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EFFECT OF COEFFICIENTS OF REGRESSION MODEL ON PERFORMANCE PREDICTION CURVES

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Abstract

As bridges age, structural weakening due to heavy traffic and aggressive environmental factors becomes more important. These factors lead to an increase in repair frequency and decrease in load carrying capacity. Structural weakening can decrease the lifetime period and prevent the serviceability of bridges. In order to avoid the disadvantages of deterioration, the lifetime performance prediction of a bridge system should be correctly predicted. Using the lifetime performance prediction, the remaining service life of the bridge system could be predicted. In addition, the best maintenance and repair strategies kept the system in safe can be obtained. In this study, a regression model is investigated as performance prediction model. Moreover, effects of the changes of the coefficients of regression model on the performance curve are examined.

Keywords: Bridge infrastructure systems, Performance prediction models, Condition rating, Polynomial-based performance prediction models, Coefficients of performance curves.

1. Introduction

Infrastructure systems are crucial facilities for communities and countries. They supply the necessary transportation, water and energy utilities for the public. An essential part of the transportation infrastructure is the bridge infrastructure. There are a large number of bridges in the developed countries in order to meet the demands. As bridges age, structural weakening due to heavy traffic and aggressive environmental factors becomes more important. These factors lead to an increase in repair frequency and decrease in load carrying capacity. Structural weakening can lead to sudden collapse of a bridge if maintenance and repair strategies do not be put into practice. Any sudden collapse of a bridge may result in irretrievable loss of life and property. In order to avoid this situation, the bridge networks should be inspected with a certain period. Using the bridge condition data obtained from inspections, maintenance and repair strategies are determined to keep the bridge condition at the acceptable level. In order to decide the best maintenance policy, the remaining service life of the bridge should be correctly predicted. Lifetime performance prediction models, therefore, are used to predict the remaining service life of the bridges. Therefore, many studies have been performed to generate these performance prediction models. These models evaluate the bridge safety and/or condition index throughout their lifetime. The models shown in Fig. 1 are the most common studied in literature. The performance prediction models may be divided into three main categories which are deterministic, stochastic and artificial intelligence models. The Stochastic model consists of Bi-linear model and Markov approach. Artificial Neural Network Networks and Case-based Reasoning constitutes the Artificial Intelligence Model.

Regression model used in Indiana BMS [1] is a deterministic model. Regression models can indicate the average condition rating of a large bridge stock regardless the condition of any bridge. The other category of the deterioration models is the stochastic deterioration models composed by Bilinear and Markovian models. First, the Bilinear model proposed by Frangopol *et al* [2] is a simulation-based model using Latin Hypercube Sampling method[3]. Second, the Markovian model is the most common stochastic model used in current Bridge Management Systems. Artificial neural network (ANN)[4] and Case-based reasoning (CBR)[5] are two kinds of artificial intelligence models applied in performance prediction models.

