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Integration of stochastic deterioration models with multi-criteria decision theory for optimizing maintenance of bridge decks

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Abstract: This paper presents a new approach for the maintenance optimization of concrete bridge decks, which combines a stochastic deterioration model and a multi-objective optimization model. The stochastic deterioration model is based on the first-order Markov chain that predicts the probabilistic time-variation of the condition of bridge decks. The multi-objective optimization model takes into account two important and conflicting criteria: the minimization of maintenance costs, and the maximization of the network condition. This approach generates the solution that achieves the best compromise between these competing criteria, while considering the uncertainty in bridge deck deterioration. The feasibility and capability of the proposed approach is demonstrated on a network of bridge decks obtained from the Ministére des Transports du Québec database. This example illustrates the effectiveness of the proposed approach in determining the optimal set of maintenance alternatives for reinforced concrete bridge decks when considering two or more relevant optimization criteria.

Keywords: Concrete bridge deck, maintenance management, multi-criteria optimization, Markov-chain, deterioration model.

Introduction

Highway bridges constitute a class of safety-critical infrastructure systems that should be analyzed with rigor as their failure can have catastrophic consequences, including multiple fatalities and injuries, complete loss of service, major traffic disruption, and considerable socio-economic impacts. A large percentage of highway bridge structures in North America are classified as structurally deficient or functionally obsolete (US DOT 1999). Their rehabilitation and renewal cost is estimated at hundreds of billions of dollars that cannot be accommodated by highway agencies. The magnitude of the problem poses great technological and economic challenges, specifically which bridge should be given high priority for maintenance and what is the optimal maintenance strategy that will reduce its risk of failure and life cycle cost.

The concrete bridge deck system is considered the weakest link of highway bridges in North America from the durability viewpoint. Many bridge deck systems are experiencing extensive deterioration, which require major rehabilitation or replacement every 15 to 20 years, while other bridge systems may last for 40 years or more (FHWA 2001). This is mainly due to the effects of direct exposure to traffic loads, frequent freezing and thawing cycles, and corrosive effects of de-icing chemicals used in winter, in addition to design/construction-related effects, such as, poor workmanship, inadequate concrete cover, and lack of inspection and preventive maintenance. These effects, with time, results in wear, fatigue, cracking, corrosion of reinforcing steel, spalling, delamination, and eventually a complete failure. The high costs associated with the maintenance of the large stock of aging and deteriorating decks and the limited funds allocated for their maintenance compound the problem and highlight the need for systematic and effective approaches to optimize maintenance decisions and ensure adequate reliability.

To address this problem, several countries have developed or initiated the development of bridge management systems (BMS) to optimize the inspection and maintenance of deteriorated structures. Different approaches to maintenance optimization have been implemented in these systems ranging from simplified economic models to sophisticated Markovian decision processes. The development of a practical and effective bridge maintenance management system depends primarily on the existence of reliable performance prediction models and effective optimization algorithms. Given the time-dependence and uncertainty of bridge performance, a stochastic modeling is required. Furthermore, bridge maintenance management aims at improving the overall performance of a bridge or a network through the satisfaction of several and possibly conflicting objectives, which may include the minimization of maintenance costs, maximization of network condition, minimization of risk of failure, minimization of bridge closures, etc. Multi-criteria optimization techniques provide a practical tool for optimal prioritization of bridges for maintenance.

In this paper, a new approach for maintenance management that integrates stochastic deterioration modeling with multi-criteria maintenance optimization is presented. This approach is based on the minimization of maintenance costs and maximization of the average condition of a network of concrete bridge decks. The compromise programming approach is used to determine the optimal solutions and first-order Markov chains are used to predict the probabilistic time-variation of deck conditions. A numerical example that illustrates the application of the proposed approach to the maintenance management of a small network of damaged bridge decks is also presented.

Stochastic Performance Prediction of Bridge Decks Using Markov-chain models

Markov chains are the most commonly used stochastic techniques for modeling and predicting the performance of different types of infrastructure facilities such as pavements, bridges, sewer pipes, and water mains (Micevski et al. 2002). Markov-chain models are based on the concept of probabilistic cumulative damage, which predicts changes of component condition over multiple transition periods (Bogdanoff 1978). The main advantages of Markov-chain models are: 1) ability to reflect the uncertainty from different sources such as, uncertainty in initial condition, uncertainty in applied stresses, presence of condition assessment errors, and inherent uncertainty of the deterioration process (Lounis 2000); 2) incremental models that account for the present condition in predicting the future condition (Madanat et al. 1995); and 3) practicality as they can be used to predict the performance of a large number of facilities because of their computational efficiency and simplicity of use (Morcous and Rivard 2003).

