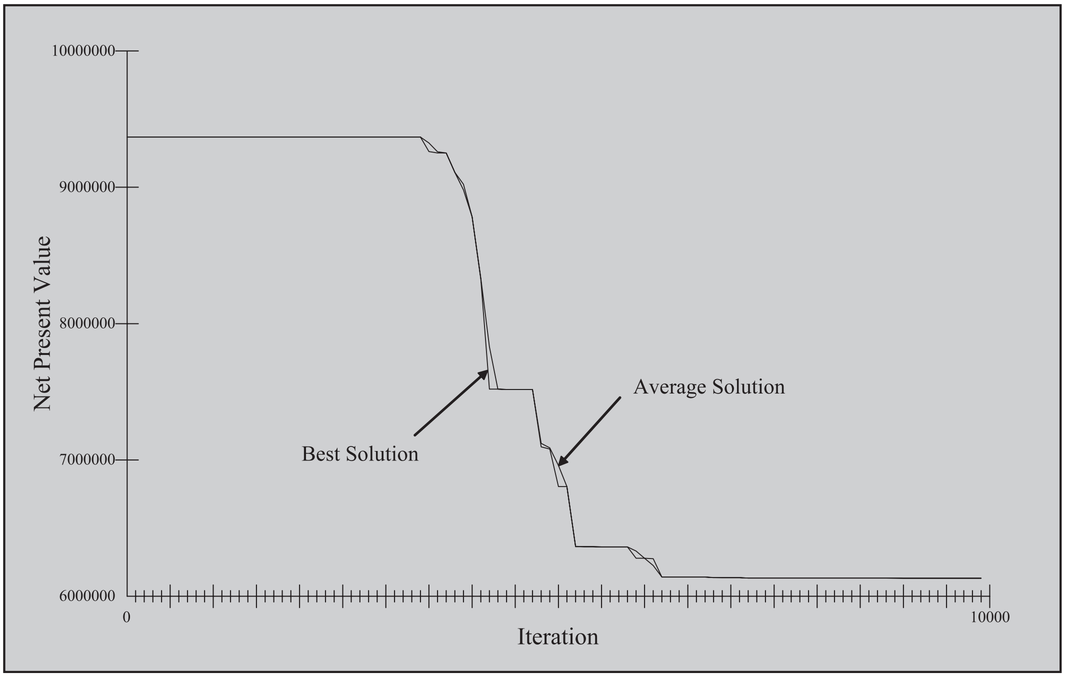

Fig. 8. Average and best solutions in GA iterations.

