Modeling the Reduction in Load Capacity of Highway Bridges with Age

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Abstract: Bridge management systems focus on optimizing the life-cycle cost of preservation and improvement activities in a network of structures. Pontis, the predominant bridge management system currently implemented in the United States, considers load-carrying capacity as static during an incremental benefit-cost approach. Including consideration of load-carrying capacity, deterioration may enhance this model. To accomplish this goal, a method to relate load-carrying capacity to physical bridge deterioration using a combination of regression analysis and Markov chains is presented. The method is applied to historic bridge data from the United States and Hungary.

INTRODUCTION

Many bridge owners, most notably state departments of transportation in the United States and countries such as Hungary in Europe, are implementing new bridge management systems to help make decisions for the expenditure of limited funds for bridge maintenance, rehabilitation, repair, and replacement [American Association of State Highway and Transportation Officials (AASHTO) 1993]. The predominant U.S. systems have resulted from efforts undertaken by the U.S. Federal Highway Administration (O'Connor and Hyman 1989) and the National Cooperative Highway Research Program (Hudson et al. 1987). Pontis (Thompson et al. 1998) and BRIDGIT (Hawk and Small 1998) resulted from these early efforts, respectively. Both systems provide comprehensive decision support for determining the optimum resource expenditures required while maintaining a specified level of service for a population of bridges.

In the United States the most prevalent bridge management system being implemented is Pontis with over 40 states currently licensing the software from the AASHTO. In Europe, several countries are evaluating Pontis, and Hungary is implementing a national bridge management system based upon Pontis. Despite this widespread activity, there are several practical issues that are not modeled adequately within such systems. Bridge owners require a method to adequately predict the relationship between physical bridge deterioration and load rating. This paper presents a method to model the interrelationship between the load rating and physical bridge deterioration. The approach is based upon a combination of regression analysis and deterioration modeling using Markov chains. The method is applied to historic bridge data from the United States and Hungary.

METHODOLOGY

The method for modeling the relationship between physical bridge deterioration and age is divided into three steps. The first step is to determine the relationship between bridge condition, as defined by condition state and load rating. This is accomplished by analyzing the available data on a population of bridges and developing regression equations for this relationship. For the two examples presented, a linear relationship was found to be adequate, but the methodology is not restricted to a linear relationship. If another type of relationshp is found to fit the data better, it should be utilized. The second step is to determine a model for bridge condition deterioration with age. The model proposed uses a Markov chain to simulate the time-dependent bridge deterioration. The third step is to combine the Markovian deterioration model with the regression relationship to predict the time-dependent load rating behavior.

The numerical methods used to develop a least-squares linear regression model are well understood and have been incorporated in a wide range of data analysis tools such as spreadsheet and statistical software packages. The details are not reported. The numerical methods used to determine the Markovian deterioration models are unique and are described below.

It is assumed that the physical condition of a bridge is described by assignment of a unique condition state number. This condition state number is assigned to the bridge based upon the results of inspection or testing. The condition state number is selected from a set S of predetermined condition states that provide for assignment of all observable condition states

$$S = \{CS_1, CS_2, \ldots, CS_N\} \quad (1)$$

where CS_1 = initial condition state that represents the observable condition state with the least deterioration; and CS_n = terminal condition state that represents the condition state with the highest level of deterioration. The number of unique and mutually exclusive condition states N is arbitrary but typically ranges from 4 to 10. A newly constructed bridge is assigned condition state CS_1. 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 N unique condition states in set S. As a bridge deteriorates, the condition state for the bridge will change.