A Markov chain is a special case of the Markov process whose development can be treated as a series of transitions between discrete states. A stochastic process is considered as a first-order 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 (Parzen 1962). Markov-chains are used as performance prediction models for bridge components by defining discrete condition states and accumulating the probability of transition from one condition state to another over multiple discrete time intervals. For a condition rating scale that has (S) number of discrete condition states, transition probabilities are represented by a matrix of order (S x S) called the transition probability matrix (P). Each element ($p^{i,j}$) in this matrix represents the probability that the condition of a bridge component will change from state *(i)* to state (*j)* during a certain time interval called the transition period. The future condition of a bridge component after any number of transition periods (t) is represented by a vector of order ($1 \times S$) called the condition vector (D_t) that can be written as follows:

$$\text{[1]} \qquad \boldsymbol{D_t} = \begin{vmatrix} d_t^S & d_t^{S-1} & \ldots\ldots & d_t^1 \end{vmatrix}$$

Each element in this vector represents the estimated percentage of the bridge component in a particular condition state after t periods or transitions. If the condition vector (D_{t-1}) that describes the present condition of a bridge component is known, the future condition vector (D_t) can be obtained as follows (Parzen 1962):

$$\text{[2a]} \qquad D_t = D_{t-1} \times P$$

$$\text{[2b]} \qquad \boldsymbol{P} = \begin{bmatrix} p^{S,S} & p^{S,S-1} & \ldots\ldots & p^{S,1} \\ p^{S-1,S} & p^{S-} & \ldots\ldots & p^{S-1,1} \\ . & . & \ldots\ldots & . \\ . & . & \ldots\ldots & . \\ p^{1,S} & p^{1,S-1} & \ldots\ldots & p^{1,1} \end{bmatrix}$$

The state-of-the-art bridge management systems (BMSs), such as *Pontis* and *BRIDGIT*, have adopted Markov-chain models for predicting the performance of bridge components, systems, and networks (Golabi and Shepard 1997; Hawk 1995). The transition probability matrices in these systems were initially obtained using an expert judgment elicitation procedure, which required the participation of several experienced bridge engineers (Thompson and Shepard 1994). A statistical updating of these matrices is possible using the Bayesian approach when a statistically significant number of consistent and complete sets of condition data become available over the years (Golabi and Shepard 1997). Such updating enables to improve the accuracy of the Markov-chain models.

Multi-Criteria Maintenance Optimization of Bridges

In the literature, most approaches to maintenance optimization of highway bridges are based on single objective optimization, and more specifically on the minimization of maintenance costs. Similarly, in most bridge management systems, the main criterion used for maintenance optimization is the minimization of life cycle cost, which represents the present value of all the costs incurred throughout the life cycle of a bridge structure or network, including, the costs of design, construction, maintenance, repair, rehabilitation, replacement, demolition, and in some instances users' costs. The actual maintenance optimization problem is multi-objective in nature as the bridge owner or manager seeks to satisfy simultaneously several and possibly conflicting criteria, such as the minimization of costs to owners and users, improvement of safety, improvement of serviceability and functionality, minimization of maintenance time, minimization of traffic disruption, etc. The solution of this maintenance management problem can be obtained using the techniques of multi-criteria or multi-objective optimization.

Concept of Pareto Optimality

For single-objective optimization problems, the notion of optimality is very well defined as the minimum or maximum value of some given objective function is sought. In multi-criteria (or multi-objective or vector) optimization problems, the notion of optimality is not obvious because of the presence of multiple, incommensurable and conflicting objectives. In general, there is no single optimal (non-dominated or superior) solution that simultaneously yields a minimum (or maximum) for all objective functions. The Pareto optimality concept has been introduced as the solution to multi-objective optimization problems (Koski 1984; Eschenauer et al. 1990). A solution **x*** is said to be a Pareto optimum if and only if there exists no solution in the feasible set of solutions that may yield an improvement of some criteria without worsening at least one other criterion. The multi-criteria optimization problem can be mathematically stated as follows:

[3a] Find: $\boldsymbol{x^*}$ = Optimum

[3b] Such that: $\boldsymbol{f}(\boldsymbol{x}) = [\, f_1(x) \;\; f_2(x) \; \ldots\ldots\ldots \; f_m(x) \,]$ = minimum

[3c] and $\boldsymbol{x} \in \boldsymbol{\Omega}$

where $\boldsymbol{f}(\boldsymbol{x})$ is the vector of optimization criteria (e.g. risk of failure, maintenance cost, traffic delay); and $\boldsymbol{\Omega}$ is the set of feasible solutions that satisfy the problem constraints (e.g. budget, condition, practicality). The concept of Pareto optimality mentioned earlier can be stated mathematically as follows (Koski 1984; Lounis and Cohn 1993): **x*** is a Pareto optimum if:

[4a] $f_i(\boldsymbol{x}) \leq f_i(\boldsymbol{x^*})$ for $i=1,2,\ldots,m$

[4b] $f_k(\boldsymbol{x}) < f_k(\boldsymbol{x^*})$ for at least one k.

In general, there are several Pareto optimal solutions (called also non-dominated solutions) for a multi-criteria optimization problem as shown in Figure 1. Once the set of Pareto optima is generated, the "best" solution that achieves the best compromise between all competing objectives is sought. Such a solution is refereed to as "satisficing" solution in the multi-criteria optimization literature (Koski 1984). Several techniques have been developed to determine the satisficing solution in multi-criteria optimization problems, including the multi-attribute utility theory (Von Neumann and Morgenstern 1947; Keeney and Raiffa 1976), weighted sum approach (Zadeh 1963), compromise programming, ε-constraint approach, sequential optimization (Koski 1984; Duckstein 1984; Osyzcka 1984; Fu and Frangopol 1990; Eschenauer et al. 1990; Lounis and Cohn 1993). In this paper, the compromise programming approach is used to solve the multi-criteria maintenance optimization problem.