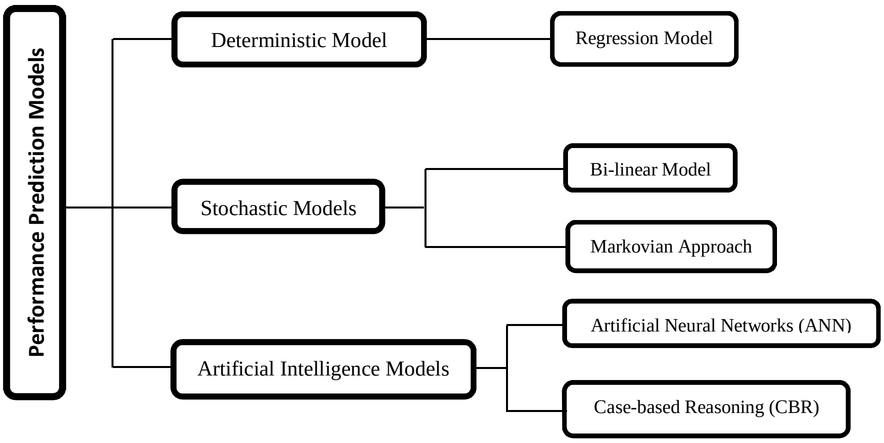

Figure 1: Classification of Performance Prediction Models

2. Regression Model

Condition ratings of bridge components at different ages can be predicted using different methods. One of these methods is the so called regression model-based method. There are several regression models used in statistical studies. Linear regression, piecewise linear regression and polynomial regression are the common types of regression models. Regression models have some important applications. The first application is to predict the average condition ratings of bridge components at different ages. The second application of regression model is to find the deterioration rates at different ages. The third one is to determine the improvement benefit gained by rehabilitation. In this study, polynomial regression model is used because it has more advantages than other regression models. Polynomial regression model is more realistic than linear regression model and easier to use than piecewise regression model.

2.1. Polynomial-based Performance Prediction Model

Condition data obtained from visual inspection can be called as condition rating. This term represents a range of numerical or alphanumerical values representing different levels of deterioration of bridge components or bridges. The condition rating ranges between 0 and 9. The best condition of a bridge is represented by condition rating 9 whereas condition rating 0 represents the worst condition for the bridge component or bridge. The condition rating values come from NBI (National Bridge Inventory) condition rating classification used in U.S [6]. According to NBI, 3 is the critical level for the bridge condition rating. In order to obtain lifetime performance curve as a function of some variables, the regression analysis can be applied. These variables are bridge age, traffic volume and bridge type. As a result of a regression analysis, a condition rating equation is obtained. The equation represents the relation between the dependent and independent variables. The dependent variable is the condition rating and the equation may include one or more independent variables. An example of a third order polynomial–based condition rating equation dependent on bridge age is shown as follows:

$$C = \beta_0 - \beta_1 T + \beta_2 T^2 - \beta_3 T^3 \tag{1}$$

In Eq. 1, C is dependent variable called as condition rating of a bridge component or system. β's are the coefficients of the polynomial regression model. T is the independent variables and represents the bridge age.

A polynomial regression equation for steel bridge deck on other state highways in Indiana obtained by Jiang [1] is given Eq. 2.

$$C_{deck} = 9 - 0.3498T + 0.0104T^2 - 0.0001T^3 \tag{2}$$

Given deck condition formula in Eq. 2 is plotted in Fig. 2.

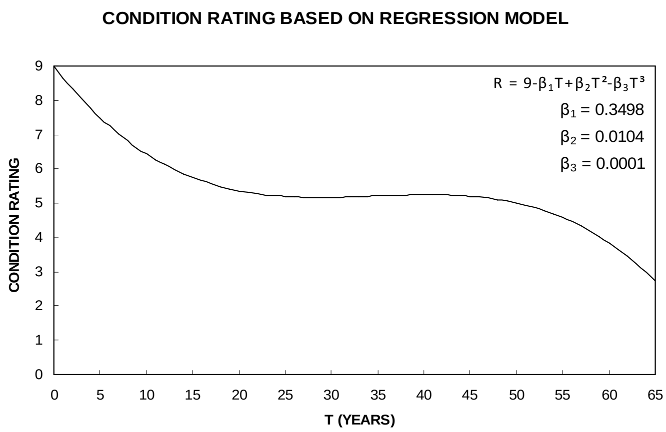

Figure 2: Polynomial regression of deck condition

In this polynomial regression model, T (years) is independent variable. Condition rating is changed at different ages. Deck polynomial regression model may give rationally different condition rating profiles when β's are changed with some order. Some figures as shown below are achieved by changing β values. This causes different polynomial regression curves but some of these curves are not rational. Therefore, β values are changed in a small range. In Fig. 3 through Fig. 11, effect of the coefficients (β's) in Eq. 2 on the condition rating profiles are investigated and displayed.

