Life-Cycle Reliability-Based Maintenance Cost Optimization of Deteriorating Structures with Emphasis on Bridges

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Abstract: The assessment of the current state and the prediction of the future condition of deteriorating structures are crucial processes in the management of civil infrastructure systems. Not only time-varying loads and resistances but also a series of maintenance interventions that are applied to keep structural systems safe and serviceable make the prediction process very difficult. In order to perform a realistic life-cycle analysis of deteriorating structures under different maintenance scenarios the uncertainties involved in this process have to be considered. This paper considers these uncertainties by providing a reliability-based framework and shows that the identification of the optimum maintenance scenario is a straightforward process. This is achieved by using a computer program for *Life-Cycle Analysis of Deteriorating Structures* (*LCADS*). This program can consider the effects of various types of actions on the reliability index profile of a group of deteriorating structures. Only the effect of maintenance interventions is considered in this study. However, any environmental or mechanical action affecting the reliability index profile can be considered in *LCADS*. Most input data are represented by random variables. In this manner, the uncertainties included in maintenance interventions, reliability index profiles, and cost evaluations are all taken into account. The present value of the expected cumulative cost associated with maintenance interventions can be evaluated for both an individual structure and a group of similar structures. Optimization and parametric analysis modules help the identification of the maintenance strategy that best balance cost and reliability index profile over a specified time horizon. Numerical examples of deteriorating bridges are presented to illustrate the capability of the proposed approach. Further development and implementation of this approach are recommended for future research.

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Introduction

In an effort to optimize maintenance, repair, and rehabilitation interventions to achieve the most cost-effective life-cycle performance for an existing group of deteriorating structures, agencies have developed several management methods. Most of these methods are based on subjective condition assessment and empirical models to predict future condition (Aktan et al. 1996). In these methods, collected data focus on structural members rather than the overall system. In addition, subjective condition rating scales requiring the judgment of experts are used. Since the process of life-cycle performance analysis should depend on quantitative data rather than qualitative information, the development of a management method that does not rely solely on subjective data is essential. Therefore, a method based on reliability concepts is necessary.

In this study, a method of analyzing life-cycle performance of deteriorating structures based on reliability is introduced by emphasizing a computer program developed at the University of Colorado. In the proposed method, the reliability index profiles and cost profiles of failure modes for a deteriorating structure are constructed based on various actions expected to occur during a given time horizon. The reliability index profile superposition method is used to combine the effects of different actions. These reliability profiles of failure modes are combined statistically to produce the reliability profile of the system. The reliability index profile superposition method is an efficient approach to evaluate the overall system reliability index profile by combining the time-dependent effects of various types of actions that may be encountered during the lifetime of structural systems. However, owing to space limitations only maintenance interventions are considered in this study. In the proposed method, the randomness of most variables is taken into account. Not only an individual structure but also a group of similar structures built during different time periods can be analyzed under different maintenance scenarios.

A computer program called *LCADS* (*Life-Cycle Analysis of Deteriorating Structures*) was developed to assure the objectivity necessary during different levels of computations requested in a life-cycle analysis of both individual and groups of deteriorating systems. This program is written in Fortran 90. Time-varying reliability of deteriorating systems is the most fundamental data to be evaluated and monitored in *LCADS*. Instead of a fixed value of the system reliability index at a specified point in time, *LCADS* considers the probability distribution of the system reliability index and its propagation over a given time horizon. This time-

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dependent system reliability index distribution is called the reliability index profile $\beta(t)$.

LCADS requests as input the initial reliability index profile $\beta_o(t)$. This represents the reliability index profile of an individual structure (or a group of similar structures) under no maintenance action. Data to describe additional reliability index profiles $\Delta\beta(t)$ caused by various actions including maintenance interventions are also required. Based on these input data, the evaluation of a system reliability index profile consists of several computational modules. Any event affecting the reliability profile can be represented by an action in *LCADS*. For instance, inspection and/or maintenance activities can also be represented by actions. The effect of rare events such as earthquakes, major traffic-structure collisions, and system failures can be modeled by using actions. As previously indicated, except where noted otherwise, only the effect of maintenance interventions is considered in this study.

LCADS does not include the computational module that evaluates the initial reliability index profile $\beta_o(t)$. There are several reasons for this. First, *LCADS* has been developed as a tool to help decision-makers to (1) compare the effects of different maintenance strategies and (2) seek an optimal solution satisfying a set of constraints. Therefore, the assessment and management modules are separated. Second, by using independent computational modules, *LCADS* is not influenced by the module evaluating the initial reliability index profile, that is, in general, an extremely complex computational process. An initial reliability index profile can be obtained by using time-dependent structural reliability methods (Chan and Melchers 1993; Mori and Ellingwood 1993; Enright and Frangopol 1999). Experimental data and inspection results may also be used to obtain a reliability index profile. The effects of inspection and/or maintenance actions on a reliability index profile may also be based on these data and results. Third, the computational efforts can be reduced significantly by this separation. In *LCADS*, most of the design variables are represented by random variables and Monte Carlo simulation is used. A typical computational time based on Monte Carlo simulation to obtain a reasonable solution for an optimal maintenance strategy is about 2 h on an ultra 10 Sun UNIX machine. Of course, this time may vary depending on the type of problem to be solved. Efforts to decrease this time may be achieved by using efficient variance reduction techniques.

The effect of each maintenance intervention is described in *LCADS* by an additional reliability index profile. The superposition of the initial system reliability index profile, $\beta_o(t)$, and the additional reliability index profiles provides the reliability index profile of the system subjected to maintenance interventions. In this study, the effects of maintenance interventions are considered in numerical examples based on results reported in Frangopol et al. (2001), Kong (2001), and Maunsell Ltd. and Transport Research Laboratory (1998, 1999).

The major features of the *LCADS* software are as follows:

- Evaluates the reliability index profile $\beta(t)$ of a structural system or a group of structural systems under different maintenance actions,
- Calculates the time required for $\beta(t)$ to down-cross a given target reliability level,
- Considers interaction between intervention costs and the reliability index profile,
- Defines the application time of an intervention by using either relative or absolute time scales,
- Uses hard or soft links between random variables to manage input data conveniently,
- Performs the life-cycle cost analysis for an individual system or a group of similar systems,
- Solves cost optimization problems defined with internal variables such as application times of interventions, maintenance costs, and structural reliability indices, and
- Provides parametric analyses.

