AN LCCA ALGORITHM FOR BRIDGES: A COMPREHENSIVE APPROACH

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Paper Resubmitted for Presentation at the Transportation Research Board’s 87th Annual Meeting, 2008, Washington, D.C. and for Possible Publication in the 2008 Transportation Research Record Serious

Abstract: 247
Word Count: 5085 without references or 5642 with references
Figures & Tables: 7 @ 250 each = 1750
Total: 7392
Resubmission Date: November 15, 2007
ABSTRACT

Bridge Life Cycle Cost Analysis (BLCCA) has received a great deal of attention, especially in the last decade. Currently, there is no consensus on the required level of detail in performing a BLCCA concerning the number of elements that should be studied to attain a certain level of accuracy. However, some analysts, as mentioned in NCHRP-483 report, suggest that considering three elements (substructure, deck, and superstructure) yields an adequately detailed description of most highway bridges. The majority of previous studies, however, focused more on developing algorithms for one individual element of the bridge or the bridge itself as one element, rather than all the components as a system. Such a system approach would make the empirical results more realistic. Thus, this paper’s main objective is to develop a comprehensive BLCCA methodology using real data available in the National Bridge Inventory. Here, this inventory is primarily used for modeling the deterioration behavior of the bridge. The methodology predicts the agency and user costs using Genetic Algorithm for cost optimization, and Markov-Chain approach for deterioration modeling. Monte-Carlo Simulation is used for dealing with uncertainties. The BLCCA algorithm developed here can be a valuable tool for allocating limited public resources efficiently and maintaining all parts of the bridges functioning at acceptable levels. To validate the effectiveness of the suggested algorithm, results from a hypothetical case study are presented, which verify that the proposed methodology can be successfully applied to steel and concrete superstructure bridges that constitute the majority of bridges.

Key Words:
Bridge
Life Cycle Cost
Markov-Chain
Genetic Algorithm
Monte-Carlo Simulation
INTRODUCTION

Transportation officials consider Bridge Life Cycle Cost Analysis (BLCCA) an important issue for investment decisions. Current regulatory requirements recognize the benefits of BLCCA and point the importance of such analysis for the infrastructure investments, including highway bridge program [1]. Moreover, the Transportation Equity Act for the 21st Century (TEA-21) defines Life Cycle Cost Analysis (LCCA) as "a process for evaluating the total economic worth of a usable project segment by analyzing initial costs and discounted future costs, such as maintenance, user, reconstruction, rehabilitation, restoring, and resurfacing costs, over the life of the project segment." [2]

According to 2006 National Bridge Inventory Data there are 596,808 bridges nationwide and 13% of them are structurally deficient and 14% of them are functionally obsolete, which means that 27% of the nation’s bridges need replacement or major repairs. The effort to deal with infrastructure repair has increased the importance of BLCCA. Therefore, good optimization techniques are needed for BLCCA. There is currently no commonly accepted methodology for BLCCA, particularly as it might be applied to bridge management.

The main objective of this paper is to develop a methodology of BLCCA with deterioration models, scheduling of the rehabilitation, repair or reconstruction activities, and estimation of the agency & user costs. (Figure 1).

![Figure 1](image_url)

FIGURE 1 Possible activities during the service life of a bridge.
The recommended methodology uses genetic algorithm for optimization and Monte-Carlo simulation as a risk analysis technique. Adding Monte-Carlo simulation into the optimization model enhances the power of BLCCA by considering the uncertainties that are available in the model. The reason for adopting a probabilistic optimization method is to be able to take uncertainty in consideration and thus to better reflect the variability in the parameters through the stochastic approach.

**LITERATURE REVIEW**

Life cycle cost optimization of bridges has received a great deal of attention, especially in the last decade. Liu and Frangopol (2004) [3] developed a maintenance planning procedure using Monte-Carlo Simulation technique for deteriorating bridges. The authors used a multi-linear deterioration model for the reinforced concrete and two performance indices: the condition index and the safety index. Condition index is based on discrete values of 0,1,2 and 3 representing visual inspection. The safety index was defined as the ratio of available to required live load capacity, describing approximately the reliability level of a deteriorating bridge component. A larger safety index value indicated a more reliable level accordingly. As a maintenance strategy, two options were considered: silane treatment (it is a time-based maintenance intervention that reduces chloride penetration in reinforced concrete structures and therefore reduces deterioration of condition as well as safety) and do nothing but rebuild. The Genetic Algorithm (GA) and Monte-Carlo Simulation were applied to optimize the maintenance problem and address the significance of uncertainties in deterioration process, respectively.