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 $\mathbf{T}$. 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 $\mathbf{T}_{ij}$. If the time interval between observations is short enough, the observed condition state transitions should be limited to transitions between two adjacent condition states. For bridges, the time period between inspections and assignment of condition states is 1 or 2 years. It is assumed that this time interval is short, relative to bridge deterioration. It is also assumed that the deterioration process is one directional and that condition states must transition from lower to higher indexes. Improvement of bridge condition states brought about by bridge rehabilitation or repair is not modeled by the condition state transition probability matrix $\mathbf{T}$. It is further assumed that bridge maintenance practices can

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Note. Discussion open until April 1, 2001. To extend the closing date one month, a written request must be filed with the ASCE Manager of Journals. The manuscript for this paper was submitted for review and possible publication on August 28, 1997. This paper is part of the ***Journal of Bridge Engineering***, Vol. 5, No. 4, November, 2000. ©ASCE, ISSN 1084-0702/00/0004-0331–0336/$8.00 + $.50 per page. Paper No. 16524.

slow deterioration, but do not result in condition state improvement. These assumptions lead to **T** being an upper triangular diagonal matrix of the form shown below

$$\mathbf{T} = \begin{bmatrix} p_{11} & 1 - p_{11} & 0 & \cdots & 0 \\ 0 & p_{22} & 1 - p_{22} & \cdots & 0 \\ 0 & 0 & \cdots & \cdots & 0 \\ 0 & 0 & \cdots & p_{N-1,N-1} & 1 - p_{N-1,N-1} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \quad (2)$$

Note that a vector **P**, containing the main diagonal of matrix **T**, can describe the complete transition probability matrix where

$$\mathbf{P} = \{p_{11}, p_{22}, \ldots, p_{N-1,N-1}, 1\} \quad (3)$$

The final condition state probability distribution $\mathbf{C}_f$ for a bridge with an initial condition state probability distribution $\mathbf{C}_i$, after M transitions is given by

$$\mathbf{C}_f = \mathbf{C}_i\mathbf{T}^M \quad (4)$$

If one assumes that a new bridge has a condition state probability distribution of {1, 0, . . . , 0}, then the condition state probability distribution for this bridge after *M* transitions will be $\{1, 0, \ldots, 0\}\mathbf{T}^M$.

Given a population of bridges of differing ages with observed condition states for each bridge, it is possible to form a matrix where the rows correspond to the number of transitions and the columns correspond to the number of bridges in each of *N* condition states. If the transition interval is selected as 1 year, then the number of transitions equals the age of the bridge. Normalizing each row by the total number of bridges in the row results in a matrix that represents an array of condition state probability distributions for all bridges in the population. This normalized observed condition state matrix is designated **O**, which is an $N \times M$ matrix, where *N* is the number of unique condition states defined in *S*, and *M* is the maximum age of the population of bridges being analyzed. Each row in **O** can be used to estimate **P**, and in essence **O** represents an overdetermined system of equations. The procedure used was to determine **P** such that $\sum_i^M \sum_j^N (\mathbf{E}_{i,j} - \mathbf{O}_{i,j})^2$ is minimized, where $\mathbf{E}_{i,j}$ is the estimated condition state, and $\mathbf{O}_{i,j}$ is the observed condition state. Note that the estimated condition state distribution after *K* transitions is $\mathbf{E}_K = \{1, 0, \ldots, 0\}T^K$.

RELATIONSHIP BETWEEN LOAD RATING AND SUPERSTRUCTURE CONDITION FOR U.S. BRIDGES

The United States National Bridge Inventory (NBI) contains data on 583,349 bridges with span lengths >6.1 m (20 ft) that carry a public road. This total includes 107,256 culverts. In the United States, culverts are not assigned a superstructure condition rating and are therefore excluded from the analysis. The bridge owners are allowed to calculate load capacities of in-service bridges using any of nine different rating vehicles. The different load rating vehicles are (1) H loading; (2) HS loading; (3) alternate interstate loading; (4) Type 3 unit, (5) Type 3-S2 unit; (6) Type 3-3 unit; (7) railroad loading; (8) pedestrian or special loading; and (9) gross load only. By far, the most common loading type used to calculate the load rating for highway bridges in the United States is the HS loading. More than 92% of all load ratings are based upon this type of loading. To simplify the analysis, only bridges where the load rating was calculated with HS loading were included in the analysis. In addition, bridges identified as having undergone significant rehabilitation at some point in time were excluded from the analysis. This eliminated the confounding effect of condition state improvement over time. The result was to limit the analysis to 409,741 bridges. The number of bridges with each of the nine possible superstructure condition ratings is tabulated in Table 1.