In compromise programming, the satisficing solution is defined as the solution that minimizes the distance from the set of Pareto optima to the so-called "ideal solution". This ideal solution is defined as the solution that yields the minimum (or maximum) values for all criteria. Such a solution does not exist, but is introduced in compromise programming as a target or a goal to get close to, although impossible to reach. The criterion used in compromise programming is the minimization of the deviation from the ideal solution (***f****) measured by the family of (L_p) metrics (Koski 1984; Lounis and Cohn 1993). In this paper, a multi-criteria optimality index introduced by Lounis (2004), "MOI", is defined as the value of the weighted and normalized deviation from the ideal solution (***f****) measured by the family of (L_p) metrics:

[5] $$MOI(x) = \left[\sum_{i=1}^{i=m} w_i^p \left| \frac{f_i(x) - \min f_i(x)}{\max f_i(x) - \min f_i(x)} \right|^p \right]^{\frac{1}{p}}$$

This family of (L_p) metrics provides a measure of the closeness of the satisficing solution to the ideal solution. The value of the weighting factors (w_i) of the optimization criteria f_i (i =1,…,m) depends primarily on the attitude of the decision-maker toward risk. The optimization will be carried out using different weights of all criteria to show the impact of weighting factors on the optimal decision. The choice of *(p)* indicates the importance given to different deviations from the ideal solution. For example, if $(p = 1)$, all deviations from the ideal solution are considered in direct proportion to their magnitudes, which corresponds to a group utility (Duckstein 1984). However, for $(p \geq 2)$, a greater weight is given to larger deviations from the ideal solution, and (L_2) represents the Euclidian metric. For $(p=\infty)$, the largest deviation is the only one taken into account and is referred to as the Chebyshev metric or mini-max criterion and (L_∞) corresponds to a purely individual utility (Duckstein 1984; Koski 1984; Lounis and Cohn 1995). In this paper, the Euclidean metric is used to determine the multi-criteria optimality index and corresponding satisficing solution.

Formulation of Bridge Deck Maintenance Optimization

The application of multi-criteria optimality concept to infrastructure maintenance management is very limited. Examples are those proposed by Lounis and Vanier (1998), Fwa et al. (2000), and Lounis (2004). These studies presented the application of multi-criteria optimization to prioritize networks of bridges or pavements for maintenance according to several and possibly conflicting criteria, such as risk of failure, cost, and traffic disruption. However, most of these models were limited to scheduling maintenance alternatives for a given year not over an entire planning horizon, which requires accounting for deterioration modeling, effectiveness of maintenance projects, and life cycle costing. The proposed formulation integrates the use of Markov-chains for modeling deterioration with the multi-criteria optimization model proposed earlier for a multi-year maintenance management. In this formulation, each bridge deck is classified into one of four predefined environmental categories that represent different combination of parameters that affect bridge deck deterioration, such as total traffic volume, truck traffic volume, highway class, and climatic region (Morcous et al. 2003). The objectives of such a classification are twofold: i) achieve reliable performance prediction; and ii) enable grouping of bridge decks that are subjected to similar environments to reduce the computational complexity of the optimization problem. The parameters of the proposed formulation are defined as follows:

N = number of bridge decks;

T = length of the planning horizon in years;

M = number of feasible maintenance alternatives for bridge decks;

X_{nt} = maintenance vector *(M x 1)* of deck *n* during year *t;*

[6] $$X_{nt} = \begin{vmatrix} x_{nt}^{1} \\ x_{nt}^{2} \\ . \\ . \\ x_{nt}^{M} \end{vmatrix}$$

where,

x_{nt}^{m} = binary variable that indicates that maintenance alternative *m* is implemented for deck *n* at year *t* (1 if implemented, 0 if not implemented).

C = unit cost matrix *(S x M)*

[7] $$C = \begin{vmatrix} c^{S,1} & c^{S,2} & \ldots\ldots & c^{S,M} \\ c^{S\text{-}1,1} & c^{S\text{-}1,2} & \ldots\ldots & c^{S\text{-}1,M} \\ . & . & \ldots\ldots & . \\ . & . & \ldots\ldots & . \\ c^{1,1} & c^{1,2} & \ldots\ldots & c^{1,M} \end{vmatrix}$$

where,

$c^{s,m}$ = unit cost of implementing maintenance alternative *m* when bridge deck is in condition state *s*.

C_{nt} = unit cost of implementing any maintenance alternative on bridge deck *n* at year *t*

[8] $$C_{nt} = D_{nt} \times C \times X_{nt}$$

where, D_{nt} is the condition vector of bridge deck *n* at year *t*. This vector is obtained using the initial condition vector and the transition probability matrix corresponding to the deck environmental category using Equation 2a. It should be noted that some constraints may be introduced to determine the applicability of various maintenance alternative according to bridge deck conditions, such as restricting the implementation of the replacement alternative for bridge decks with very poor or critical conditions, and assigning the "do-nothing" alternative to those decks with "like new" or "good" conditions. These constraints may vary significantly from one agency to another and are defined by bridge experts based on their performance requirements and budget availability (i.e., user defined). Other constraints, such as non-negativity constraints, are applied to this optimization model in order to guarantee the feasibility of the solutions obtained.