Reliability Index Profile

Two of the most important questions in reliability-based management of structural systems are (1) how to evaluate the effects of various maintenance interventions that may be applied during the lifetime of a system? and (2) how to select the next maintenance intervention from a set of available interventions? Once an intervention is selected and applied, its effect on system reliability is evaluated in *LCADS* as an additional reliability index profile. To produce an efficient computational module for the prioritization of maintenance interventions, properties of maintenance actions are investigated within four intervention types. The prioritization algorithm to select an appropriate maintenance intervention among available actions is developed based on these four types of interventions. In this section, the basic concepts and definitions used to establish the computational algorithms in *LCADS* are introduced.

Safety of structural systems can be evaluated by several methods. Among them, methods based on reliability are the most powerful tools. Reliability-based methods can be classified into different categories according to the level of evaluation and the input information. The reliability index of a structural system is evaluated based on demand, such as loading effect, and capacity, such as resistance. Both demand and capacity vary during the system lifetime. Therefore, the reliability index varies with time. The variation of reliability index with time is called the reliability index profile. Efforts to maintain the performance of a system above a minimum prescribed reliability level need inspection, maintenance, and rehabilitation. All these actions can affect the reliability index profile of the system. The basic level of computation used in *LCADS* is associated with the reliability index and its profile. All types of information should be used at this level.

Events

A failure mode is represented by an event. In *LCADS*, different events can be considered. For instance, a bridge may be segmented into different structural elements such as deck, girder, cap, pier, bearing, and expansion joint. Each element may have different loading conditions, structural responses, and target reliability levels. On the other hand, the same system may experience different failure modes such as bending or shear. The failure modes are expressed in *LCADS* by using events. Results based on different events are combined statistically at a later stage of computation to obtain the final result for the entire system.

Actions

Anything that might influence the reliability index profile of a system, such as maintenance, rehabilitation, inspection, or accident, is defined as an action (also called intervention). An action is the lowest-level component to influence the system reliability index profile and the most basic data structure in *LCADS*. Each action is described by an additional reliability index profile. Random variables are used to define the effect of an action on the reliability index profile or to provide additional information such as action cost.

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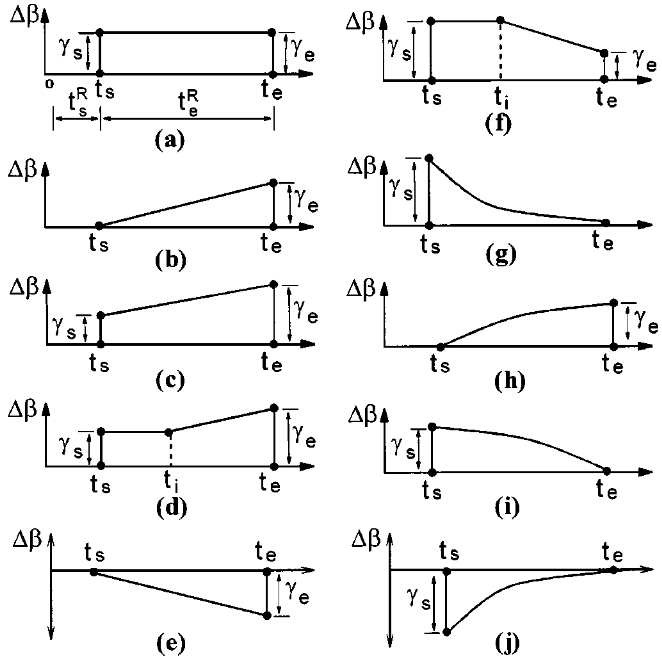

Fig. 1. Examples of additional reliability index profiles associated with different actions

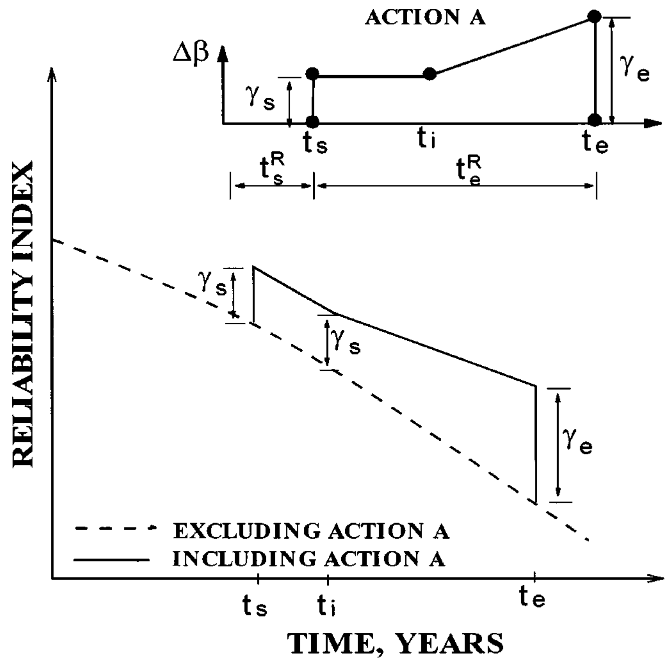

Fig. 2. Effect of additional reliability index profile of action on reliability index profile of failure mode

The time variant effects over the life cycle of an individual structure or groups of structures caused by mechanical loading or environmental conditions, such as corrosion, are included into the reliability index profile by adopting appropriate actions. In *LCADS*, an additional reliability index profile $\Delta\beta_i(t)$ is generated by the action *i*. The reliability index profile associated with the failure mode *j* includes the effects of all actions expected over a given time horizon. This profile is obtained by superposing the initial reliability index profile and additional reliability index profiles associated with all subsequent actions as follows:

$$\beta_j(t)=\beta_{j,o}(t)+\sum_{i=1}^{n}\Delta\beta_{j,i}(t) \tag{1}$$

where n = number of actions associated with the failure mode j during the lifetime. Finally, the reliability index profile of the system $\beta_{\text{system}}(t)$ is obtained by statistically combining the reliability index profiles of all failure modes.

Fig. 1 shows examples of additional reliability index profiles associated with different actions. In this figure, $\Delta\beta$ is the additional reliability index profile; t_s, t_i, and t_e are starting, intermediate, and ending times of an action; and γ_s and γ_e are the initial and ending values of $\Delta\beta$, respectively. Fig. 2 shows the effect of an action on an existing reliability index profile associated with a failure mode. Using the superposition indicated in Fig. 2, the effect of any type of action on the reliability index profile can be obtained. For instance, Fig. 1(a) represents an essential maintenance intervention that improves the reliability index during the time interval t_e-t_s; and Fig. 1(b) represents a preventive maintenance action that reduces the reliability index deterioration rate during the time period t_e-t_s. Fig. 1(e) represents an increase in the reliability index deterioration rate under environmental stressors due to the transition from a redundant system to a nonredundant system, and Fig. 1(j) represents the sudden drop of system reliability index due to an extreme event (e.g., earthquake) followed by repair effects over a certain time period.