In Fig. 3, condition rating is examined based on regression model for bridge deck. Every variables except β_1 have been kept as a constant, and effect of β_1 on condition rating of bridge deck is observed. The values of β_1 vary between 0.1 and 0.6. Some results from the polynomial regression model for the bridge deck element are irrational because condition rating curve must decrease gradually but the mentioned values which are 0.1, 0.2, 0.3 increase condition rating curve after 20 years. This leads to conceptual error for the deterioration model. Therefore, condition rating curves leading irrational results are removed from the Fig. 3, and as a result, Fig. 4 is obtained. As shown in Fig. 4, the smallest acceptable value for β_1 a value between 0.3498 and 0.4 the condition rating profile of bridge deck when the other β values are kept constant. Therefore, increasing β_1 value causes a decrease in the service life of the bridge deck. When the value of β_1 is increased to 0.4, 0.5, 0.6, condition rating decreases radically and reaches 3 after 44 years, 17 years and 12 years, respectively.

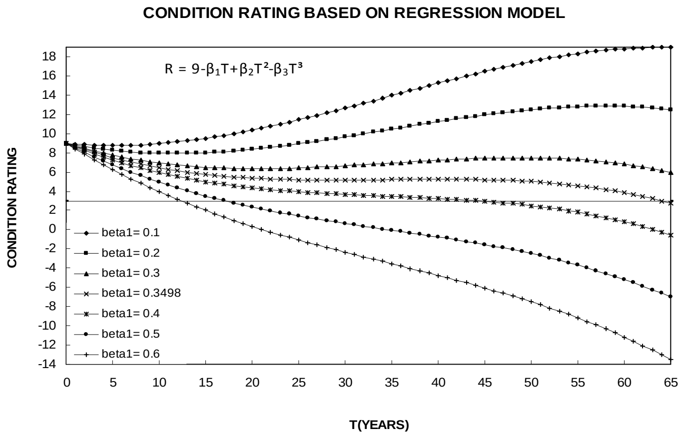

Figure 3: Polynomial regression of deck condition when only β_1 changes from 0.1 to 0.6

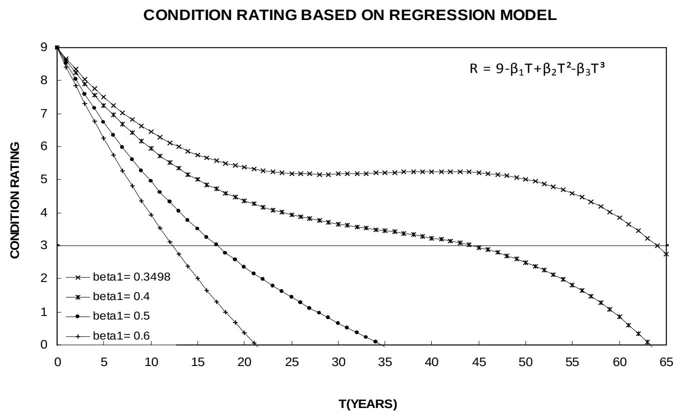

Figure 4: Polynomial regression of deck condition when only β_1 changes from 0.3498 to 0.6

In Fig. 5, condition rating profiles are examined based on the values of β_2. Every variables except β_2 are kept constant, and effect of β_2 on condition rating of bridge deck is observed. The values of β_2 vary between 0.0098 and 0.011. Acceptable value for β_2 is 0.0102 based on a visual inspection of the profiles in this graph. As shown in Fig. 5, if the value of β_2 is increased, irrational results arise from regression model for bridge deck because the condition rating profile starts increasing (for $\beta_2 \geq 0.0104$) after approximately 30 years.

Fig. 6 is obtained by removing the condition curves using values of β_2 than 0.0102 from Fig. 5. As shown in Fig. 5, the largest acceptable value for β_2 is 0.0102 and when value of β_2 is decreased keeping other variables constant, deterioration of the bridge condition accelerates more rapidly. Therefore, decreasing of value of β_2 leads to a reduction of the service life of the bridge deck based on the regression model for bridge deck element. For example, when the 0.0098 is used as the value of β_2, condition rating of deck condition reaches 3 at the end of 54 years.