Liu et al. (1997a & 1997b) [4] and [5] proposed an optimization method for bridge deck rehabilitation using a nonlinear equation as a model for the deterioration of bridge deck. The deterioration level of bridge deck was decided from 0 (new condition) to 1 (potentially hazardous condition). As an optimization method, Genetic Algorithm (GA) was deemed sufficient to find a satisfactory optimal set in a short calculation time.

Table 1 shows a summary of selected studies on the life cycle optimization of bridges [4-5-6-7-8-9-10-11-12-13-14-23]. Currently, there is no consensus on the required level of detail in performing a BLCCA concerning the number of elements that should be studied to attain a certain level of accuracy. However, some analysts, as mentioned in [1], suggest that considering three elements (substructure, deck, and superstructure) yields an adequately detailed description of most highway bridges. The majority of previous studies shown in Table 1, however, focused more on developing algorithms for one individual element of the bridge such as deck, superstructure, substructure or pavement, or the bridge itself as one element, rather than all the components as a system. Such a systems approach would make the empirical results more realistic.

**GENERAL RESEARCH METHODOLOGY**

The flowchart of the recommended methodology for LCCA is presented in Figure 2. Accordingly, the recommended BLCCA starts with characterization of the bridge and its elements such as the length, width of the bridge, number of the girders, number of the piers, ADT etc..

- In the second step, planning horizon, analysis scenario(s) and base case are defined.
- Third step is to select an appropriate deterioration model and its parameters.
### TABLE 1 Summary of Bridge Deterioration and Life Cycle Cost Optimization Studies

<table>
<thead>
<tr>
<th>Author</th>
<th>Year</th>
<th>Life Cycle Cost</th>
<th>Deterioration Model</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Deck</td>
<td>Superstructure</td>
</tr>
<tr>
<td>Mohammadi et.al</td>
<td>1995</td>
<td>O (NM)(AC)</td>
<td>LE</td>
<td>LE</td>
</tr>
<tr>
<td>Liu et.al</td>
<td>1997</td>
<td>O (GA)(AC, UC)</td>
<td>NLE</td>
<td>---</td>
</tr>
<tr>
<td>Frangopol et.al</td>
<td>1999</td>
<td>O (NM)(AC, UC)</td>
<td>LE, RB</td>
<td>LE, RB</td>
</tr>
<tr>
<td>Pratik, Roychoudhury</td>
<td>2001</td>
<td>O (NM)(AC, UC)</td>
<td>NLE</td>
<td>---</td>
</tr>
<tr>
<td>Estes &amp; Frangopol</td>
<td>2001</td>
<td>O (NM)(AC, UC)</td>
<td>NLE (CID)</td>
<td>---</td>
</tr>
<tr>
<td>Zayed et.al</td>
<td>2002</td>
<td>O (NM)(AC)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Kong &amp; Frangopol</td>
<td>2003</td>
<td>O (NM)(AC, UC)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Jawad, Dima</td>
<td>2003</td>
<td>O (GA)(AC, UC)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Liu &amp; Frangopol</td>
<td>2004</td>
<td>O (GA)(AC)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Morcous et.al</td>
<td>2005</td>
<td>O (GA) (AC, UC)</td>
<td>EJ (MC)</td>
<td>---</td>
</tr>
<tr>
<td>Robelin &amp; Madanat</td>
<td>2007</td>
<td>O (NM) (AC)</td>
<td>NLR (MC)</td>
<td>---</td>
</tr>
<tr>
<td>Ertekin et. al</td>
<td>2007</td>
<td>O (GA)(AC, UC)</td>
<td>NLR (MC)</td>
<td>NLR (MC)</td>
</tr>
</tbody>
</table>

**MCS** ≡ Monte-Carlo Simulation; **EJ** ≡ Expert Judgment; **UC** ≡ User Cost; **NLE** ≡ Non Linear Equation; **LE** ≡ Linear Equation; **MC** ≡ Markov-Chain; **CID** ≡ Chlorine Induced Deterioration; **GA** ≡ Genetic Algorithm; **O** ≡ Optimization; **A** ≡ Analysis; **RB** ≡ Reliability Based; **NM** ≡ Numerical Means; **NLR** ≡ Non Linear Regression; **P** ≡ Probabilistic; **AC** ≡ Agency Cost
Characterize Bridge and Its Elements

Define Planning Horizon

Select Traffic Models and Deterioration Models. Estimate ESALs and CESALS

Rehabilitation Activity Integer Decision Variable (α)? GA Generation (For Pavement, Deck, Superstr & Substr)