Time-Controlled and Reliability-Controlled Actions

For each possible failure mode, multiple actions might be applied at different times. In this study, class type is used to classify actions. For some actions, the time of application is prescribed. For instance, painting a steel bridge every ten years or applying preventive maintenance every five years belong to this group. These kinds of actions are classified as time controlled. Conversely, other actions are applied when a specific condition is encountered. For instance, an element should be replaced after it reaches a target reliability level or a bridge component can be maintained if its condition state changed. These interventions called event-controlled actions depend on both the initial information on the system and the history of actions. They are also called reliability-controlled actions, if the event is related to the reliability deterioration of the system.

Both time-controlled and reliability-controlled actions can be applied only once or cyclically during system lifetime. Table 1 shows the class of actions considered in this study, their corresponding identification numbers in the computer program *LCADS*, and examples. Each event can consist of several actions defined by different classes. Fig. 3 qualitatively shows reliability index profiles for each class of action defined in Table 1.

Rehabilitation Time

Kong and Frangopol (2002) considered the event that, at a specified time t^*, the reliability index of the system $\beta(t^*)$ is less than the target reliability index β_{target} [i.e., $\beta(t^*)<\beta_{\text{target}}$]. The probability of this event $P[\beta(t^*)<\beta_{\text{target}}]$ can be evaluated by Monte Carlo simulation or it can be approximated using the assumption that the distribution of $\beta(t^*)$ is of a particular type. If the normal distribution approximation is used, this probability is (Kong and Frangopol 2002)

$$P[\beta(t^*)<\beta_{\text{target}}]\simeq\Phi\left(\frac{\beta_{\text{target}}-E[\beta(t^*)]}{\sigma[\beta(t^*)]}\right) \tag{2}$$

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Table 1. Action Types

Action types	Class types in life-cycle analysis of deteriorating structures	Example
Time controlled		
• applied once	1	Essential maintenance based on a probability distribution of application time.
• applied cyclically	2	Preventive maintenance every five years or painting steel components every 10 years.
Reliability controlled		
• applied once	3	Member replacement required when the system reliability down crosses a given target level.
• applied cyclically	4	Repair required whenever the reliability of the system is in state 2.[a]

[a]Reliability states are defined in Frangopol et al. (2001).

where $E[\beta(t^*)]$, $\sigma[\beta(t^*)]$, and $\Phi(\cdot)$ = mean value of $\beta(t^*)$, standard deviation of $\beta(t^*)$, and the standard normal probability, respectively. The probability (2) can be evaluated by Monte Carlo simulation as follows:

$$P[\beta(t^*)<\beta_{\text{target}}]\simeq\frac{m}{M} \tag{3}$$

where m and M are the number of samples satisfying the condition $\beta(t^*)<\beta_{\text{target}}$ and the sample size of the simulation, respectively. The probabilities (2) and (3) are computed at a specific point in time. If the probability of the event $\beta(t^*)<\beta_{\text{target}}$ is evaluated over a time period $(0,t]$, the probability of down crossing the target reliability index over this time period, $F_R(t|\beta_{\text{target}})$ can be represented by the probability of occurrence of the event $\beta(t)<\beta_{\text{target}}$ as follows:

$$F_R(t|\beta_{\text{target}})=P[\beta(t)<\beta_{\text{target}}] \tag{4}$$

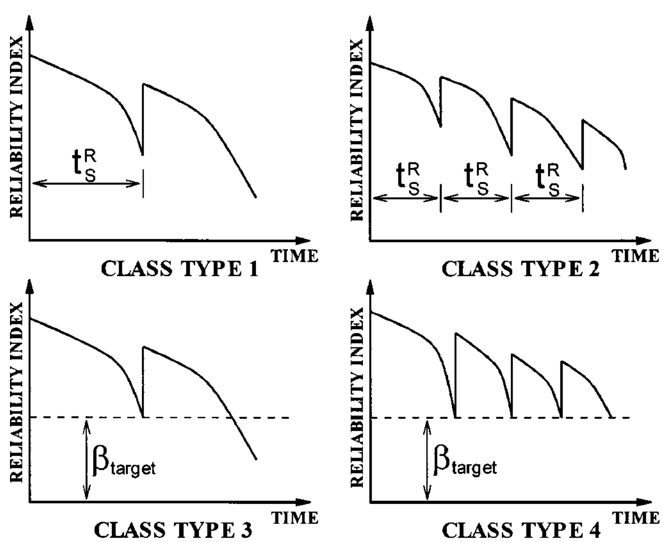

Fig. 3. Graphical interpretation of classes of actions

Cost Analysis

One of the major deficiencies of the classical management methods of civil infrastructure systems is the cost evaluation procedure. Inspection, maintenance, and rehabilitation costs invested during the lifetime of a system should be closely related to the reliability index profile of the system and interaction between cost and reliability should be considered. For instance, the cost of maintenance depends not only on the maintenance type but also on the reliability level when the maintenance is applied, the improvement of reliability due to the applied maintenance, and the effective duration of the maintenance action. Conversely, the reliability index profile is also influenced not only by the maintenance cost spent but also by the time when the maintenance is applied. If the cost of an intervention is a function of the time-dependent reliability and the effect of previous actions, the expected overall cost cannot be evaluated without considering this function. If the probability density distribution of an action with respect to time, $f_T(t)$, and the action cost are functions of several variables that are time dependent, then the expected overall cost associated with the action is computed as follows:

$$\text{Cost}_{\text{action}}=\int_{t_l}^{t_u} f[\beta(t),\Delta\beta(t),\alpha(t)]f_T(t)dt \tag{5}$$

where $f[\cdot]$ = cost function; $\beta(t)$ = reliability index profile; $\Delta\beta(t)$ = change in reliability index due to the applied action; $\alpha(t)$ = reliability deterioration rate depending on the type of the maintenance action applied (Frangopol et al. 2001); and t_l and t_u = lower and upper limits depending on the probability-density function $f_T(t)$. By using this time-dependent cost function, the optimal maintenance strategy considering reliability-cost interaction can be obtained. If the present value of the expected maintenance cost (Tilly 1997) is evaluated based on the discount rate of money ν, Eq. (5) is expressed as follows:

$$\text{Cost}_{\text{action}}=\int_{t_l}^{t_u}\frac{f[\beta(t),\Delta\beta(t),\alpha(t)]}{(1+\nu)^t}f_T(t)dt \tag{6}$$

Different cost profiles and optimal solutions are obtained if different discount rates are used. In general, cost invested for a certain time period is important in life-cycle cost analysis. In this case, the time horizon t_H is used. Because $f_T(t)=0$ when $0<t<t_l$, the expected cost spent until the time horizon is calculated as follows:

$$\text{Cost}_{\text{action}}(0,t_H]=\int_0^{t_H}\frac{f[\beta(t),\Delta\beta(t),\alpha(t)]}{(1+\nu)^t}f_T(t)dt \tag{7}$$