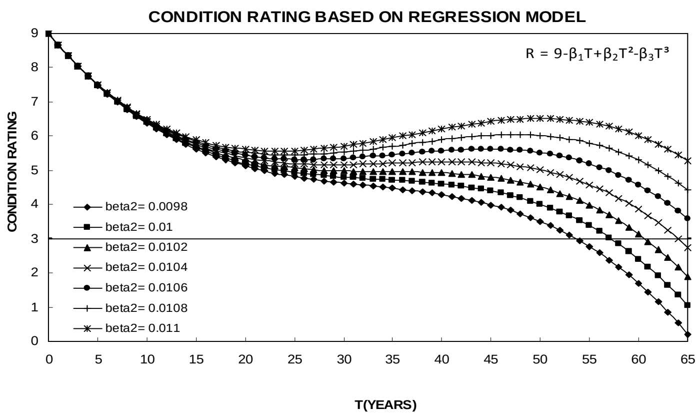

Figure 5: Polynomial regression of deck condition when only β_2 changes from 0.0098 to 0.011

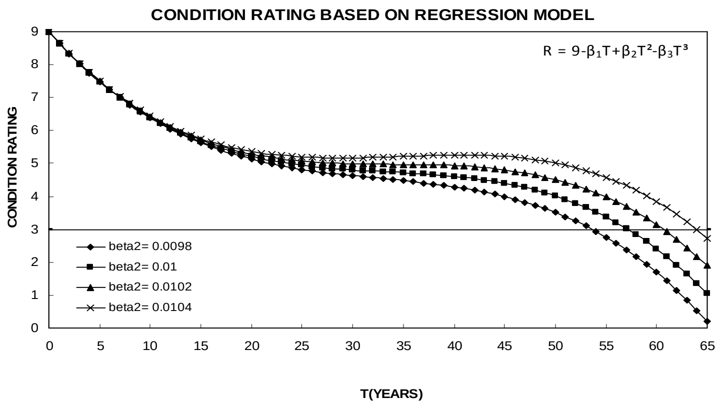

Figure 6: Polynomial regression of deck condition when only β_1 changes from 0.0098 to 0.0104

Fig. 7 shows the effect of the coefficient β_3 on the condition rating curve of the bridge deck based on polynomial regression model. In order to obtain Fig. 7, every coefficient except β_3 are kept constant, and effect of β_3 on condition rating of bridge deck is observed. The value of β_3 is varied between 0.00008 and 0.00014. The smallest acceptable value for β_3 is between 0.0001 0.00011. As shown in Fig. 7, if value of β_3 is decreased, irrational results arise from regression model for bridge deck and the condition rating increases after 30 years.

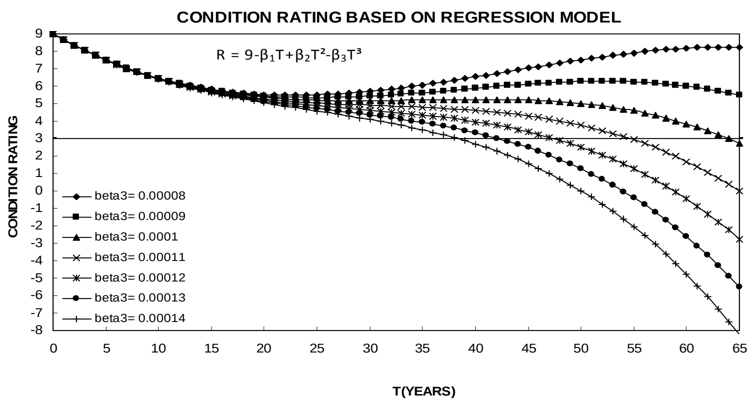

Figure 7: Polynomial regression of deck condition when only β_3 changes from 0.00008 to 0.00014

Fig. 8 is obtained by removing the irrational regression curves from Fig. 7. When value of β_3 is taken as 0.0001, an acceptable regression curve is obtained for 65 years' service life. The larger values of β_3 (larger than 0.0001) causes deterioration of the bridge condition to accelerate more rapidly. Therefore, increasing of the value of β_3 leads to reduction of the service life of the bridge deck based on regression model for bridge deck component. For example, if the 0.00014 is used for β_3, condition rating of deck reaches 3 at the end of 37 years. However, service life of bridge deck extends to 65 years when value of β_3 is taken as 0.0001.