Using Rehabilitation Effectiveness, Update Performance Level

Using Performance Models, Calculate Pavement Roughness

Using PVOC Model for Commercial Cars Calculate CPVOCC

Using PVOC Model for Passenger Cars Calculate PPVOCC

Using Pavement Accident Cost Model Calculate PACC

Using Work-Zone Cost Model Calculate PUWZC Cost

Sum and Discount User Costs

Using Construction Cost Models Calculate and Discount Agency Cost

Using UORC Model Calculate CUORC

Using Performance Models Update δ (Bridge Operating Rating)

Using Vehicle Operation Cost Model Calculate BVOC

Using Accident Cost Model Calculate BACC

Using BTPC Model Calculate Third Party Cost

Calculate and Discount Bridge Inspection Costs

Calculate Salvage Value and Discount

Calculate Objective Function (WNPV)

FIGURE 2 Flowchart of BLCCA algorithm.
• Fourth step is defining alternative bridge management strategies.
• Fifth step is estimating cost (Agency and user costs) due to the different bridge management strategies.
• Sixth step is calculating net present values.
• Seventh step is reviewing the results.
• Eighth step is modifying management strategies if needed.
• Ninth step is selecting the preferred strategy.

The main components of the recommended BLCCA are explained in the following subsections.

**Deterioration Model**

NCHRP 483 [1] recommends a deterioration model based on statistical regression which allows the development of various relationships between condition measures and parameters presumed to have a causal influence on condition. These relationships maximize the likelihood that the output parameter (i.e., condition) will be in the particular range calculated if the causal parameters are in their particular assumed range.

Chase et al. (1999) [15] attempted to use regression analysis for bridge deterioration modeling. However only the age of the bridge and ADT were used as bridge variables and in a few of them they also include the effect of the environment on bridge deterioration.

In this paper, the bridge deterioration model is based on a non-linear regression analysis incorporated into the Markov-Chain simulation method similar to the one employed by Chase et al. (2000) [16]. In the proposed model, the Nation’s map is divided into 9 different regions according to National Climatic Data Center to represent the different environmental conditions [17]. By this way the bridges in each region are grouped separately and 9 different populations of bridges are formed reflecting 9 different environmental and climatic conditions. Using the same methodology in each case, a deterioration model is prepared for each region reflecting their different climatic conditions. Also different models are developed for different bridge types (steel and concrete superstructures), representing the majority of the bridges throughout the nation thus ending up with a total number of 18 deterioration models (e.g. deterioration model of bridges with steel superstructure in northeast region of the nation or deterioration model of bridges with concrete superstructure in southwest region of the nation, etc.). Condition ratings of each bridge element from SI&A data for regression analysis are obtained from National Bridge Inventory database. About 30,000 bridge data per region is selected among 592,246 bridges from year 2006 data. To get more reliable data, the bridges which are younger than 30 years are used which are less susceptible to any major repairs. Using this data, deterioration models are prepared and up to additional 45 years deterioration is forecasted. The reliability of this forecasting depends on the transition probabilities calculated by Markov-Chain simulation as described below in detail.

Deterioration models are prepared for superstructure, substructure, deck and pavement. For the first three of them, deterioration level is arranged with condition rating indices, which were used by NBI. This is a numeric ranking system from “0” to “9” with “0” representing “Failed Condition” and “9” representing “Excellent Condition” (Table 2). This data is available for deck, superstructure and substructure in NBI database.

Initial condition state of the bridge is called $C_S$. As the bridge is inspected or tested periodically, a different condition state number is assigned based upon the results of the inspection or testing and criteria assigned to each of the 10 unique condition states in Table 2.
### TABLE 2 Bridge Condition (Deterioration) Ratings

<table>
<thead>
<tr>
<th>Condition Rating</th>
<th>Interpretations</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>Excellent Condition</td>
</tr>
<tr>
<td>8</td>
<td>Very Good Condition – no problems noted.</td>
</tr>
<tr>
<td>7</td>
<td>Good Condition – some minor problems.</td>
</tr>
<tr>
<td>6</td>
<td>Satisfactory Condition – some minor deterioration of structural elements.</td>
</tr>
<tr>
<td>5</td>
<td>Fair Condition – minor section loss of primary structural elements.</td>
</tr>
<tr>
<td>4</td>
<td>Poor Condition – advanced section loss of primary structural elements.</td>
</tr>
<tr>
<td>3</td>
<td>Serious Condition – seriously deteriorated primary structural elements.</td>
</tr>
<tr>
<td>2</td>
<td>Critical Condition – facility should be closed until repairs are made.</td>
</tr>
<tr>
<td>1</td>
<td>Imminent Failure Condition – facility is closed. Study if repairs feasible.</td>
</tr>
<tr>
<td>0</td>
<td>Failed Condition – facility is closed and beyond repair.</td>
</tr>
</tbody>
</table>

As a bridge deteriorates, the condition state for the bridge will change. This final state of the bridge is called $CS_f$.