To more fully understand and visualize the relationship between load rating and superstructure condition rating, a comparison of the normalized cumulative frequency distributions for each condition state category is presented in Fig. 1.

As can be seen, approximately 19% of all bridges with a superstructure condition rating of 9 have a load rating of 36 tons or less, while about 90% of all bridges with a superstructure condition rating of 2 have a load rating of 20 tons or less. The almost vertical break in many of the cumulative distribution curves is due to the fact that the current design standard for highway bridges in the United States is 36 tons. The normalized cumulative distributions of bridges within each superstructure condition rating follow a reasonable and expected pattern, with the exception of condition category 0. The average condition rating for bridges with a superstructure condition rating of 0 is 19.2 tons. This does not agree with the general trend for all other condition rating categories. The difference in the superstructure condition rating 0 curve is attrib-

TABLE 1. Number of Bridges by Superstructure Condition Rating Code (HS Ratings Only)

Code (1)	Description (2)	Number of bridges (3)
0	Failed	1,303
1	"Imminent" failure	371
2	Critical	1,423
3	Serious	8,188
4	Poor	21,969
5	Fair	46,390
6	Satisfactory	79,610
7	Good	120,199
8	Very good	114,525
9	Excellent	15,764

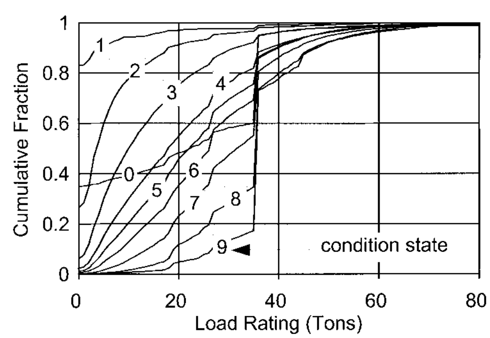

FIG. 1. Normalized Cumulative Frequency Distributions of Load Ratings for Bridges with Different Superstructure Condition Ratings

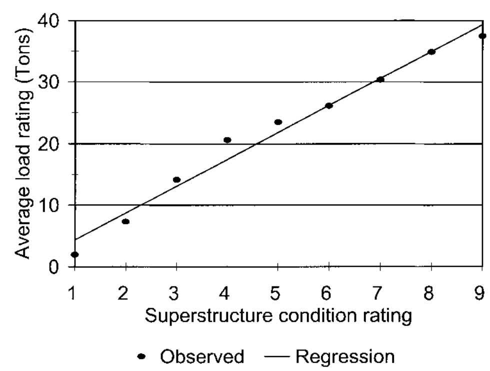

FIG. 2. Relationship between Average Load Rating and Superstructure Condition Rating

uted to having many out of service bridges with higher load ratings being assigned a superstructure condition category of 0. These 1,303 bridges were excluded from the subsequent analysis. The relationship between superstructure condition and average load rating for the remaining 408,438 bridges is shown in Fig. 2. The two are highly correlated. The least-squares linear regression for load rating as a function of superstructure condition is

$$\text{load rating} = 4.37 \cdot \text{superstructure condition rating} \tag{5}$$

The correlation coefficient r is 0.98. This relationship could be useful if the rate of superstructure deterioration could be determined. The following section presents the results of an analysis of superstructure deterioration with age.