Each of Fig. 9, Fig. 10 and Fig. 11 consist of two regression curves. The two regression curves are obtained using the same regression model of bridge deck and have same values for β_1 except β_2 and β_3.

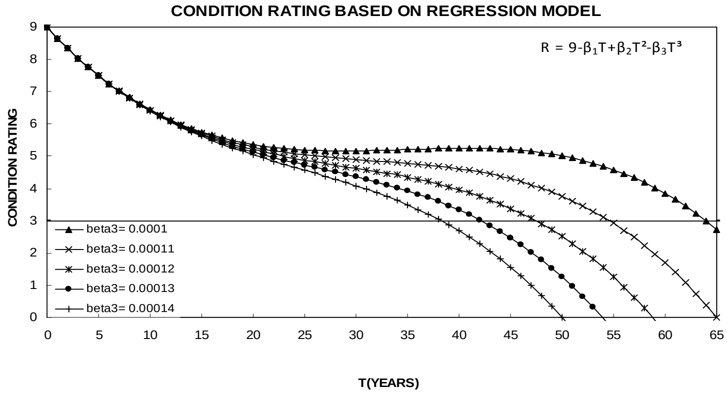

Figure 8: Polynomial regression of deck condition when only β_3 changes from 0.0001 to 0.00014

The value of coefficient β_1 is 0.4 for each regression curve in Fig. 9. The values of β_2 and β_3, on the other hand, are signed the values shown in Eq. 2. In other words, β_2 and β_3 are assumed independent of β_1. For the other regression curve, values of β_2 and β_3 are determined depending on β_1. To achieve this, β_2 and β_3 are divided by β_1 in order to find a ratio between β_1 and the other coefficients. In Eq. 2, ratio between β_1 and β_2, and β_1 and β_3 are 0.029731 and 0.000286, respectively. If β_1 is changed, the value of β_2 and β_3, depending on the value of β_1, are found using these ratio constant.

As shown in Fig. 9, two polynomial curves are obtained. β_1 is equal to 0.4 for both regression curves. However, values of β_2 and β_3 are different for each curve. All coefficients are independent for one of the polynomial curves. In the other curve, β_2 and β_3 values change with respect to ratio depending on β_1. β_2 and β_3 values in independent curve are 0.0104 and 0.0001, respectively. On the other hand, β_2 and β_3 values in dependent curve are 0.01189 and 0.000114, respectively. This application gives good regression model because regression curve obtained based on the coefficient ratios leads bridge deck member to have larger service life than ones in which β_2 and β_3 are kept as constant even if the values of β_1 is varied. Regression curve obtained from application mentioned above is rational. For example, service life of the regression curve whose coefficients are related to each other is approximately 62 years. However, the other regression curve whose coefficients are not related to each other has 44 years of service life.

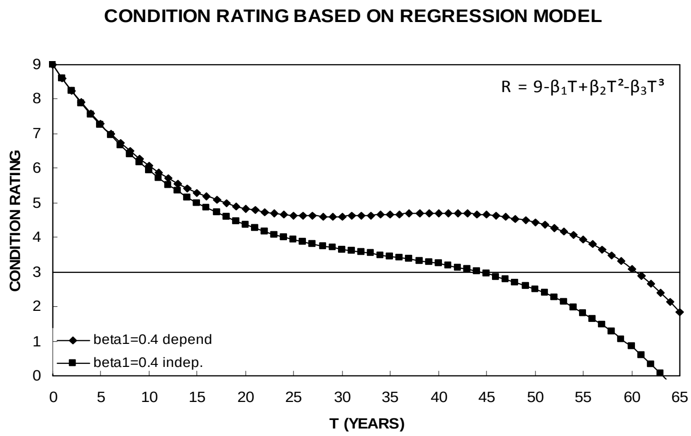

Figure 9: Comparison of polynomial regression of deck condition based on 0.4 value of β_1 as an independent or dependent variable

In Fig. 10, both of the regression models of deck member have $\beta_1 = 0.5$. The regression curve for which the coefficients β_2 and β_3 depend on β_1 gives a more rational result than the other curve. The first regression curve starts from condition rating 9 and decreases sharply to rating 5 in approximately 12 years, then remains nearly at rating 3.5, starting from 20 years old for a duration of approximately 27 years. The regression curve reaches the condition rating 3 when the bridge deck member is approximately 54 years old. The other regression curve obtained by changing β_1 value only submits little service life profile. When the bridge deck member is approximately 18 years old, condition rating reaches the rating 3.