Cost evaluation during Monte Carlo simulation requires modification of Eq. (7). For instance, the present value of the expected annual cost of an action at a specific point in time t^* is evaluated as follows (Frangopol and Kong 2001):

$$\text{ACost}_{\text{action}}(t^*)=\frac{1}{(1+\nu)^{t^*}}\frac{C_S(t^*)}{M}=\frac{1}{(1+\nu)^{t^*}}\frac{\sum_{i=1}^{M}f_i[\beta(t^*),\Delta\beta(t^*),\alpha(t^*)]}{M} \tag{8}$$

where M = sample size of simulation; $f_i[\cdot]$ = cost associated with each sample evaluated from a cost function; and $C_S(t^*)$ = cost obtained after performing the whole simulation process. The expected total cost due to an action until the time horizon can be

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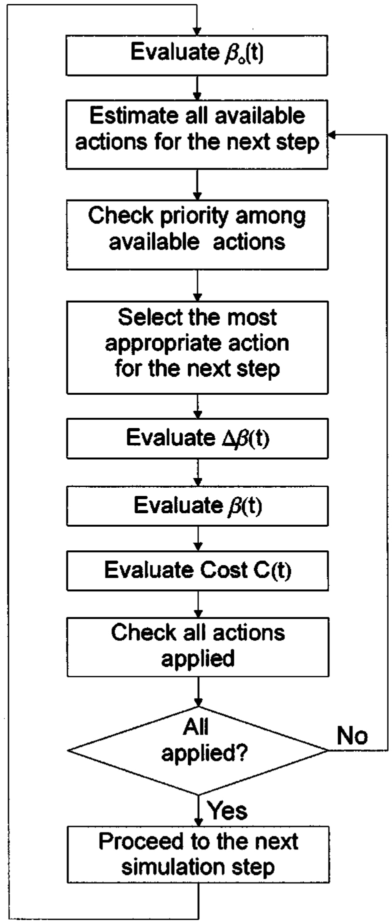

Fig. 4. Flowchart for evaluating reliability profile for failure mode and costs associated with actions (i.e., maintenance interventions)

obtained by integrating (or summing for the case of discrete time points) the expected annual costs for the associated time period $(0,t_H]$.

There are two important additional issues in life-cycle cost analysis: (1) the loss of the service time during inspection/maintenance activities and (2) the failure cost. In general, the loss of the service time is converted into the user cost. Failure cost is an important parameter for the optimization of the life-cycle analysis of inspection and/or maintenance scenarios.

The general flowchart for evaluating the reliability index profile and costs associated with maintenance interventions (i.e., actions) is shown in Fig. 4. Both the user and failure costs are included in the life-cycle cost analysis for the numerical examples presented in this paper. However, only the results based on deterministic cost data are used in those examples (i.e., $f[\cdot]=\text{constant}$). Information on the cost-reliability interaction can be found in Kong (2001).

Group of Structures

In general, the number of structures in a stock that must be managed by relevant authorities such as Departments of Transportation and Highways Agencies is hundreds or thousands. The optimal (usually the cost minimal) maintenance stock strategy changes depending on the individual structures in the stock. Usually, a project level analysis, that is, a series of analyses for all individual structures in a stock, requests a tremendous amount of

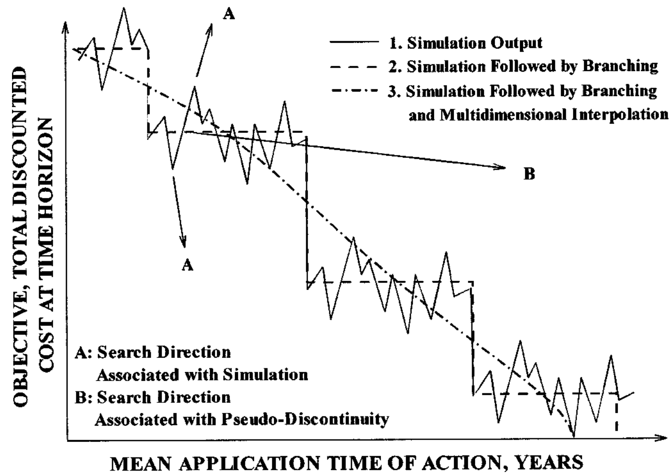

Fig. 5. Search directions associated with simulation and pseudo-discontinuity

computational effort. In *LCADS*, an efficient method is used to identify the optimal maintenance strategy for a group of similar structures built in different years. In this method, two assumptions are used: (1) the types of structures in a group are similar and (2) the expected maintenance histories for the group of similar structures are identical.

To increase the effectiveness of computation for a group of bridges, the effect of discount rate is calculated separately. The annual cost profile of a single bridge for a certain time period, calculated by *LCADS* according to the bridge history and the expected time horizon, includes the effects of all (i.e., past, present, and expected future) actions during the time period. This annual cost profile does not include the effect of discount rate. The effect of the discount rate is taken into account based on the selected base year of discounting. For instance, the expected annual discounted cost of an action to be applied t^* years from now for a bridge built t_c years ago is computed as follows:

$$\text{ACost}_{\text{action}}(t_c,t^*)=\frac{1}{(1+\nu)^{t^*}}\frac{\sum C_S(t_c+t^*)}{M} \tag{9}$$

where the base year of discounting is the current year.

In the case of a bridge group consisting of similar bridges with different ages, under the same maintenance scenario, Eq. (9) is used for each individual bridge and the cost for the group is computed by summation of the expected annual discounted costs of all bridges in the group (Frangopol and Kong 2001).