Table 3
Optimal maintenance vectors for bridge decks in group 3

Year	Overall condition vector							Optimal maintenance vectors																	
								Do nothing						Repair						Replace					
	6	5	4	3	2	1	Average	6	5	4	3	2	1	6	5	4	3	2	1	6	5	4	3	2	1
0	1.00	0.00	0.00	0.00	0.00	0.00	6.00																		
1	0.83	0.17	0.00	0.00	0.00	0.00	5.83	1.00	-	-	-	-	-	0.00	-	-	-	-	-	0.00	-	-	-	-	-
2	0.75	0.23	0.02	0.00	0.00	0.00	5.73	1.00	0.63	-	-	-	-	0.00	0.37	-	-	-	-	0.00	0.00	-	-	-	-
3	0.68	0.28	0.04	0.00	0.00	0.00	5.65	1.00	0.75	0.58	-	-	-	0.00	0.25	0.21	-	-	-	0.00	0.00	0.21	-	-	-
4	0.57	0.38	0.05	0.00	0.00	0.00	5.53	1.00	0.98	0.21	-	-	-	0.00	0.02	0.51	-	-	-	0.00	0.00	0.28	-	-	-
5	0.49	0.45	0.06	0.00	0.00	0.00	5.43	1.00	1.00	0.21	-	-	-	0.00	0.00	0.55	-	-	-	0.00	0.00	0.24	-	-	-
6	0.83	0.17	0.00	0.00	0.00	0.00	5.83	1.00	0.97	0.94	-	-	-	0.00	0.03	0.03	-	-	-	0.00	0.00	0.03	-	-	-
7	0.71	0.27	0.02	0.00	0.00	0.00	5.69	1.00	0.86	-	-	-	-	0.00	0.14	-	-	-	-	0.00	0.00	-	-	-	-
8	0.59	0.36	0.05	0.00	0.00	0.00	5.53	1.00	1.00	0.74	-	-	-	0.00	0.00	0.12	-	-	-	0.00	0.00	0.14	-	-	-
9	0.51	0.42	0.07	0.00	0.00	0.00	5.43	1.00	1.00	0.40	-	-	-	0.00	0.00	0.21	-	-	-	0.00	0.00	0.39	-	-	-
10	0.44	0.46	0.10	0.00	0.00	0.00	5.33	1.00	1.00	0.65	-	-	-	0.00	0.00	0.11	-	-	-	0.00	0.00	0.24	-	-	-
11	0.43	0.51	0.06	0.00	0.00	0.00	5.36	1.00	0.98	0.00	-	-	-	0.00	0.02	0.78	-	-	-	0.00	0.00	0.22	-	-	-
12	0.36	0.53	0.10	0.00	0.00	0.00	5.25	1.00	1.00	0.53	-	-	-	0.00	0.00	0.33	-	-	-	0.00	0.00	0.14	-	-	-
13	0.30	0.55	0.15	0.00	0.00	0.00	5.14	1.00	1.00	0.79	-	-	-	0.00	0.00	0.21	-	-	-	0.00	0.00	0.00	-	-	-
14	0.28	0.55	0.17	0.00	0.00	0.00	5.09	1.00	1.00	0.65	-	-	-	0.00	0.00	0.16	-	-	-	0.00	0.00	0.19	-	-	-
15	0.24	0.52	0.22	0.02	0.00	0.00	4.99	1.00	1.00	0.89	-	-	-	0.00	0.00	0.04	-	-	-	0.00	0.00	0.07	-	-	-

the progress graph indicated no increase in the average fitness beyond this number.

Table 3 lists portions of the optimal solution that represent the maintenance vectors of the concrete bridge decks in group 3. This solution describes the percentage of the deck area in each condition state that requires each maintenance alternative for each year in the planning horizon. Additionally, the overall condition vectors that represent the results of applying these alternatives are listed. For example, at year 3 (the shaded row), the optimal solution indicates that: (i) 100% of the bridge decks in condition 6 will have the "do-nothing" alternative; (ii) 75% of bridge decks in condition 5 will have the "do nothing" alternative, while the remaining 25% will have the "repair" alternative; (iii) 58% of the bridge decks in condition 4 will have the "do nothing" alternative, 21% will have the "repair" alternative, and the remaining 21% will have the "replace" alternative. These are percentages from the overall condition vector of the previous year (i.e. the year 2 in this example), which has the following condition distribution: 75% of the bridge decks are in condition 6, 23% are in condition 5, and only 2% are in condition 4. Applying these maintenance vectors will result in the overall condition distribution shown in the shaded row (i.e. 68% of the bridge decks are in condition 6, 28% are in condition 5, and 4% are in condition 4), which in turn will be used in calculating the optimal maintenance vectors of the following year (i.e. the year 4 in this example).

In order to demonstrate the impact of applying the optimal solution on concrete bridge decks, the deterioration curves of the four bridge deck groups over the entire planning horizon are plotted in Fig. 9. This figure shows a significant improvement in the overall condition at year 6 for all bridge deck groups and a less significant improvement at year 11 for groups 3 and 4 in particular. The timing of the first maintenance indicates that in order to minimize the long-term maintenance costs, early treatments of deck defects are required. The amount of these treatments and their frequency differ considerably from one group to another. For example, bridge decks in group 4 (severe environment) required extensive treatments every 5 years, while those in group 1 (benign environment) required slight treatment only once during the 15-year period. The total cost of these