SUPERSTRUCTURE DETERIORATION

The *Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges* [U.S. Department of Transportation (U.S. DOT) 1995] provides instructions for the coding of condition rating for bridge superstructures. These instructions are summarized in Table 2. The somewhat subjective nature of the rating scale should be noted as well as the reliance upon visible indications of deterioration to define the condition states. Each bridge is assigned a superstructure condition rating based upon the above scale at the time of each inspection. Federal regulations require each bridge to be inspected at least once every 2 years. The current NBI contains records for more than 580,000 bridges. A superstructure deterioration model was developed based upon an analysis of the data in the NBI. A number of different methods is available to model deterioration. Many researchers have developed linear and stepwise linear regression relationships, but these usually fail to capture significant nonlinear behavior. It is important to note that the condition rating scale presented above is somewhat arbitrary, and no attempt was made to make it a linear scale. A condition rating of 4 is not twice as bad as a condition rating of 8. There can be many factors affecting the deterioration of bridge superstructures, and it was decided that it would be most useful to develop a model that not only predicted the average performance of bridge superstructures but also provided information on the distribution of condition with age as well. In addition, the data in the NBI are reported at least once a year, but the data are collected and the deterioration of the bridges is observed only when the bridge is inspected. As noted above, inspections are required at least once every 2 years. If one assumes that bridge superstructures deteriorate continuously but that the deterioration is observed and recorded periodically, then it is reasonable to use a probabilistic Markovian approach to model the observed superstructure deterioration.

TABLE 2. NBI Instructions for Superstructure Condition States

Code (1)	Description (2)
9	Excellent condition
8	Very good condition: No problems noted.
7	Good condition: Some minor problems.
6	Satisfactory condition: Structural elements show some minor deterioration.
5	Fair condition: All primary structural elements are sound but may have minor section loss, cracking, spalling or scour.
4	Poor condition: Advanced section loss, deterioration, spalling or scour.
3	Serious condition: Loss of section, deterioration, spalling, or scour has seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present.
2	Critical condition: Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed structural support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken.
1	"Imminent" failure condition: Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structural stability. Bridge is closed to traffic but corrective action may put back in light service.
0	Failed condition: Out of service. Beyond corrective action.

For the problem at hand, the transition probabilities for a 10-condition state vector with a significant historical record available needs to be determined. To develop a useful data set, the following criteria were used to provide an observed condition state array. Highway bridges constructed after 1900 were selected. Culverts were excluded from the analysis as well as bridges that had been rehabilitated. It was decided to determine the annual transition probabilities based upon the observed condition state record. Using these selection criteria, 409,741 bridges were included in this analysis. The number of bridges in each of the superstructure condition state categories was determined and was placed in an array where each row corresponded to the number of transition periods the bridge had been exposed to. This resulted in a 10 × 96 array. Some new bridges have only experienced 1 transition period, whereas the bridges built in 1900 have experienced 96 transitions.

A 10 × 10 Markovian transition probability matrix was determined through a constrained nonlinear optimization procedure that minimized the square of the deviations between the simulated and observed condition states for each transition period. The constraints were that the lower triangular elements of the transition probability matrix were zero (no condition improvements were allowed), all transition probabilities must be greater than or equal to zero and that the probabilities for each condition state must total to unity. The resulting transition probability vector is

$$\mathbf{P}_{US} = \{0.71, 0.95, 0.96, 0.96, 0.97, 0.97, 0.97, 0.93, 0.86, 1\} \tag{6}$$

The relationship between the simulated and observed values for the average superstructure condition for the 96 transition periods is shown in Fig. 3. The observed and simulated normalized condition state distributions for 5, 25, 50, and 75 transitions are compared in Figs. 4–7.

