Design Factors That Affect Joint Faulting for Jointed Plain Concrete Pavements

JPCP의 폴팅에 영향을 미치는 설계 인자 고찰

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1. INTRODUCTION

The primary objective of this paper was to identify and quantify the design and construction features that contribute to different levels of joint faulting using the Long Term Pavement Performance (LTPP) database. Joint faulting is a major distress type for jointed concrete pavements (JCP) because of the negative effect on ride quality that can result in costly rehabilitation. It is a differential elevation across the joint and the result of a combination of poor load transfer across a joint or crack, heavy axle loads, free moisture beneath the pavement, and pumping of subgrade material from under the slab(Simpson et. al 1994, Owusu-Antwi et al. 1997, and Titus-Glover et al. 1999).

This paper also presents analytical procedures for evaluating factors that affect joint faulting for JointedPlain Concrete Pavements (JPCP). Preliminary analysis such as univariate and bivariate analysis used in the past may lead to contradictory and misleading results because of confounding the effects between independent variables. More sophisticated multivariate analysis tools are needed to develop guidelines for pavement design and construction features. Therefore, emphasis was placed on using a series of modern multivariate data analysis techniques to identify design and construction features most importantto long-term performance, and to quantify the specific contributions of these features to the long-term performance of JPCP. Multivariate analysis is concerned with the simultaneous investigation of two or more variable characteristics that are measured over multivariate collinearities (S-PLUS 2000, and Kachigan 1986). This paper details how cluster analysis, canonical discriminant analysis, and classification and regression tree (CART) can be used to investigate multivariate-relationships between variables and develop design recommendations.

2. ANALYSIS APPROACH

The first step of the analysis approach was to establish a database containing all the data elements required. This database included significant calculated variables such as cumulative ESAL, new climatic

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variables, joint opening, drainage coefficient, bearing stress, and load transfer efficiency (LTE). Univariate analysis is performed to obtain basic statistics such as the total number of sections, mean, and standard deviation. Plots in the form of histograms were used to show visually the distribution of selected data elements. The results of bivariate analysis showed the relationship between joint faulting and key design and construction features. New climatic cluster variables to account for total temperature effects (TTEMP) and total precipitation effects (TPRECIP), were developed using principal component analysis (PCA) because of the wide variety of climatic variables available in the LTPP database.

Cluster analysis was used to partition the pavements into three distinct groups or clusters characterized by the categorical variables good, normal, and poor representing their performance.Joint faulting and loading rate was selected for k-mean cluster analysis. Canonical discriminant analysis was used to discriminate between performing groups classified by cluster analysis. Classification and regression tree (CART) was use to quantify the influence of key design and constructions features on joint faulting. The canonical discrimiant functions developed can be used to classify newly designed pavements and to check for their adequate performance throughout the pavement's design life. The results of the CART analysis can provide guidelines for evaluating the effect of key design and construction features under different sites conditions on joint faulting for JPCP.

3. ESTABLISHINGDATABASE

Typical LTPP pavement sections evaluated are 152.5 m (500 ft) section with 3.66 (12 ft) wide traffic lanes and either asphalt concrete (AC) or tied PCC shoulders. Spreadsheets were created for checking and analyzing the data that were obtained from the LTPP database. Table 1 shows the abbreviations of variables used in this paper and significant variables affecting joint faulting for JPCP. After cleaning the joint faulting data, a total of 281 observations on 115 JPCP sections were available for analyzing joint faulting. It measured varied from 0 to 9.4 mm with a mean of 1.525 and a standard deviation of 1.63. About 53 percent of average jointfaulting was less than 1 mm (148 of 281 observations).

4.Traffic Loading(ESAL)

Repeated traffic loading contributes greatly to the performance of PCC pavement. The cumulative traffic loading data corresponding to joint faulting at a particular time is required for analysis. The cumulative 80KN equivalent single axle loads (ESAL) weredetermined by extracting data from three LTPP database sources: Historical ESAL estimate, ESAL estimate form traffic monitoring, and ESAL obtained from weigh-in-motion (WIM) devices. These three sources of ESAL data were used for developing the cumulative ESAL that was assigned to a pavement section. A best-fit exponential curve was fitted to the time sequence data from thethree sources of ESAL at each site. In some cases there was good agreement in the trends, while in other cases there were significant differences between trends. If the trend showed good agreement between traffic data, they were combined and used as estimates of the ESAL per year. If the trend did not show good agreement, a best-fit exponential curve was fitted based on engineering judgment (Owusu-Antwi et. al. 1997 and Perera et al. 2001).