The two optimization criteria or objective functions defined in this formulation include: 1) minimization of the present value of the total maintenance cost for all bridge decks over the entire planning horizon using a discount rate *(r)*, and 2) maximization of the weighted average of the network condition of bridge decks over the entire planning horizon. These objective functions can be written as follows:

[9] $$Minimize \sum_{t=1}^{t=T} \frac{\sum_{n=1}^{n=N} A_n \times C_{nt}}{(1+r)^t}$$

[10] $$Maximize \ \frac{\sum_{t=1}^{t=T} \sum_{n=1}^{n=N} k_n \times D_{nt}}{T}$$

where,

A_n = total surface area of bridge deck *n*;

k_n = factor that indicates the importance of bridge deck *n* relative to other decks.

This importance factor is a function of the traffic volume, detour length, and deck area. It is a factor that indirectly account for users' costs. The two objective functions formulated above are examples of conflicting criteria in maintenance optimization that will be solved using the multi-criteria optimality index shown earlier. Figure 1 is a schematic illustration of the conflicting nature of these two criteria and the corresponding Pareto optimal solutions (called also non-dominated solutions). Also, two dominated solutions are shown to illustrate the concept of dominance. Other objective functions, such as minimization of risk of failure and minimization of traffic disruption, can be added in the future using the same procedures. Also, users' costs and failure costs can be discounted and added to the above maintenance cost when adequate cost data become available.

Illustrative Example

The approach presented in this paper is applied to the maintenance optimization of 10 concrete bridge decks using field data obtained from the Ministére des Transports du Québec (MTQ) database. This database includes: i) inventory data**,** which consist of bridge identification, description, environment, and geometry; ii) condition data**,** which contain the results of the detailed visual inspections carried out on all bridges approximately every three years; and iii) maintenance data**,** which include the estimated costs and expected times for recommended maintenance and rehabilitation activities. The condition data comprises two condition ratings (MTQ 1995): (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 PCR are represented in an ordinal rating scale that ranges from 6 to 1, 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. Table 1 shows the definition of each condition state in the MCR scale for bridge deck components as listed in the MTQ inspection manual. Table 1 also lists the definition of the four environmental categories and the four maintenance alternatives that will be used in this illustrative example.

The MTQ data are screened by filtering out the records with inadequate inventory data, missing condition data, or non-negative deterioration rates. The filtered data were used in developing transition probability matrices for concrete bridge decks protected with asphaltic concrete (AC) overlay in four environmental categories (benign, low, moderate, and severe). These matrices developed for a 1-year transition period when the “do-nothing” maintenance alternative is implemented (i.e. no maintenance is undertaken) using the percentage prediction method. In this method, the probability that the condition of an element will change from state *(i)* to state *(j)* during a certain time interval is calculated as the ratio of the number of transitions from state *(i)* to state *(j)* within this time period to the total number of elements in state *(i)* before the transition. Since, the MTQ bridge decks are inspected approximately every three years, transition probabilities were calculated for a 3-year transition period first, and then modified to generate those corresponding to a 1-year transition period. Table 2 shows the transition probability matrices developed for different combinations of environmental categories and maintenance alternatives (Morcous and Lounis 2005). For simplification, the cells of the matrices shown in Table 2, when the “do-nothing” maintenance alternative is implemented, 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. For the other three possible maintenance alternatives, three matrices were obtained from the literature and based on personal judgment to represent the impact of each maintenance alternative on the condition of concrete bridge decks.

Table 3 shows the estimated unit cost matrix that lists the estimated unit cost of each maintenance alternative when applied to different condition states. Actual unit costs may slightly differ from those listed, however, the unit costs of each alternative relative to other alternatives are similar. The feasibility of each maintenance alternative depends on the aggregated MCR (AMCR) of a bridge deck as shown in Table 3. The AMCR is calculated as the sum of product of the deck condition vector by the condition state vector (i.e., a vector of MCR). A maintenance alternative cannot be applied to a bridge deck unless its AMCR falls into the specified range. This constraint was made to avoid unrealistic maintenance decisions and improve the efficiency of the optimization model by eliminating infeasible alternatives.

Table 4 lists the actual data of 10 bridge decks representing a small network used for validating the proposed approach. The surface area, importance factor, and environmental category of each bridge required by the maintenance optimization model presented earlier are also listed in Table 4. The importance factor that represents the relative importance of different bridge decks in the network is calculated by multiplying the deck area, average daily traffic, and detour length. This factor is used to assign a high priority to bridge decks with higher traffic volumes, longer detours, and larger surface areas. Table 4 also shows the initial condition vector of each deck, which represents the deck condition at the beginning of the planning horizon. This vector was computed based on the current MCR of the five elements of a bridge deck, which is determined during the periodic visual inspection. Table 5 lists these five elements along with their weights (i.e., balancing factors) as defined by the MTQ bridge experts in the MTQ inspection manual (MTQ 1995).