This deterioration can be described as a stochastic process, where the probability of a bridge transitioning from condition state $CS_i$ to $CS_{i+1}$ over a given time interval is defined by a condition state transition probability matrix $T$. The probability that the condition state of a bridge will change from $CS_i$ to $CS_j$ for a given time interval is given by $T_{ij}$. Considering the bridges are inspected every other year, time between observations is short enough; the observed condition state transitions should be limited to transitions between two adjacent condition states. Considering there are 10 unique condition states $T$ will be a 10 x 10 matrix. The diagonals ($P_{11}$, $P_{22}$, $P_{33}$, ..., $P_{1010}$) will be representing the probability of the condition to remain the same for the next year. The cells above the diagonal ($P_{12}$, $P_{23}$, $P_{34}$, ..., $P_{910}$) will be representing the probability of the condition to change in the next year. The rest of the cells will be all 0. It is assumed that at every transition period the bridge can only deteriorate to the next lower condition state. $P_{1010}$ is always 1, because this is the worst condition state and bridge cannot continue deteriorating after this condition.

Also the whole transition matrix $T$ can be represented by a vector $P$ which contains the diagonal of the matrix.

$$P = \begin{bmatrix} P_{11} & P_{22} & P_{33} & P_{44} & P_{55} & P_{66} & P_{77} & P_{88} & P_{99} & P_{1010} \end{bmatrix} \quad \text{(Eq. 1)}$$

Final condition state probability distribution $CS_f$ for a bridge part with an initial condition state probability distribution $CS_i$ after $N$ number of transitions can be shown as:

$$CS_f = CS_i T^N \quad \text{(Eq. 2)}$$
To illustrate, consider the following. A new bridge has a condition state probability distribution of \( \{1,0,0,\ldots,0\} \), then the condition state probability distribution of bridge after \( N \) transitions is: \( \{1,0,0,\ldots,0\}^T \).

The nonlinear regression to calculate the transition probabilities from one condition state to another is summarized as follows: Similar to Chase et al. (2000) \[16\], considering one of the population of bridges decided among the 18 (e.g. bridges with steel superstructure in northeast region) with differing ages and observed condition states for each bridge, a matrix is formed where the rows correspond to the number of transitions \( N \) and the columns correspond to the normalized value of bridges in each of \( M \) condition states. If the transition interval is selected as 1 year, then the number of transitions will be equal to the age of the bridge, which is considered to be 30 years (or transitions) with the remaining 45 years forecasted as mentioned above. As a result, a matrix that represents an array of condition state probability distributions for all bridges according to their ages in the population is obtained. This normalized bridge condition state matrix is called \( R \), which is an \( M \times N \) matrix, where \( M \) is the number of unique condition states defined in Table 2, and \( N \) is the maximum age of the population of bridges being analyzed. Each row in \( R \) can be used to estimate \( P \), and in essence \( R \) represents an indeterminate system of equations.

The aim here is to determine the \( T \) value that minimizes Equation 3; where \( S_{ij} \) is the simulated condition state, \( R_{ij} \) is the real condition state, \( S_{iwmean} \) is the weighted mean of the simulated condition states and \( R_{iwmean} \) is the weighted mean of the real condition states.

\[
\text{Min } \left[ \sum_i^N \sum_j^M (S_{ij} - R_{ij})^2 + \sum_i^N (S_{iwmean} - R_{iwmean})^2 \right] \quad (\text{Eq. 3})
\]

The minimization problem given by Equation 3 is applied to the superstructure, substructure, and the deck. In each case, the simulated and the actual values were very close, with an absolute mean error of only 1.75%, 1.86%, 1.58%, respectively, when applied to the 30-year real data that is available. These small errors also verify the accuracy of the remaining 45-years data forecast using the results of this minimization process.