Optimization and Parametric Study

Many recent studies on maintenance and rehabilitation of deteriorating structures focus on how to obtain the most cost effective maintenance scenario (Thompson et al. 1998; Miyamoto et al. 2000). Limited financial resources are often smaller than those associated with a computed optimal solution. In this case, decision makers have to select the second, third, or fourth best option satisfying constraints on reliability. In general, a computer program seeking a minimum (or maximum) value may be divided into two modules: (1) optimization module that evaluates search direction and trial values for design variables and (2) main computational module that evaluates the value of an objective func-

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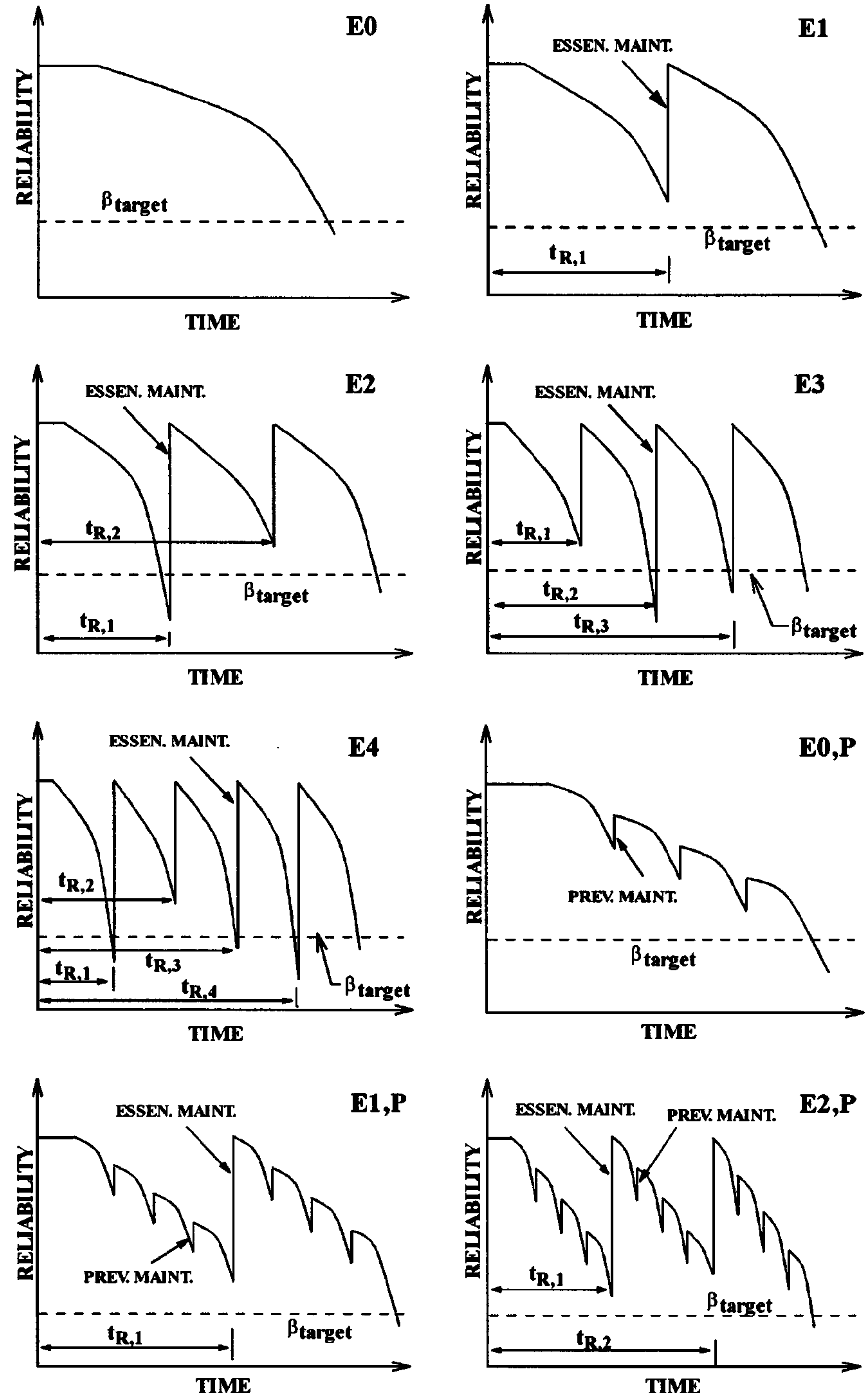

Fig. 6. Different maintenance scenarios

tion based on trial values and returns it to the optimization module. Optimization procedures and results depend on the structure of the main computational module because only the design variables, constraints, and objective functions defined in the main computational module can be used to formulate optimization problems. If the capability of the main module is restricted, then the result obtained is also restricted. The formulation of an optimization procedure is quite straightforward, once the objective function, design variables, and constraints are selected. In *LCADS*, various variables can be used as objective functions, design variables, and/or constraints by relying on the concepts defined in the previous sections. Different optimization problems can be defined and solved easily. The detailed user-friendly interface structure between the main computational module and the optimization module can be found in *LCADS user's manual* (Kong and Frangopol 2001). In this study, the feasible direction method is chosen as the mathematical programming tool.

For a cost minimal problem associated with the management of structures, the present value of the expected cumulative cost at a prescribed time horizon is the most appropriate objective to be selected. Discrete annual costs are summed until reaching the time horizon and saved in a vector variable. Since the results are saved as discrete values (i.e., annual costs) obtained by simulation, the search direction obtained from the discrete annual cost is

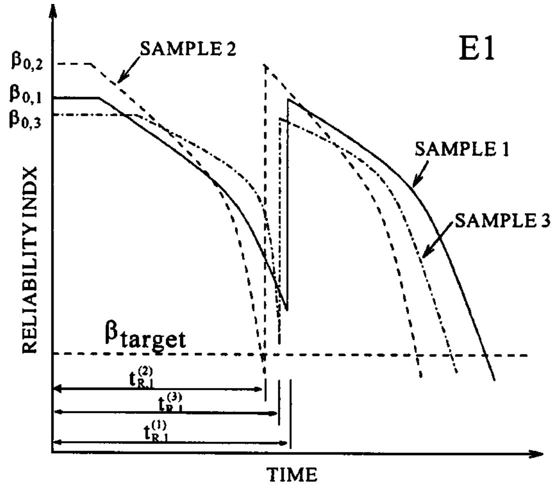

Fig. 7. Reliability profile samples generated by Monte Carlo simulation for maintenance scenarios $E1$ and $E1,P$

inefficient. For this reason, the branching method (Reklaitis et al. 1983) and multidimensional interpolation method (Press et al. 1992) are used to increase the efficiency of computation. The combination of these methods is very efficient when the hypersurface of the objective function after a multidimensional interpolation with respect to continuous design variables is relatively smooth and changes monotonically in the region close to the design point. Fig. 5 indicates the numerical problems encountered by Monte Carlo simulation using search directions for the case of a discrete annual cost associated with a continuous design variable represented by the mean application time of a maintenance action. It also shows results obtained by using improved solving techniques and the search directions associated with pseudo-discontinuity. It should be emphasized that different starting points should be examined to increase the possibility of obtaining a global optimum solution. Additional information on the mathematical programming method used in *LCADS* can be found in Kong and Frangopol (2001).