In order to apply the proposed multi-criteria optimization approach, the extreme values of each objective function have to be determined to be used in calculating the multi-criteria optimality index (MOI) as shown in Equation 5. Because the minimization of the maintenance cost results in minimum deck condition and the maximization of the maintenance cost results in maximum deck condition, only two optimization cases are required. The results of these two cases are listed in the first two rows of Table 6. Figure 2 shows the details of these two cases by plotting the annual cost and aggregated MCR of the 10 bridge decks over the ten-years period. Case # 1 represents the minimum maintenance requirements of the 10 decks, which results in a continuous decline in the average condition. While, case # 2 represents the immediate fulfillment of all maintenance needs of the 10 decks, which results in steady excellent condition.

Using the compromise programming and the (L_2) metric, the proposed MOI is determined for the 10 bridge decks for three cases: (i) Case # 3, equal weights are assigned to both condition and cost criteria; (ii) Case # 4, weights of 0.75 and 0.25 are assigned to the condition and cost criteria respectively; and (iii) Case # 5, weights of 0.25 and 0.75 are assigned to the condition and cost criteria, respectively. These three cases are just examples of possible maintenance and expenditure practices that transportation agencies may adopt. The last three rows of Table 6 list the total present value and global aggregated MCR (AMCR) of each of the three cases. Figure 3 shows the details of each case by plotting the annual cost and AMCR of the 10 bridge decks over the ten-year period. Case # 3 represents the spending plan that maintains a satisfactory condition of the network, while keeping maintenance expenditures at an average level. Case # 4 represents the spending plan that is close to case # 2, where more importance is given to improving the network condition than reducing maintenance budget. On the other hand, case # 5 represents the spending plan that is close to case # 1, where more importance is given to limiting maintenance budget than upgrading the network condition.

For illustrative purposes, the schedule of maintenance activities of case # 4 is shown in Table 7. This schedule lists the maintenance alternative chosen for each bridge deck, total annual cost, average condition vector, and AMCR for every year in the planning horizon. The global AMCR and the total present value calculated using a 5% discount rate are also shown at the bottom of the table.

Summary and Conclusions

This paper presents a new approach to programming maintenance alternatives for a network of concrete bridge decks, which can be applied to other infrastructure components, facilities, and networks. This approach integrates a multi-criteria optimization model with a Markov-chain deterioration model to perform a stochastic multi-criteria decision analysis for maintenance management of structurally deteriorated bridge decks. The major merits of the approach are: (i) consideration of all possible (even conflicting) objective functions; (ii) ability to account for the uncertainty associated with bridge deck deterioration; and (iii) rational and efficient decision-making regarding the selection of maintenance alternatives for a network of bridge decks.

The multi-objective optimization problem was formulated to achieve a satisfactory trade-off between two competing criteria: maximization of deck condition, and minimization of maintenance cost. The use of compromise programming and the proposed multi-criteria optimality index yield the optimal solution as the one that has the minimum weighted and normalized deviation from the ideal solution in a set of Pareto optima. A small network of 10 concrete bridge decks was used to implement and illustrate the capabilities of the proposed approach. Inventory and condition data of these decks were obtained from the Ministére des

Transports du Québec database. Several transition probability matrices were developed using the condition data of thousands of bridge decks to represent the impact of four different environments. The total present value and the average aggregated material condition rating were obtained for different trade-offs between the condition and cost criteria. This investigation shows that the use of multi-criteria optimization with Markov-chain models is another step towards the development of more powerful bridge management systems that will enable the decision-maker to select several and conflicting criteria, while accounting for uncertainty to determine the optimal maintenance alternatives.

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List of symbols

S = number of discrete condition states

P = the transition probability matrix

D_{nt} = condition vector of bridge deck n at year t

$p^{i,j}$ = transition probability from state i to state j

N = number of bridge decks;

T = length of the planning horizon in years;

M = number of feasible maintenance alternatives for bridge decks;

X_{nt} = maintenance vector (M x 1) of deck n during year t;

x_{nt}^{m} = binary variable that indicates that maintenance alternative m is implemented for deck n at year t

C = unit cost matrix (S x M)

$c^{s,m}$ = unit cost of implementing maintenance alternative m when bridge deck is in condition state s.

C_{nt} = unit cost of implementing any maintenance alternative on bridge deck n at year t

A_n = total surface area of bridge deck n;

k_n = factor that indicates the importance of bridge deck n relative of other decks.