Also to simulate the rehabilitation, repair or reconstruction activities, 10 X 10 Markovian transition probability matrices are formed. These matrices can be prepared according to every states bridge management system. In this paper it is assumed that a bridge that had a rehabilitation activity shall have min condition of 5 (Fair), a bridge that had a repair shall have min condition of 7 (Good), and a bridge that had a replacement shall have condition of 9 (Excellent). The proposed transition probability vectors are in the format of:

\[
P_{\text{rehabilitation}} = [p_{11}(<1), p_{22}(<1), p_{33}(<1), p_{44}(<1), 1, 1, 1, 1, 1, 1] \\
P_{\text{repair}} = [p_{11}(<1), 1 1, 1, 1, 1, 1, 1, 1, 1, 1] \\
P_{\text{replacement}} = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
\] (Eq. 4)

Although the bridge deterioration models are prepared for different material types and different climatic conditions, if we consider an individual bridge, its deterioration models still have uncertainty. To consider this uncertainty, the mean and the standard deviation of the deterioration values are formed and 3 different deterioration models prepared by Markov-Chain simulations. These 3 transition matrixes are \( P_{\text{mean}} \), \( P_{\text{mean} \pm \text{standard deviation}} \) and \( P_{\text{mean} - \text{standard deviation}} \).
After that, Monte Carlo Simulation is performed on Markov-Chain simulation considering a triangular distribution in which \( P_{\text{mean}} \) is the most likely value, \( P_{\text{mean}} + \text{standard deviation} \) and \( P_{\text{mean}} - \text{standard deviation} \) are the upper and lower bounds.

Following Chase et al. (2000) \[16\], a linear regression equation representing the operating rating of the bridge due to the Bridge Condition Rating is developed (Equation 5). According to this rating the allowable truck weight on the bridge is decided and this process was included in the BLCCA for rehabilitation decision and user cost purposes. The statistically significant regression coefficient in Equation 5 verifies that this simple linear regression model can be very useful in estimating the operating rating if the bridge condition rating data is available.

\[
\delta = \beta \cdot V + C \quad \text{(Eq. 5)}
\]

where
\( \delta \): Operating rating
\( \beta \): Regression coefficient, calculated as 5.31 through regression analysis (t-stat: 12.9, \( R^2 = 0.96 \))
\( V \): Bridge condition rating

For the deterioration model of the bridge and approaches pavement the international roughness index (IRI) will be used. Pavement roughness, which is generally defined as an expression of irregularities in the pavement surface, is used as a measure of pavement condition. Roughness is typically quantified using some form of either present serviceability rating (PSR), ride quality index (RQI), or international roughness index (IRI), with IRI being the most prevalent. According to the FHWA, IRI is an objective measure of pavement roughness and is accepted as a standard in the pavement evaluation community. IRI is based on the accumulated suspension of a vehicle (inches or mm) divided by the distance traveled by the vehicle during the measurement (miles or kilometers). The lower values of IRI correspond to higher quality pavements. IRI value typically increases as the pavement ages \[18\]. The roughness prediction model will be used in BLCCA to estimate the agency and user costs.

IRI depends on the traffic. The consideration of traffic should be consisting of loading magnitude and number of load repetitions. The annual average daily traffic data (AADT) collected by highway agencies is converted to the equivalent single axle load (ESAL), which is the number of repetitions of a standard 18-kip axle load. In addition to the AADT, the conversion accounts for the heavy vehicle proportions, the lane distributional factor and the directional distributional factor \[19\].

\[
\text{ESAL} = \text{ADT} \cdot \text{HV} \cdot \text{LEF} \cdot D \cdot L \cdot 365 \quad \text{(Eq. 6)}
\]

\[
\text{CESAL} = \text{ESAL} \cdot \frac{(1 + g_c)^n - 1}{g_c} \quad \text{(Eq. 7)}
\]

where
\( \text{ADT} \): Average Daily Traffic
\( g_c \): Combined axle weight and traffic volume growth rate
\( \text{HV} \): Heavy vehicle proportions
\( \text{LEF} \): Load equivalency factor
D : Directional distribution proportion  
L : Lane distribution proportion  
ESAL : 18-kip equivalent single axle load  
CESAL: Cumulative 18-kip equivalent single axle load

According to the Strategic Highway Research Program (SHRP) the equation of IRI for Flexible pavement is:

$$IRI = \left[ \frac{CESAL}{1000} \right]^{0.25} \times 10^Z$$

(Eq. 8)

where

$$Z = 0.0403 + 0.00014 \times AC_{visc} + 0.0704 \times AC_{void} + 0.314 \times \log(AC_{thick}) - 0.00162 \times B_{thick}$$

$$- 0.00165 \times DGT + 0.00001628 \times FI \times AC_{void}$$

(Eq. 9)

where

CESAL: Cumulative 18-kip equivalent single axle load  
IRI : International Roughness Index  
AC_{visc} : Asphalt viscosity  
AC_{void} : Asphalt air voids  
B_{thick} : Base layer thickness  
DGT : Annual days of temperature greater than 90 F°  
FI : Freeze index

Cost Model

A cost model should reflect the main characteristics of the real life such as the user costs as well as the agency cost. The ultimate goal is finding the most economical and safe scenario considering both of these variables.