Numerical Examples

In this section, three numerical examples are presented. To avoid confusion, relatively simple but realistic examples associated with life-cycle maintenance scenarios are selected. Each maintenance scenario consists of a series of different maintenance actions. More complex applications can be found in Kong (2001). The first example shows how the proposed method can be used to predict the reliability profile for an individual bridge associated with different maintenance scenarios. The second example analyzes the same bridge and a group of bridges under the same maintenance scenarios. Finally, the third example describes an optimization problem aimed to obtain the best application times for maintenance actions achieving the minimum lifetime maintenance cost for a group of bridges. The examples concentrate on steel/concrete bridges. The database for these bridges is provided in Maunsell Ltd. and Transport Research Laboratory (1998, 1999), Nowak et al. (1997), and Frangopol et al. (2001).

Reliability Index Profiles

The first example shows how *LCADS* can handle various scenarios composed of different maintenance actions to obtain the reliability index profiles. Eight different scenarios ($E0$; $E1$; $E2$; $E3$; $E4$; $E0,P$; $E1,P$; and $E2,P$) for steel/concrete composite bridges are assumed. $E0$ represents the no maintenance scenario and $E1$, $E2$, $E3$, and $E4$ represent maintenance scenarios with one, two, three, and four essential maintenances, respectively. $E0,P$, $E1,P$, and $E2,P$ represent cyclic preventive maintenance scenarios with zero, one, and two essential maintenances, respectively. Fig. 6 qualitatively shows reliability index profiles associated with all these eight scenarios, and Fig. 7 indicates samples of reliability profiles generated by Monte Carlo simulation for maintenance scenarios $E1$ and $E1,P$. As indicated in Fig. 6, it is assumed that the system reliability index returns to its initial value when an essential maintenance is applied. This is an ideal case representing the upper limit of the improvement of the reliability index. As mentioned previously, users can define the improvement of the reliability index due to an action (see Fig. 1) if the effect of a certain type of maintenance on the reliability index profile is available. *LCADS* has the capability to control the upper bound of reliability index profile by using the function $\beta_{upper}(t)$.

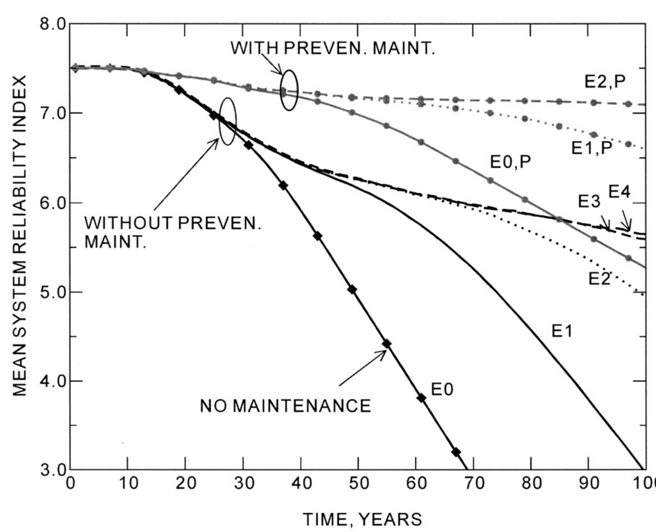

Fig. 8. Mean reliability index profiles associated with different maintenance scenarios

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Table 2. Estimated Unit Maintenance Cost for Superstructure of Steel/Concrete Composite Bridges (Maunsell Ltd. and Transport Research Laboratory 1998, 1999)

Cost type	Without preventive maintenance £/m^2 (\$/m^2)[a]	With preventive maintenance £/m^2 (\$/m^2)
Preventive maintenance cost	0 (0)	92 (132)
Essential maintenance cost	677 (968)	265 (379)
User cost for a preventive maintenance	0 (0)	124 (177)
User cost for an essential maintenance	2,141 (3,061)	403 (576)

[a]Costs are indicated in both pound sterling £ and equivalent US \$.

Using this function, the maximum improvement of the reliability index of an action can be controlled.

Fig. 8 shows the mean reliability index profiles associated with the maintenance scenarios defined in Fig. 6. The data used for computing the results in Fig. 8 is available in Frangopol et al. (2001).

Cost Profiles for Single Bridge and Group of Bridges

As explained previously, the proposed method can calculate the cost by taking into account the cost-reliability interaction. Table 2 shows the maintenance cost data [in pound sterling (£) per square meter of deck area] used in this example for different types of maintenance actions (Maunsell Ltd. and Transport Research Laboratory 1998, 1999) considered for the superstructure of steel/concrete composite bridges. These cost data are deterministic, but random variables may be used if the probability distributions of the maintenance costs are evaluated. In order to take into account the service time lost during preventive and essential maintenance activities, the user cost is included in computations (see Tables 2 and 4). Figs. 9 and 10 show the present value of expected annual and cumulative unit maintenance costs associated with five different maintenance scenarios. Three of these scenarios were also analyzed in Kong and Frangopol (2002). A discount rate of 0.06 is used for all the cases. To obtain the best maintenance scenario, the cost profiles (Fig. 10) have to be considered in conjunction with the mean reliability index profiles shown in Fig. 8. Also the time horizon is requested for this comparison. For this specific example considering a time horizon of 50 years, the maintenance scenarios associated with preventive maintenance ($E0,P$; $E1,P$; and $E2,P$) show lower costs (see Fig. 10) and higher reliabilities (see Fig. 8) than those without preventive maintenance ($E1$; $E2$) or without any maintenance ($E0$).

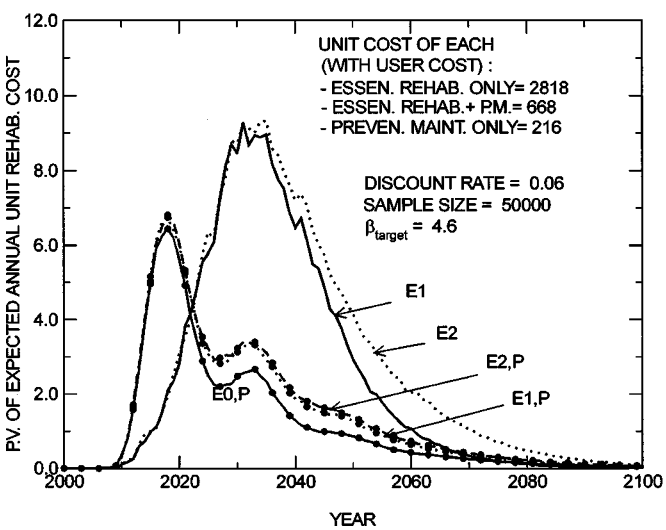

Fig. 9. Present value of expected annual unit maintenance costs: Essential maintenance applied once or twice with ($E1,P$; $E2,P$) or without ($E1$; $E2$) preventive maintenance; discount rate=0.06; cost in pound sterling (1£≃\$1.43)