The Markovian deterioration model yields good agreement between the observed and simulated condition state distributions for multiple transitions. The gradual deterioration of the superstructure condition is nonlinear, but it was adequately simulated with a stationary stochastic process. It is emphasized that the model developed is dependent upon the somewhat subjective and arbitrary condition state definitions of Table 2, which were used to describe the deterioration process. The

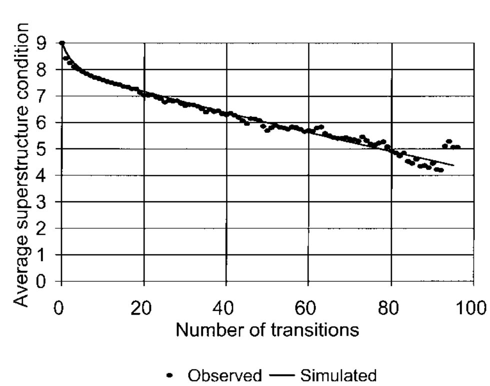

FIG. 3. Comparison of Markov Simulation and Observed Superstructure Condition

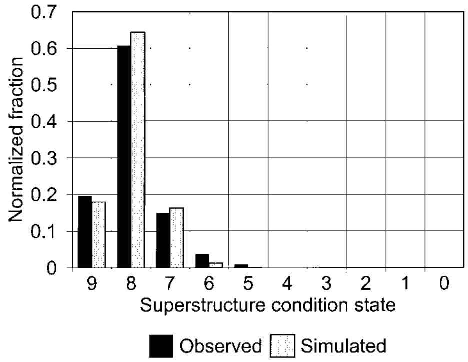

FIG. 4. Comparison of Observed and Simulated Normalized Condition State Distributions after Five Transitions

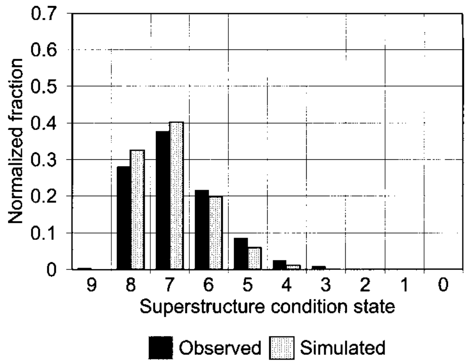

FIG. 5. Comparison of Observed and Simulated Normalized Condition State Distributions after 25 Transitions

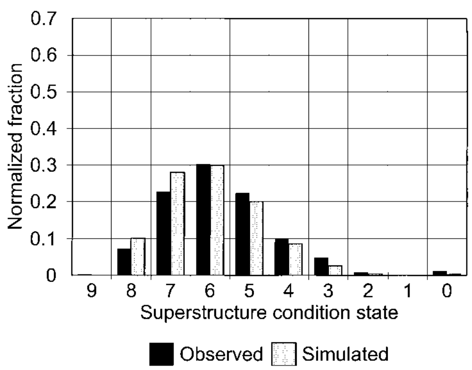

FIG. 6. Comparison of Observed and Simulated Normalized Condition State Distributions after 50 Transitions

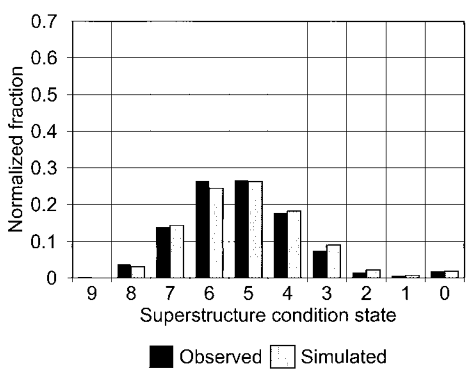

FIG. 7. Comparison of Observed and Simulated Normalized Condition State Distributions after 75 Transitions