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Table 1. Definition of condition ratings, maintenance alternatives, and environmental categories

Item	Code	Name	Description
Material Condition Ratings	6	Like New Condition	No observed material defects
	5	Good Condition	Observed material defects are up to 5% of deck surface area
	4	Fair Condition	Observed material defects are over 5% to 10% of deck surface area
	3	Poor Condition	Observed material defects are over 10% to 15% of deck surface area
	2	Urgent Condition	Observed material defects are over 15% to 20% of deck surface area
	1	Critical Condition	Observed material defects are over 20% of deck surface area
Maintenance Alternatives	1	Do Nothing	Activities that do not change the deck structure (e.g. routine cleaning)
	2	Repair	Activities that require partial bridge closure (e.g. patching, sealing)
	3	Rehabilitate	Activities that require full bridge closure (e.g. add overlay or cover)
	4	Replace	Complete replacement of the deck
Environmental Categories	1	Benign	There are no environmental factors that affect the element deterioration
	2	Low	Environmental factors have minor impacts on the element deterioration
	3	Moderate	Environmental factors maintain the progress of element deterioration
	4	Severe	Environmental factors speed up the element deterioration significantly

Table 2. Transition probabilities for different maintenance alternatives and environmental categories

Maintenance Alternative	Environmental Category	Material Condition Rating (MCR)	MCR / Transition Probability					
			6	5	4	3	2	1
1	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	0.00
		2	0	0	0	0	0.92	0.08
		1	0	0	0	0	0	1.00
	2	**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
	3	**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
		2	0	0	0	0	0.84	0.16
		1	0	0	0	0	0	1.00
	4	**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	1.00
2	1,2,3,4	**6**	1.00	0	0	0	0	0
		5	1.00	0	0	0	0	0
		4	0	1.00	0	0	0	0
		3	0	0	1.00	0	0	0
		2	0	0	0	1.00	0	0
		1	0	0	0	0	1.00	0
3	1,2,3,4	**6**	1.00	0	0	0	0	0
		5	1.00	0	0	0	0	0
		4	1.00	0	0	0	0	0
		3	0	1.00	0	0	0	0
		2	0	0	1.00	0	0	0
		1	0	0	1.00	0	0	0
4	1,2,3,4	**6**	1.00	0	0	0	0	0
		5	1.00	0	0	0	0	0
		4	1.00	0	0	0	0	0
		3	1.00	0	0	0	0	0
		2	1.00	0	0	0	0	0
		1	1.00	0	0	0	0	0

Table 3. Unit costs of selected maintenance alternatives

MCR	Maintenance Alternative / Unit Cost ($/m^2)			
	1	2	3	4
6	0	0	0	400
5	0	40	120	400
4	0	80	180	400
3	0	120	240	400
2	0	160	300	400
1	0	200	360	400
$AMCR_{max}$	6	6	4	3
$AMCR_{min}$	3	2	1	1

Table 4. Bridge deck data used in illustrative example

Deck ID	Surface Area (m^2)	Average Daily Traffic	Detour Length (km)	Importance Factor	Enviorn. Category	Deck Element / MCR					MCR / Condition Probability					
						3	4	5	6	7	6	5	4	3	2	1
00005	1296	9000	6	22.7%	2	4	4	5	5	5	0	0.6	0.4	0	0	0
00006	193	3070	47	9.0%	4	4	4	3	4	4	0	0	0.8	0.2	0	0
00018	210	1120	111	8.5%	3	4	4	4	4	4	0	0	1	0	0	0
00048	378	1669	46	9.4%	3	6	6	5	5	5	0.4	0.6	0	0	0	0
00076	235	1272	51	5.0%	3	3	3	5	5	5	0	0.6	0	0.4	0	0
00088	452	4300	20	12.6%	3	4	4	5	6	5	0.2	0.4	0.4	0	0	0
00109	254	2390	25	4.9%	2	3	4	5	5	5	0	0.6	0.2	0.2	0	0
00150	1273	1110	55	25.2%	4	4	3	2	3	2	0	0	0.2	0.4	0.4	0
00204	1380	690	8	2.5%	2	6	6	5	5	5	0.4	0.6	0	0	0	0
00241	197	100	29	0.2%	1	5	5	5	4	5	0	0.8	0.2	0	0	0

Table 5. Bridge deck elements and corresponding balance factors

Element ID	Description	Balance Factor
3	Exterior Face 1	0.20
4	Exterior Face 2	0.20
5	End Portion 1	0.20
6	Middle Portion	0.20
7	End Portion 2	0.20

Table 6. Optimization results for different cases of compromise programming

Optimization Case		Total Present Value	Global AMCR
No.	**Description**		
1	Min. Condition + Min Cost	$ 336,666	4.11
2	Max. Condition + Max. Cost	$ 840,285	5.95
3	50% Condition + 50% Cost	$ 497,192	5.20
4	75% Condition + 25% Cost	$ 664,399	5.74
5	25% Condition + 75% Cost	$ 418,989	4.49