Agency cost is basically formed from the costs related with, construction, repair, rehabilitation and inspection.

On the other hand user cost is formed from operating cost of the vehicles due to the bridge condition or repair or replacement activity. Also the effect of repairs on the third parties (gas stations or shopping centers around the bridge) is considered for the cost model. In these calculations the parameters such as detour length, vehicle speeds, bridge operating limits, bridge speed limits, and vehicle operating costs are considered. These costs can be summarized as shown below. These are the cost models that are used efficiently in other researches before. For more information see the related references.

- Vehicle Operation Cost (PVOC) Model due to Pavement Condition [20]
- Accident Cost Model (PACC) due to Pavement Condition [20]
- Delay Time Cost During Pavement Work Zone Operations (PUWZC) [12]
- User Costs Due To Operating Rating of the Bridge (UORC) [21]
- Vehicle Operation Cost (BVOC) Model due to Bridge Rehabilitation Activity [8,21]
- Accident Cost (BACC) Model due to Bridge Rehabilitation Activity [8]
• Third Party Cost (BTPC) Model due to Bridge Rehabilitation Activity [8]

**Decision Process**

Genetic algorithm is used for decision making process for the optimization. The main reasons for this are:
• There are no mathematical limitations for the decision variables, objective functions and formulations of the constraints.
• GA is already a proven robust and effective optimization tool, which can reach to optima in a relatively short time compared to the other search algorithms.
• GA is simple to use. It does not show “Black Box Syndrome”, which means a very complicated methodology that analyst cannot understand clearly the solution.

**OPTIMIZATION FORMULATIONS**

**The Decision Variables**

The decision variables (string structure) are:

\[
\alpha_{at} \quad \text{an integer} \in \{0,1,2,3,...m\} \text{ where } m \text{ represents the type of activity}
\]

\[t \quad \text{the time periods (year) in the analysis period}
\]

\[a \quad \text{member type (overlay, deck, superstructure, substructure) that decision variable belongs to.}
\]

**Constraints**

\[
\sum_t \text{Count}(\alpha_{at}) \leq n \quad \text{(Eq.10)}
\]

where
\[\alpha_{at} \geq 1 \]

\[n \] is the maximum possible number of rehabilitation activities, and Count is a function that counts the number of \(\alpha_i\) that is larger than or equal to zero.

\[
\text{WNPV} = \sum_{t=0}^{T} \left[ \sum_{k \in K} \sum_{j \in t} \omega_k \cdot \text{Cost}(k,j,t) \right] \frac{1}{(1+r)^t} \quad \text{(Eq. 11)}
\]

where
\[\text{WNPV}: \text{Weighted Net Present Value}
\]
\[\omega_k \quad \text{weight of cost } k \text{ mentioned above in the decision making process}
\]
\[K \quad \text{Set of costs classified on the basis of the bearing entity ($)} \text{ (ie, Agency Cost, User Costs, Social Costs)}
\]
This objective is assigning different weights for the different type of costs. By this way it will be prevented that the user costs will not overwhelm the analysis. The aim here is to minimize the net present economic worth of the project over its lifetime.

\[ OR \geq n \]  
\[ \beta \geq m \]

Where: OR is the operating rating of the bridge and n is a number less then one. The lowest value of the OR for the bridges needs to be decided based on the traffic and location of the bridge. After exceeding that rating value bridge needs a major repair or reconstruction.

The objective function is given by:

\[
WNPV_i(T) = \sum_{t} \alpha_i \{AC_i(\alpha_t) - SV_t\} + \omega \{TAVOC_i(\text{IRI}_t) + ACC_i(\text{IRI}_t) + UORC(\delta_t) + UC_i(\alpha_t)\} \frac{1}{(1 + r)^t}
\]

where:

- \( \alpha \): is an integer representing the type of rehabilitation activity to be scheduled at year t and equal to zero if no rehabilitation activity planned for pavement, deck, superstructure and substructure.
- \( \omega \): is the weight of the cost in decision making process.
- \( \delta \): is operating rating factor of the bridge.
- \( r \): is discount rate (decimals)
- \( WNPV_i(T) \): is the weighted net present economic worth of the life cycle strategy in project I due to the agency and the users over a planning period of T years.
- \( IRI_t \): is a function modeling the deterioration of pavement roughness
- \( AC_t \): is the agency cost at year t depending on construction, rehabilitation or reconstruction activity.
- \( SV_t \): is the salvage value at the end of the service life (T).
- \( TAVOC_t \& ACC_t \): are the total annual vehicle operating costs and the total annual accident costs at year t respectively which are functions of the pavement roughness in that year.
- \( UORC_t \): is user cost (detour) due to operating rating of the bridge at that year.
UC$_t$ : is the user work zone costs during the rehabilitation activities for pavement, deck, superstructure and substructure.