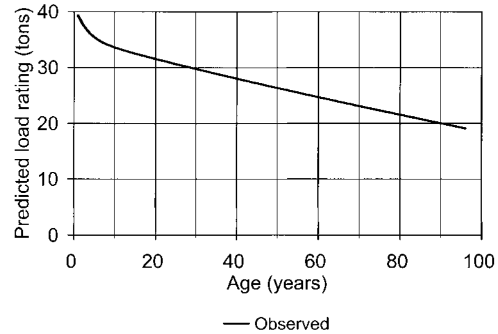

FIG. 8. Predicted Reduction in Load Capacity with Age

subjective nature of the condition state definitions probably contributes to the nonlinear behavior of the model. However, many deterioration processes such as corrosion, fatigue, and yielding are decidedly nonlinear and also contribute to the nonlinear behavior. The proposed stationary Markovian model for stochastic condition state transitions can be applied regardless of the particular condition state definitions used. In fact, a similar approach is being applied in the bridge management systems Pontis and BRIDGIT, but with totally different condition state definitions and with application to individual elements of the bridges rather than to the entire superstructure.

Combining the linear relationship developed above between superstructure condition state and load rating with the Markovian deterioration model provides a new model for load rating reduction with age. The results are presented in Fig. 8, which presents the expected value for load rating as a function of age for bridges designed for an HS 20 load, which corresponds to a load rating of 36 tons. The model predicts a reduction in load rating of approximately 16 tons over a 90-year period. The model was based upon a sample of over 400,000 bridges and excluded the effects of rehabilitation.

RELATIONSHIP BETWEEN LOAD RATING AND SUPERSTRUCTURE CONDITION FOR HUNGARIAN BRIDGES

A similar analysis was performed on Hungarian bridges that carry public roads. Excluding the culverts with span lengths

TABLE 3. Load Rating Distribution of Hungarian Bridges

Load rating (tons) (1)	Number of bridges (2)	Percent of population (3)
80	1,810	34
60	383	7
40	2,417	47
36	429	8
20 or less	168	4

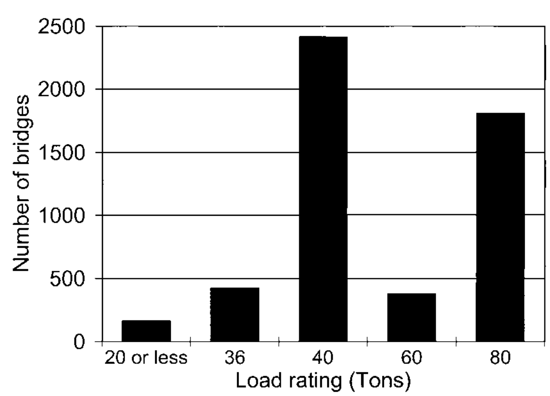

FIG. 9. Distribution of Hungarian Bridges by Load Rating

below 2.0 m, the Hungarian Bridge Data Bank contains all of the necessary load capacity and superstructure condition data for about 5,207 bridges. Table 3 shows the distribution of bridges as a function of their load capacities (ratings). This distribution is also shown in Fig. 9. During the annual bridge inspections, a superstructure condition rating is assigned based upon a five-code scale. The main instructions for the coding are summarized below. A superstructure in good condition with no deterioration is assigned a code of 1. If minor deterioration is starting with only surface defects, a code of 2 is assigned. A code of 3 is assigned if medium deterioration is present (not only surface defects). Advanced deterioration is assigned a code of 4. Advanced deterioration affecting structural stability is assigned a code of 5. Notice that there is no direct mapping between the U.S. condition state definitions and the Hungarian condition state definitions. Fig. 10 presents the percentage distribution of bridges in each of the superstructure rating categories. Fig. 11 shows the normalized cumulative distribution of load rating of the Hungarian bridges by the superstructure condition category. It can be seen that a high share of bridges have a load rating of 40 tons in each superstructure condition category. Once again, the behavior of the terminal condition rating is unexpected. No explanation can be offered, except for the very low number of bridges in this group (15 out of 5,753). As was done with the bridges in the terminal condition state for American data, the bridges in condition state 5 were excluded from the analysis. The relationship between superstructure condition and load rating for the remaining 5,738 Hungarian bridges investigated is shown in Fig. 12. The least-squares linear regression for load rating as a function of superstructure condition is

$$\text{load rating} = 61.0 - 6.46 \cdot \text{superstructure condition} \quad (7)$$

The correlation coefficient r is 0.97.