Table 7. Schedule of maintenance activities for optimization case # 4

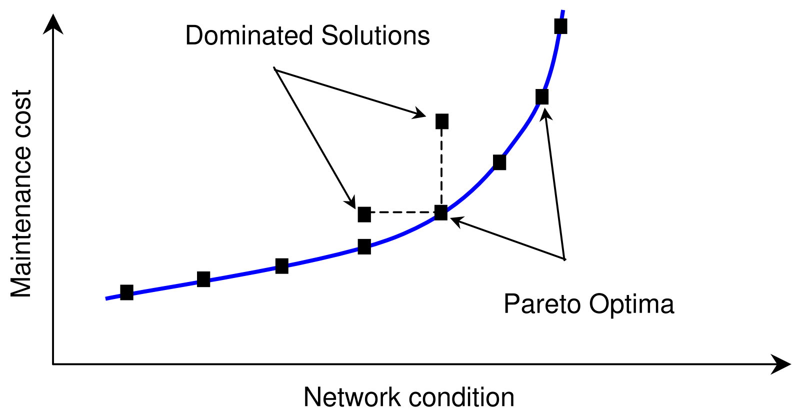
Year	Bridge Deck / Maintenance Alternative										Annual Cost	MCR / Condition Probability						Annual AMCR
	00005	00006	00018	00048	00076	00088	00109	00150	00204	00241		6	5	4	3	2	1	
1	2	3	1	1	1	2	2	2	1	2	319,899	0.36	0.31	0.20	0.12	0.00	0.00	4.90
2	2	1	3	2	1	2	2	2	1	1	195,997	0.68	0.19	0.11	0.02	0.00	0.00	5.52
3	2	2	1	1	1	2	2	2	1	2	68,133	0.79	0.18	0.02	0.02	0.00	0.00	5.73
4	1	2	2	1	3	1	1	2	1	1	67,006	0.88	0.10	0.01	0.00	0.00	0.00	5.87
5	2	2	2	2	1	2	2	2	1	1	14,166	0.95	0.04	0.01	0.00	0.00	0.00	5.94
6	1	2	2	1	2	2	2	2	1	1	6,233	0.94	0.06	0.01	0.00	0.00	0.00	5.93
7	1	2	2	2	1	2	1	2	1	2	3,815	0.93	0.06	0.01	0.00	0.00	0.00	5.92
8	1	2	1	1	1	2	2	2	1	2	787	0.88	0.10	0.01	0.00	0.00	0.00	5.86
9	2	2	2	2	1	2	1	1	1	1	15,788	0.89	0.10	0.01	0.00	0.00	0.00	5.87
10	1	2	2	1	1	1	1	2	1	2	11,676	0.88	0.10	0.02	0.00	0.00	0.00	5.86
										Total Present Value	664,399						***Global AMCR***	5.74

Figure Captions

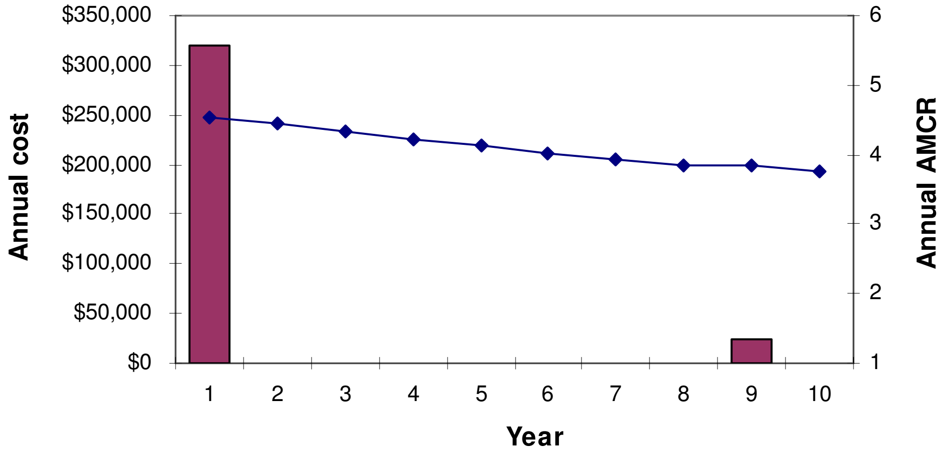
Fig. 1. Schematic illustration of Pareto optima and conflicting optimization criteria

Fig. 2. Annual cost and aggregated MCR for optimization cases: (a) Case # 1 and (b) Case # 2

Fig. 3. Annual cost and aggregated MCR for optimization cases: (a) Case # 3, (b) Case # 4 and (c) Case # 5


Dominated Solutions
Maintenance cost
Pareto Optima
Network condition

(a)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$250,000
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$50,000
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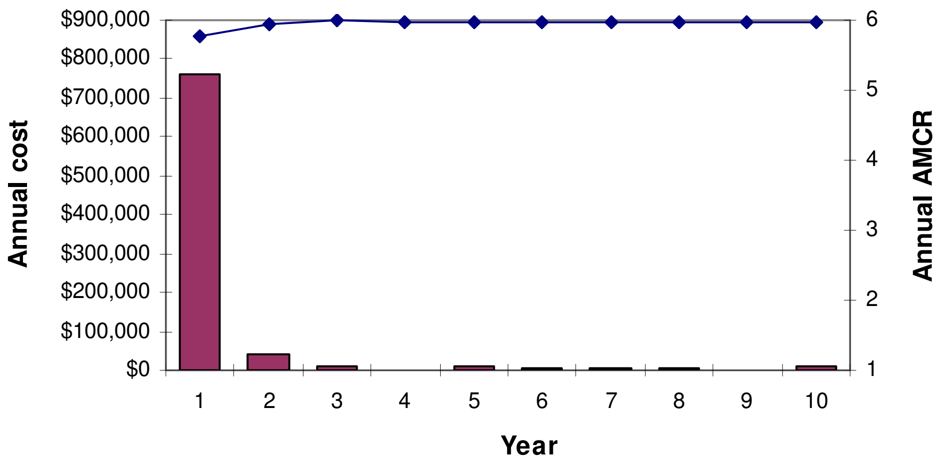
Annual cost
6
5
4
3
2
1
Annual AMCR
1
2
3
4
5
6
7
8
9
10
Year