**Steps in Implementing BLCCA**

**Step A:** Initial Input Entry – Determine uncertain input parameters like discount rate, traffic characteristic and deterioration characteristic. Prepare their probability distributions. Choose genetic algorithm operators.

**Step B:** GA Commencement - generate a parent pool which will be the initial pool: for each solution assign a value for 4 different “α” s (pavement, deck, superstructure, and substructure) for all t values randomly (it is always better to prepare a logical parent pool for a quick and accurate optimization process).

**Step C:** LCCA Algorithm

For each solution in the parent pool

**Step C-1:** Monte-Carlo Simulation – Using random sampling from the probability distributions of the uncertain parameters calculate.

**Step C-1-1:** Bridge Condition – For all t, using traffic equations and regression with Markov-Chain calculate the condition of the bridge members. (Eqs 1 to 9).

**Step C-1-1-1:** Updating facility condition – If $α > 0$ (for pavement) then, update IRI$_t$ otherwise calculate roughness level using performance models (Eq. 8 and 9).

**Step C-1-1-2:** Updating facility condition – If $α > 0$ (for deck) then, update condition rating using proper repair vector (Eq. 4); otherwise calculate condition rating by using transition matrix (Eq. 1).

**Step C-1-1-3:** Updating facility condition – If $α > 0$ (for substructure) then, update condition rating using proper repair vector (Eq. 4); otherwise calculate condition rating by using transition matrix (Eq. 1).

**Step C-1-1-4:** Updating facility condition – If $α > 0$ (for superstructure) then, update condition rating using proper repair vector (Eq. 4); otherwise calculate condition rating by using transition matrix (Eq. 1). Also no matter what $α$ value is, update the operating rating of the bridge (Eq. 5).

**Step C-1-1-5:** Cost Estimation – If $α > 0$ for pavement, deck, superstructure or substructure, calculate agency costs for the repair or replacement activity and user work zone costs.

**Step C-1-1-6:** Cost estimation – Calculate total annual vehicle operating costs and accident costs. Also calculate annual inspection cost for the bridge.

**Step C-1-1-7:** Discounting – Calculate present value of total cost (user costs and agency costs) (Eq. 11).

**Step C-1-2:** Objective function calculation – Record system response for the iteration and calculate objective function (Eq. 14).

**Step C-2:** Fitness of Solution – Construct probability distribution of the objective function from the system response in each Monte-Carlo iterations.

**Step C-3:** Legitimacy of Solution – Check for constraints (Eqs. 10 to 13). If constraints are violated, ignore the solution. Otherwise, include the solution in the parent pool.

**Step D:** Stopping Rule – Repeat Steps F, G, H then C until the preset stopping criteria is met.

**Step E:** Optimum Solution – Stop and present the optimum life cycle strategy that yields the minimum mean value for the objective function.

**Step F:** GA Selection of parent offspring – Evaluate the valid solutions based on their fitness, and select the best two solutions as the parents for the offspring.
**Step G:** GA Next pool generation – Generate the next parent pool of solutions.

**Step H:** GA Operations Perform – GA operations of cross over and mutation on the parent pool of the next generation and go back to Step C.

**RESULTS**

To validate the effectiveness of the suggested algorithm, results from a hypothetical case study are presented. Most of the bridge input parameters are hypothetical yet consistent with real world observations. A logical initial repair-reconstruction scenario for each part of the bridge is defined.

Some of the variables such as discount rate, average daily traffic growth rate and superstructure deterioration matrix are considered uncertain variables. They are included in the algorithm in terms of their probabilistic distributions and Monte-Carlo simulation is applied on these uncertain variables to better demonstrate the power and effectiveness of the probabilistic BLCCA optimization. Distributions for discount rate and average daily traffic volume growth rate are obtained from [21].