Next, the transition probabilities were determined for the superstructure condition state vectors using the available Hungarian historical data. Regular bridge inspections have been carried out in Hungary since the early 1980s. There was a change in the standards used to define condition states in 1991, and the current data bank contains condition data based upon annual inspections using these new standards. It is assumed that the current condition of a bridge represents the combined and cumulative effects of design, materials, deterioration, and maintenance practices.

Based on the superstructure condition data for 100 transition periods between 1896 and 1996, a 5 × 5 Markovian transition probability matrix was determined through an optimization procedure that was similar to the one applied for the calculation of P_{US} for the American data. The resulting Hungarian transition probability vector is

$$\mathbf{P}_H = \{0.481, 0.998, 0.947, 0.884, 1\} \quad (8)$$

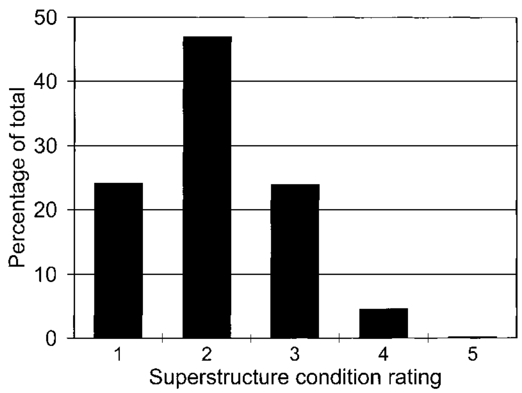

FIG. 10. Distribution of Superstructure Condition Ratings for Hungarian Bridges

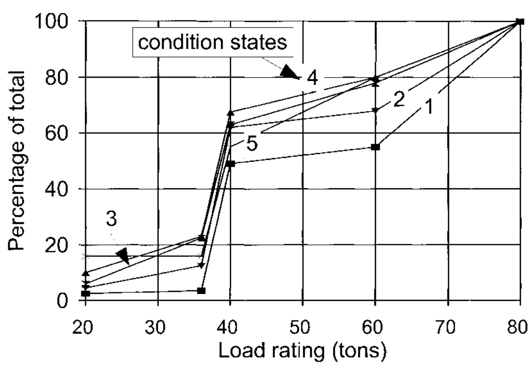

FIG. 11. Normalized Cumulative Frequency Distributions of Load Ratings for Hungarian Bridges with Different Superstructure Condition Ratings

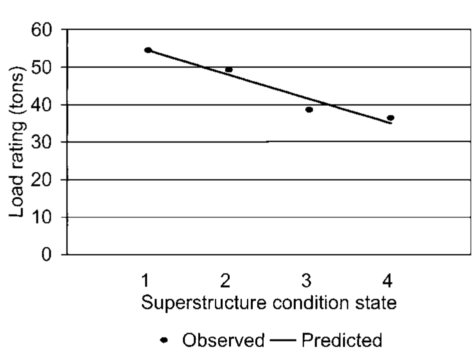

FIG. 12. Relationship between Average Load Rating and Superstructure Condition Rating for Hungarian Bridges

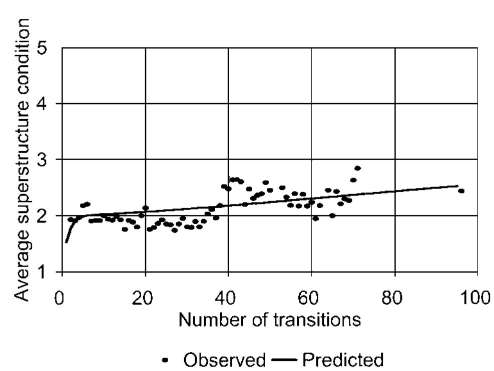

FIG. 13. Comparison of Markov Simulation and Observed Superstructure Condition for Hungarian Bridges