(b)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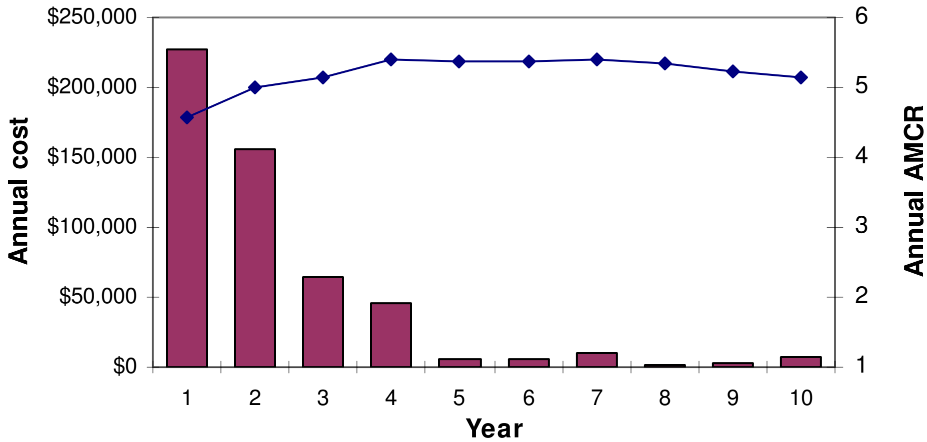
$0
Annual cost
6
5
4
3
2
1
Annual AMCR
1
2
3
4
5
6
7
8
9
10
Year

(a)



$250,000
$200,000
$150,000
$100,000
$50,000
$0
Annual cost
6
5
4
3
2
1
Annual AMCR
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3
4
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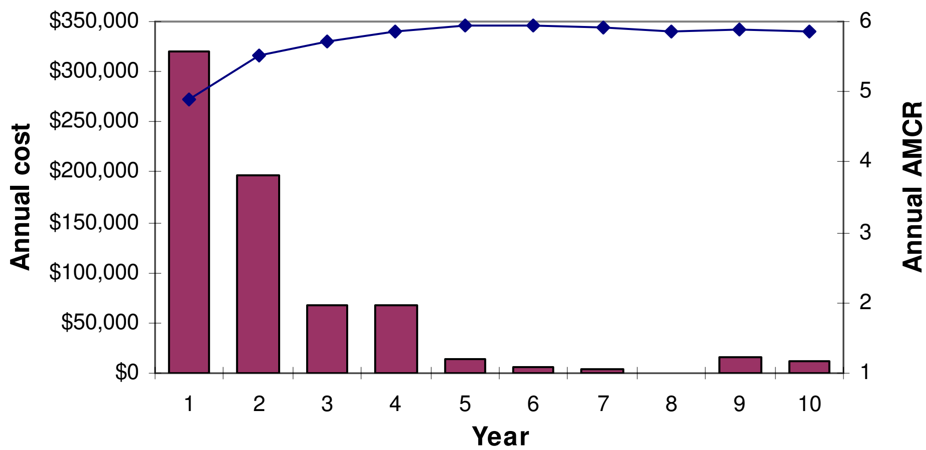
6
7
8
9
10
Year

(b)



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$250,000
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$150,000
$100,000
$50,000
$0
Annual cost
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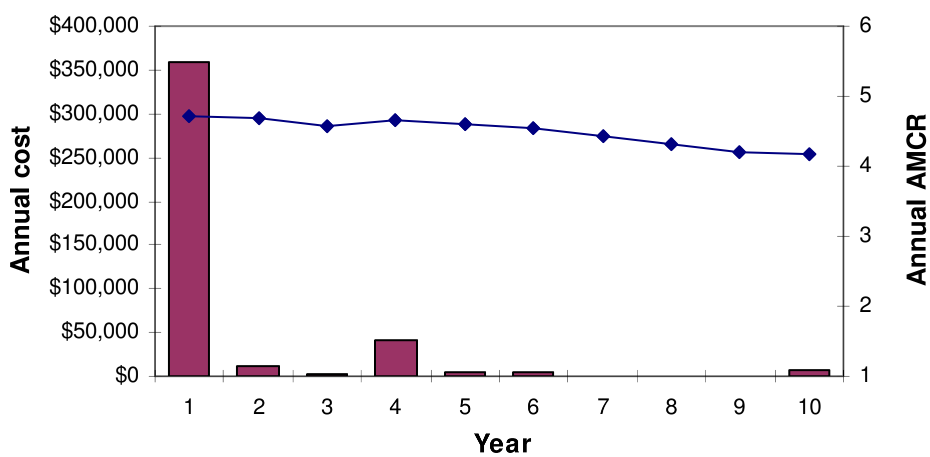
4
3
2
1
Annual AMCR
1
2
3
4
5
6
7
8
9
10
Year

(c)



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$250,000
$200,000
$150,000
$100,000
$50,000
$0
Annual cost
6
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Annual AMCR
1
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Year