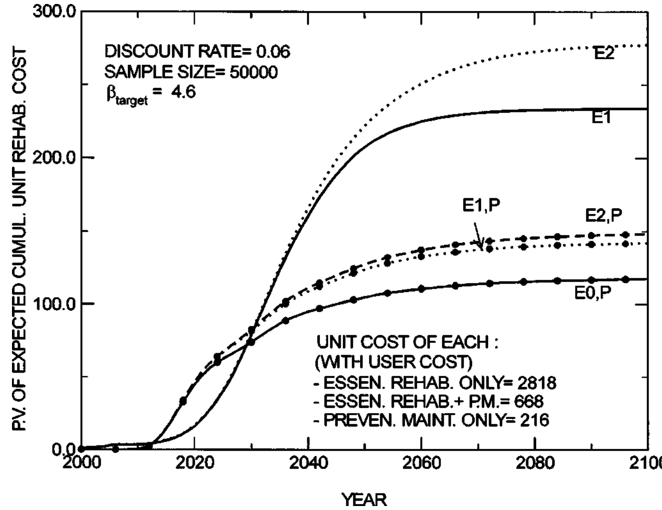

Fig. 10. Present value of expected cumulative unit maintenance costs: Essential maintenance applied once or twice with ($E1,P$; $E2,P$) or without ($E1$; $E2$) preventive maintenance; discount rate=0.06; cost in pound sterling (1£≃\$1.43)

A cost analysis for a group of similar structures built in different years is also possible using *LCADS*. Let us consider the steel/concrete composite bridge stock in Fig. 11 composed of 713 steel/concrete composite bridges defined in Frangopol et al. (2001). For this stock, Fig. 12 indicates the present value of the expected cumulative maintenance cost under different maintenance scenarios. In this case, the base year of discounting is the year 2000.

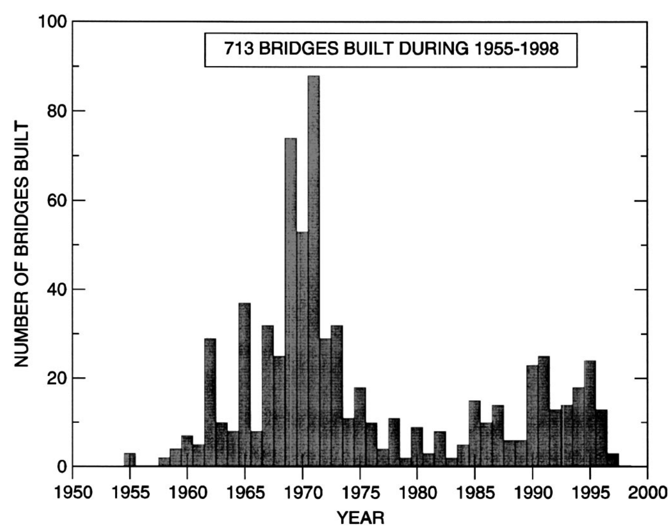

Fig. 11. Stock of steel/concrete composite bridges built during 1955–1998

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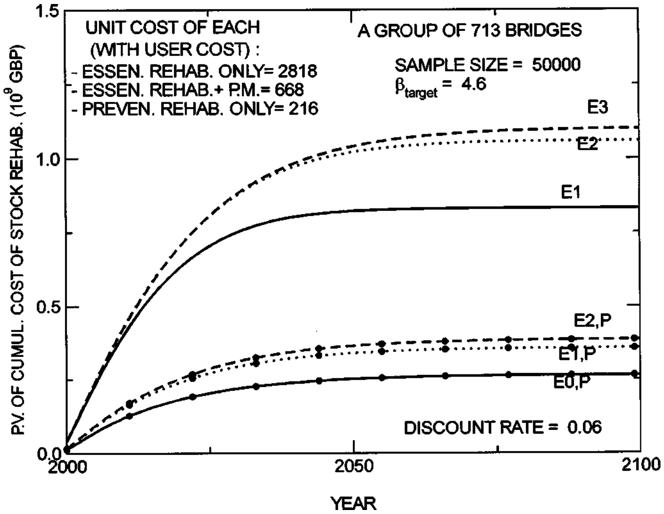

Fig. 12. Present value of cumulative maintenance cost for stock of 713 bridges under different maintenance scenarios; base year of discounting is year 2000; cost in pound sterling (1£≃$1.43)

Again, the scenarios associated with preventive maintenance show lower costs than those without preventive maintenance.

Cost Optimization

To illustrate the optimization process in *LCADS*, a minimum cost maintenance strategy satisfying given constraints is investigated. The present value of the expected cumulative maintenance cost associated with a given time horizon (i.e., 50 years) is selected as the objective to be minimized and the mean application time of maintenance actions, μ_{T_i}, μ_{T_P}, and $\mu_{T_{i,P}}$, are chosen as the design variables. The values μ_{T_i}, μ_{T}, and $\mu_{T_{i,P}}$ are the mean application time of an essential (without preventive) maintenance intervention, a preventive, and a hybrid (i.e., essential with preventive) maintenance intervention, respectively. It should be emphasized that the user may define different optimization problems by choosing other objective functions and design variables. Table 3 shows the maintenance scenarios to be optimized and the associated design variables, and Table 4 describes the design variables, corresponding maintenance types, probability distribution types, coefficients of variation, and associated unit costs.

Fig. 13 shows the obtained optimum mean application times of maintenance actions for different scenarios and the present value of the expected minimum cumulative total unit costs associated with the optimum results. Note that an optimal solution is given for each maintenance scenario. The most cost effective maintenance scenario is $E2,P$. As mentioned earlier, the best solution is obtained from comparing the cost profiles and the mean reliability index profiles. Fig. 14 shows the mean reliability index profiles for all maintenance scenarios associated with the optimum solutions in Fig. 13. It is easy to recognize that the maintenance scenario $E2,P$ has the highest mean reliability index at the 50-year time horizon. Since this scenario is also the most cost effective up to this time, it represents the optimal solution.

Table 3. Maintenance Scenarios and Associated Design Variables

Maintenance scenarios	Number of design variables	Design variables
$E1$	1	μ_{T_1}
$E2$	2	μ_{T_1}, μ_{T_2}
$E3$	3	μ_{T_1}, μ_{T_2}, μ_{T_3}
$E0,P$	1	μ_{T_P}
$E1,P$	2	μ_{T_P}, $\mu_{T_{1,P}}$
$E2,P$	3	μ_{T_P}, $\mu_{T_{1,P}}$, $\mu_{T_{2,P}}$

Note: Properties of design variables are defined in Table 4.