The two regression curves shown in Fig. 11 have $\beta_1 = 0.6$. Both curves reach the condition rating 3 earlier than the curves shown in Fig. 9 and Fig. 10. The polynomial curve with independent coefficient values reaches the condition rating 3 approximately at 12 years. However, the other polynomial curve reaches the condition rating 3 at 18 years. It can be noted that, β_1 has an important effect on condition rating. The larger values of β_1 leads bridge condition rating to faster deterioration.

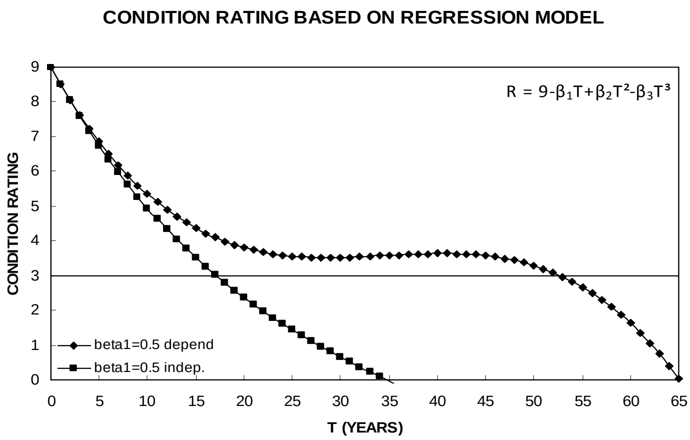

Figure 10: Comparison of polynomial regression of deck condition based on 0.5 value of β_1 as an independent or dependent variable

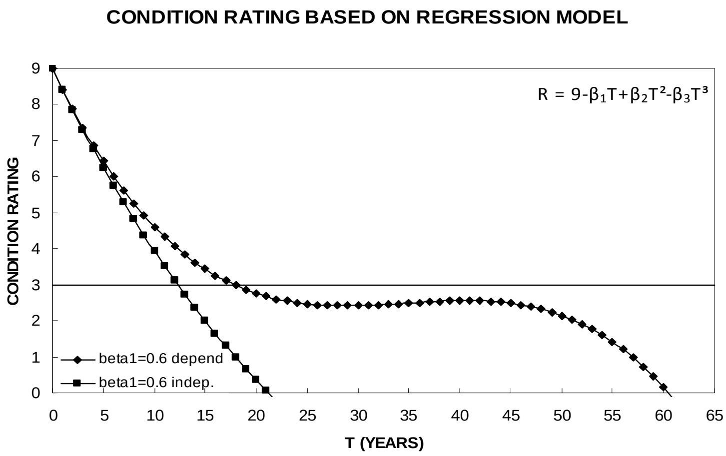

Figure 11: Comparison of polynomial regression of deck condition based on 0.6 value of β_1 as an independent or dependent variable

3. Conclusions

In this paper, polynomial-based performance prediction model is investigated. Effects of the changes of the coefficients of polynomial equation on the performance curve are examined. The coefficient values are changed in a small range in order to examine the effect of these coefficients on performance curve. In addition, the polynomial-based performance curves are reproduced by establishing a relation between the coefficients of regression equation.

As a result, acceptable range for the coefficient values is investigated. It is noted that the change of the coefficient values in a big range leads to irrational performance curves. In addition, even small changes of the coefficient variables arise important effect on performance curves. Therefore, the coefficient values have essential importance for performance curves. Finally, it is noted that good polynomial performance model is obtained if all coefficients are changes according to the coefficient rations.

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