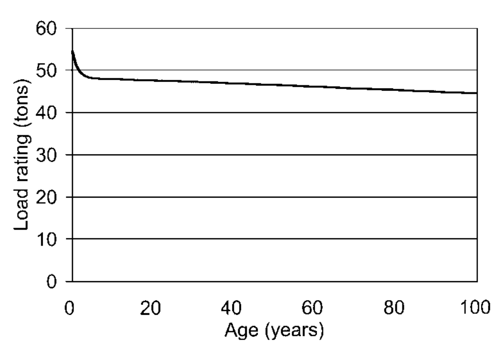

FIG. 14. Predicted Reduction in Load Capacity with Age for Hungarian Bridges

These transition probabilities were determined based upon a minimization of the deviations between the predicted and observed expected values for each of the transition periods. Transition periods with fewer than 10 bridges were excluded from the analysis because a reasonable estimate for the normalized condition state distribution was not possible. The resulting matrix was based upon an analysis of 5,650 bridges. Fig. 13 compares the simulated and observed average superstructure condition ratings for 100 transition periods. The Hungarian data exhibits significantly different behavior than the American data. The early deterioration (transition from condition state 1 to condition state 2) is very rapid, and then very slow deterioration is exhibited. Some of this might be explained by the difference in the condition state definitions or differences in maintenance practices. However, the very low percentage of bridges in condition state 5 (0.26%) is extraordinary. Despite these differences, once again it has been demonstrated that the Markovian deterioration model provides reasonable agreement between the observed and simulated expected values for condition states. For the Hungarian data, even the highly nonlinear initial deterioration rates were simulated well with a stationary stochastic model.

As was done for the American data, the linear relationship developed between superstructure condition state and load rating was combined with the Markovian deterioration model to develop a new model that predicts the reduction in load rating with age. This relationship is presented in Fig. 14. The model predicts a reduction in load rating of approximately 10 tons over a 100-year period with most of the reduction occurring within the first 10 years.

CONCLUSIONS

A general method was developed to predict the relationship between physical bridge deterioration and load rating. The method combines regression analysis, to determine the relationship between load rating and condition rating, and deterioration modeling based upon Markov chains. The deterioration model is based upon the assumptions of short transition intervals and no improvements in condition due to repairs or rehabilitation. The method was applied to bridge data from the United States and Hungary with good results despite significant differences in the condition state definitions, the number of bridges included in the analysis, and design and maintenance practices between the two counties.

APPENDIX. REFERENCES

American Association of State Highway and Transportation Officials (AASHTO). (1993). *Guidelines for Bridge Management Systems*, Washington, D.C.

Hawk, H., and Small, E. (1998). ''The BRIDGIT bridge management system.'' *Struct. Engrg. Int.*, 8(4), 309.

Hudson, S., Carmichael, R., Moser, L., and Hudson, W. (1987). ''Bridge management systems.'' *NCHRP Rep. 300*, Transp. Res. Board, National Research Council, Washington, D.C.

O'Connor, D., and Hyman, W. (1989). ''Bridge management systems.'' *Final Rep., Demonstration Proj. 71*, Ofc. of Technol. Applications, Fed. Hwy. Admin., U.S. Department of Transportation, Washington, D.C.

Thompson, P., Small, E., Marshall, A., and Johnson, M. (1998). ''The Pontis bridge management system.'' *Struct. Engrg. Int.*, 8(4), 303.

U.S. Department of Transportation (U.S. DOT). (1995). *Recording and coding guide for the structure inventory and appraisal of the nation's bridges*, Ofc. of Engrg., Bridge Div., Bridge Mgmt. Branch, Federal Highway Administration, Washington, D.C.