Conclusions

1. A computational tool that can be used to predict the life-cycle reliability performance, cost, and optimal maintenance interventions of deteriorating structural systems was described. This tool uses random variables to describe reliability index profiles and cost functions of individual or groups of deteriorating structural systems. The reliability index profile superposition method provided in this study is an efficient approach to evaluate the overall system reliability index profile by combining the time-dependent effects of various types of actions, including maintenance and environmental actions that may be experienced during the lifetime of structural systems;
2. Both individual structures and groups of similar structures built during different time periods can be analyzed by considering various maintenance scenarios;
3. By using a user-friendly interface, the user can solve various types of optimization problems. The feasible search direction method enhanced by the branching technique and multidimensional interpolation makes it possible to solve an optimization problem having a pseudo-discrete objective function and discontinuities caused by Monte Carlo simulation. By comparing optimum reliability and cost profiles of different maintenance scenarios, the user can select the optimal solution associated with minimum expected cumulative cost over a given time horizon;
4. One of the difficulties in using the proposed method is the quality and quantity of information used as input data. This information may be obtained from observed data and professional judgment. The probabilistic approach proposed is able to combine observed data with professional judgment. In-

Table 4. Design Variables of Optimization Problem

Design variables	Maintenance type	Probability distribution	Coefficient of variation	Unit maintenance cost including user cost, £/m^2 (\$/m^2)
μ_{T_P}	Preventive maintenance	Triangular (symmetric triangular)	0.169	216 (309)
μ_{T_i}	Essential maintenance *i* without preventive maintenance	Log-normal	0.312	2,818 (4,030)
$\mu_{T_{i,P}}$	Essential maintenance *i* with preventive maintenance	Log-normal	0.355	668 (955)

Note: Data in third, fourth, and fifth columns are from Maunsell Ltd. and Transport Research Laboratory (1998, 1999). The equivalent cost in U.S. $ is indicated in parentheses.

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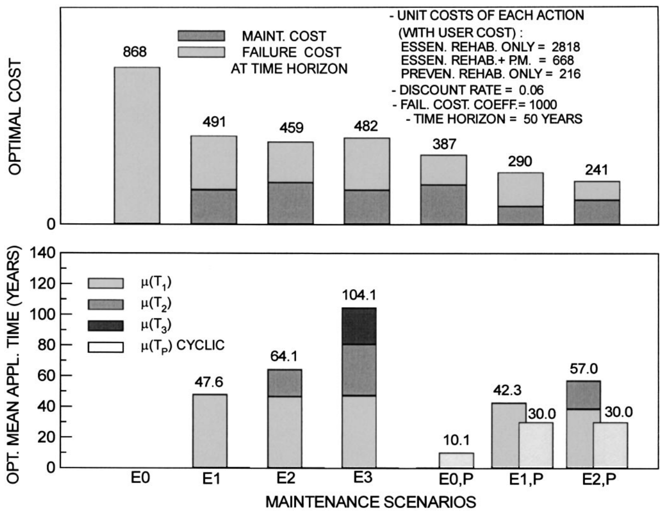

Fig. 13. Optimal mean application times of maintenance actions and associated minimum unit costs; cost in pound sterling (1£≃$1.43)

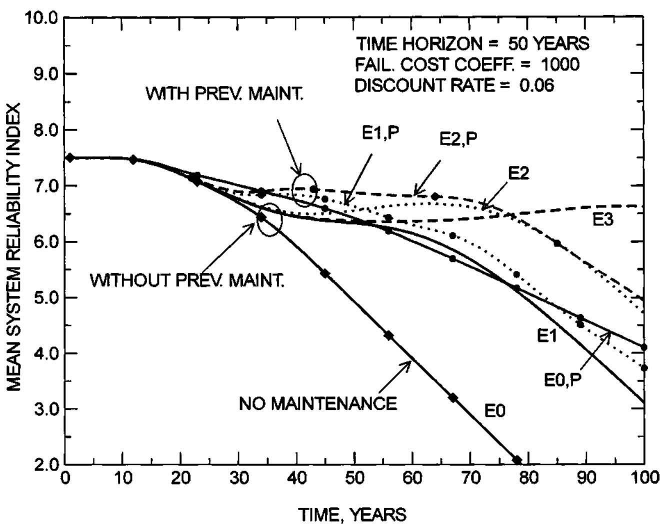

Fig. 14. Mean system reliability index profiles associated with optimization results

deed quality and quantity of the data expected in the future will reduce uncertainty and in turn will increase confidence in the predicted optimal lifetime maintenance strategies for deteriorating structures; and

5. Future research should concentrate on the further development and implementation of the computational procedure proposed. Groups of different types of structures should be considered, and the procedure should include both serviceability and ultimate limit states in a time-variant reliability perspective (Estes and Frangopol 2001).

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Notation

The following symbols are used in this paper:

$\mathrm{ACost}_{\mathrm{action}}$ = annual cost associated with action at point in time;
$\mathrm{Cost}_{\mathrm{action}}$ = total cost associated with action for time period;
$E[\cdot]$, $\sigma[\cdot]$ = mean and standard deviation of variable (or function);
Ei = maintenance scenario associated with i essential maintenance action(s);
Ei,P = maintenance scenario associated with i essential maintenance action(s) and cyclic preventive maintenance actions;
$f[\cdot]$ = cost function with respect to reliability parameters;
$f_T(t)$ = probability density function of occurrence of action;
M = sample size of Monte Carlo simulation;
m = number of the cases satisfying condition $P[\beta(t)<\beta_{\mathrm{target}}]$;
$P(A)$ = probability of occurrence of event A;
t_H = time horizon (years);
t_l, t_u = lower and upper limits of probability-density function $f_T(t)$;
t_s^R = time measured from a reference point;
t_s, t_i, t_e = starting, intermediate, and ending time of action;
$\alpha(t)$ = reliability deterioration rate;
β = reliability index;
$\beta_j(t)$ = reliability index profile of failure mode j;
$\beta_{j,o}(t)$ = initial reliability index profile of failure mode j with respect to time t;
$\beta_o(t)$ = initial reliability index profile with respect to time t;
$\beta_{\mathrm{system}}(t)$ = system reliability index profile;
β_{target} = target reliability index;
$\beta_{\mathrm{upper}}(t)$ = reliability index profile restricting upper limit of reliability improvement by action;
$\Delta\beta_i(t)$ = additional reliability index profile caused by ith intervention;
γ_s, γ_e = initial and ending values of $\Delta\beta$ (improvement in reliability index by maintenance action);
μ_{T_i} = mean application time of ith essential maintenance action;
$\mu_{T_{i,P}}$ = mean application time of ith essential maintenance action associated with preventive maintenance actions;
μ_{T_P} = mean application time of cyclic preventive maintenance actions;
ν = discount rate of money; and
$\Phi(\cdot)$ = standard normal probability distribution function.

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