- **Discount rate:** Triangular distribution (0.02, 0.04, 0.06)
- **Average daily traffic volume growth rate:** Triangular distribution (0.015, 0.025, 0.035)

Distribution for superstructure deterioration matrix is calculated by analyzing the National Bridge Inventory (NBI) data and preparing deterioration models at the mean, upper and lower limits of the NBI data. Northeast region, steel bridges are used to prepare the model for this case study, to simulate the bridge deterioration. Below are the calculated deterioration matrixes for Markov-Chain.

- **Superstructure:**
  
  Triangular
  
  $P_{\text{mean+standard deviation}} = [0.92, 0.92, 0.97, 1.00, 1.00, 0.82, 0.73, 0.65, 0.57, 1.00]$
  
  $P_{\text{mean}} = [0.62, 0.89, 0.93, 0.99, 0.82, 0.73, 0.65, 0.58, 1.00]$
  
  $P_{\text{mean-standard deviation}} = [0.00, 0.21, 0.91, 0.90, 0.90, 0.91, 0.70, 0.57, 1.00]$

Being the most dominant member among deterioration models for user cost, only Superstructure deterioration matrix is considered with distribution. Deterioration models for the other parts of the bridge are as follows.

- **Substructure:** $P = [0.07, 0.84, 0.93, 0.94, 0.99, 0.80, 0.70, 0.62, 0.56, 1.00]$
- **Deck:** $P = [0.56, 0.88, 0.96, 0.97, 0.90, 0.79, 0.72, 0.65, 0.57, 1.00]$
- **Pavement IRI:** 67 inch/mile

Weight of user cost is assumed %15 and agency cost assumed %100 in the decision making process.

Probabilistic BLCCA is run to obtain an optimized result for the hypothetical bridge which satisfies the objective function. The deviations in the order of the rehabilitation activities from initial condition to optimized condition for every part of bridge are shown in Figure 3 and Figure 4. These changes are shown in the graphs as the change on the mean condition rating of the bridge parts and IRI indices for the pavement due to the repair activities.

The change in superstructure condition rating due to the probabilistic BLCCA optimization is shown in Figure 5. Also the yearly user cost for 75 years due to the probabilistic BLCCA optimization is shown in Figure 5. In these graphs the dark thick line represents the mean values surrounded by two margins which are ±1 standard deviation and %5 to %95.
FIGURE 3 Bridge and pavement mean condition ratings according to initial solution.

FIGURE 4 Bridge and pavement mean condition ratings according to BLCCA optimization.
FIGURE 5 Superstructure Condition Rating (upper) and User Cost (below) according to probabilistic BLCCA optimization.
probability range. As it is seen from the graphs, the more years pass the more variable user cost and superstructure condition rating become. This variance is due to the uncertainty of the variables (Discount rate, average daily traffic growth rate and superstructure deterioration rate).

According to the initial solution, the total discounted 75 year life cycle cost for the bridge is $141,091,400 and the optimal solution is obtained by running the probabilistic optimization algorithm using genetic algorithm. The optimal total 75 year life cycle cost for the bridge is $128,038,200 which is %9.3 lower than the initial value.

CONCLUSIONS

A comprehensive Bridge Life Cycle Cost Analysis algorithm is developed. The real bridge data from the National Bridge Inventory Database is used for preparing the deterioration models of the algorithm. This methodology takes into consideration all the structural components of the bridge and predicts the agency and user costs of rehabilitating, repairing, and reconstructing the bridges more accurately. Within the framework of this approach, Genetic Algorithm for cost optimization, Markov-Chain for deterioration modeling, and Monte-Carlo Simulation for dealing with uncertainties are adapted. The effectiveness of the suggested algorithm is evaluated by using a case study with hypothetical bridge data. The results of this case study are presented. Considering the bridge elements as a system ensures making more precise calculations. (i.e. only considering deck results in user cost for speed restriction due to deck condition, however including the superstructure in the model as well ensures checking the user cost for speed reduction due to operating rating of the bridge, plus user cost for bridge weight limit due to operating rating of the bridge). Moreover, the probabilistic optimization resulted in a better understanding of the bridge life cycle cost, showing final cost as a range rather than a single value. This probabilistic approach is superior to the deterministic methods as it reflects the real-world cases to a greater extent and gives the agencies a better view for how to manage their resources. Main results show that the recommended approach can be successfully applied to concrete or steel superstructure bridges that constitutes the majority of bridges.

This approach is a highly effective optimization algorithm that can be incorporated into a network level bridge management system for a specific time period (i.e. 5 to 20 year budget management of 20 bridges in a network).

ACKNOWLEDGMENTS

The writers express their gratitude to Federal Highway Administration and New Jersey Department of Transportation for providing data to develop the deterioration models and cost models.
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