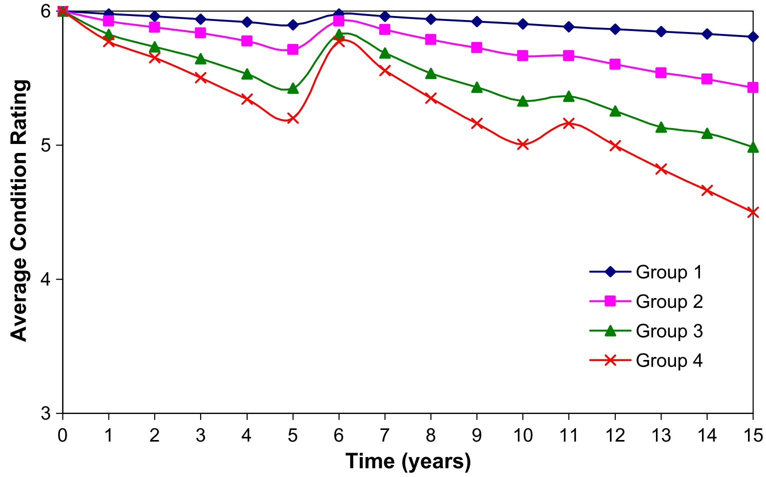

Fig. 9. Impact of optimal maintenance alternatives on average condition rating of bridge decks.

treatments in every year is shown in Fig. 10 for each group. This figure shows different spending policies on the maintenance, rehabilitation, and replacement of bridge decks. For instance, bridge decks in group 1 do not require spending on maintenance in the first years as much as in the last years because of their low deterioration rate, while bridge decks in groups 2 and 3 require almost the same amount of spending on

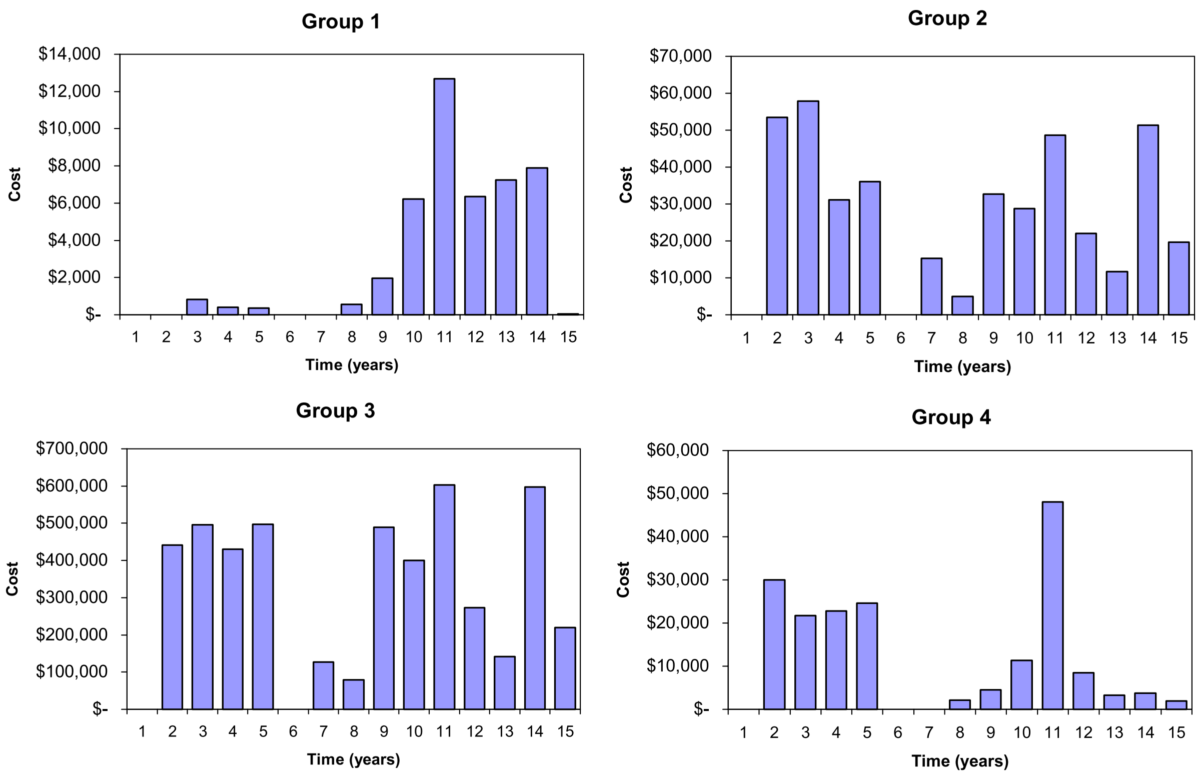

Fig. 10. Annual cost of optimal maintenance alternatives for all four groups.

maintenance over the entire planning horizon. Due to the high deterioration rate of bridge decks in group 4, replacement may be required for some bridge decks, which is evident from the clear peak shown in year 11.

5. Conclusions

This paper presents a new approach to programming maintenance alternatives for a network of infrastructure facilities. This approach uses genetic algorithm optimization techniques to resolve the computational complexity of the optimization problem and Markov-chain performance prediction models to account for the uncertainty in infrastructure deterioration, condition assessment, and measurement errors. The formulation of the optimization problem minimizes the life-cycle cost of an infrastructure network over a given time period while keeping the network condition above a predefined threshold value. In this formulation, infrastructure facilities are classified into groups according to some explanatory variables, such as type, material properties, operating loads, and environmental conditions, which govern the facility performance. This classification achieves reliable performance prediction modeling and reduces the computational complexity of the optimization problem.

The proposed approach was applied to programming the maintenance activities of concrete bridge decks protected with asphaltic concrete overlay. Field data obtained from the Ministére des Transports du Québec were used to develop four transition probability matrices that represent the deterioration of concrete bridge decks in four environmental categories (benign, low, moderate, and severe). These categories were used to set up the bridge deck groups required for the proposed optimization formulation. The output of this approach comprises the percentages of the bridge deck areas in each group that requires specific maintenance action in every year of the planning horizon. These percentages minimize the total maintenance costs and ensure that the overall average condition of each group is within acceptable limits. This application illustrated the feasibility, efficiency, and capability of using genetic algorithms in conjunction with Markov-chain models.

Future research is recommended to compare the proposed approach for maintenance optimization with conventional stochastic optimization techniques, such as stochastic dynamic programming, that can accommodate the use of Markov chains for performance prediction. This comparison might consider the latest developments in Neuro-dynamic programming, which uses artificial neural networks and other approximation architectures to overcome the limitations of the standard dynamic programming.

Notations

G	number of facility groups
T	number of years in the planning horizon
S	number of condition states in the adopted rating system
Q_{g}	quantity of facilities in group g
M_{g}	number of possible maintenance alternatives for facilities in group g
D_{gt}	condition vector ($1\times S$) of group g at the beginning of year t
d_{gt}^{s}	percentage of deck area from group g in condition state s at year t
$\mathbf{P}_{gm}$	transition probability matrix ($S\times S$) of group g when the maintenance alternative m is implemented
$p_{gm}^{i,j}$	transition probability of group g from condition state i to condition state j during 1 year when the maintenance alternative m is implemented
$\boldsymbol{X}_{gmt}$	maintenance vector ($1\times S$) of group g for maintenance alternative m during year t
x_{gmt}^{s}	percentage of facilities in group g and condition state s that had the maintenance alternative m during year t
$\boldsymbol{C}_{gm}$	cost vector ($S\times 1$) of group g and maintenance alternative m
c_{gm}^{s}	unit cost of implementing maintenance alternative m on the facilities in group g and conditon state s
$\boldsymbol{I}$	unit vector ($S\times 1$)
r	discount rate
PV_{g}^{T}	present value of the total cost of maintenance alternatives implemented on facilities from group g over the entire planning horizon T
$\boldsymbol{D}_{gt}^{\mathrm{Cum}}$	cumulative condition vector of group g at the beginning of year t
$\boldsymbol{D}_{g}^{\mathrm{Thr}}$	threshold condition vector ($1\times S$) of group g
B_{t}	maintenance budget available for year t

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