5. New Climatic Variables

Using Principal component analysis (PCA), two new climatic variables were developed. TTEMP mainly consists of temperature variables that are highly correlated, while TPRECIP mainly constitutes precipitation variables that are highly correlated. Together two cluster variables, TTEMP and TPRECIP, explain 86.8 percent of the total variance of all climatic variables. For the purpose of this study, TTEMP were divided into three zones representing zones with low, intermediate, and high temperature-related effects. Similarly, TPREICP was divided into zones with low, intermediate, and high precipitation-related effects. These climatic zones were determined by examiningthe 95 percent confidence interval associated with each zone and statistically significant clear distinctions were observed between zones.

Table 1. The Significant Variables That Influence Joint Faulting For JPCP

ABBREVIATION	BRIEF DESCRIPTION
FAULT	Average faulting (mm)
AGE	Pavement age (year)
CKESAL	Cumulative thousand ESAL
PRECIP	Total precipitation for year (mm)
WDAYS	Number of wet days for year
MTEMP	Mean average temperature (C)
A32C	Average number of days with temperature above 32C
B0C	Average number of days with temperature below 0C
FI	Freeze index
FT	Freeze thaw cycles
TTEMP	Total temperature effects
TPRECIP	Total precipitation effects
PTHICK	PCC slab thickness (cm)
LWIDTH	Lane width (m)
EMOD	Elastic modulus (kPa)
CSTREN	PCC compressive strength (kPa)
TSTREN	PCC tensile strength (kPa)
JSPACE	Joint spacing (m)
JOPEN	Joint opening (mm)
PSTEEL	Design percent longitudinal steel (%)
SEAL	The presence of seal types (seal = 1, no = 0)
BATYPE	Types of base (treated = 1, untreated = 0)
DOWDIA	Round dowel diameter (cm)
LTE	Load transfer efficiency (%)
BSTRESS	Bearing stress (kPa)
JSKEW	Joint skewness (skew=1, no=0)

SGTYPE	Subgrade type (coarse=1, fine=0)
P200	Percent passing of number 200 sieve (%)
KVAL	Dynamic backcalulated k-values (MPa/m),
SHJOINT	The presence of should joint (yes=1, no=0)
SHTYPE	Shoulder types (Concrete shoulder type = 1, otherwise= 0)
Cd	Drainage Coefficient
DRATYPE	The presence of sub drainage (Yes=1, no=0)

* Typically, dynamic backcaluated k-value is two times of static backcaluated k-value.

6. CLUSTER ANLAYSIS

Cluster analysis is a multivariate analysis technique that seeks to organize information about variables so that relatively homogenous groups can be formed. An essential step in the cluster analysis procedure is to obtain a measure of the similarity between each pair of objects under study (Kachigan 1986 and S-PLUS 1999). A measure of the similarity between two objects commonly used is the Euclidean distance based on the object's values on each of the k variables. Partitioning methods are based on specifying an initial number of groups with similarities as measured by the Euclidean distance. Centeroids of each group are calculated using least square and observations were assigned to the closet centeroid based on least square until the F-ratio (the ratio of the first sample variance to the second sample variance) is maximized (Kachigan 1986 and S-PLUS 1999).

For this study, joint faulting and loading rate were selected for k-mean cluster analysis to classify the pavements into three performance groups: good, normal, and poor performance groups. The loading rate was defined as the logarithm of the cumulative ESALs in thousand divided by pavement age. Table 2 presents the results of the cluster analysis relating to loading rate, expected joint faulting, performance range, the number of observations, and performance classification. The results of cluster analysis for joint faulting were validated by the comparison of the results with those from previous studies (Titus-Glover et al. 1999).

Table2.The results of Cluster Analysis for the Joint Faulting of JPCP

2.47	0.45	0.00~1.10	157	Good
2.44	2.26	1.20~3.80	99	Normal
2.71	5.38	3.95~9.40	25	Poor

7.DISCRIMINANT ANALYSIS

Discriminant analysis can be used to classify observations into two or more qualitative groups and to develop model that can be used to classify additional observations into the proper group. Using the classes determined previously from cluster analysis as the qualitative groups (good, normal, and poor performance groups), the objective was to use discriminant analysis to identify the key design, construction, and site condition factors that the best discriminate between the performance classifications. Canonical discriminant functions use a weighted combination of those predictor variable values to classify an observation into performance classification.

Based on the results of preliminary analysis, nine variables were selected for use in classifying the pavements into groups. Using S-Plusthe following two canonical functions were developed for classifying JPCP according to performance.

$$CAN1 = -0.1122\,TTEMP + 0.2939\,TPRECIP - 0.3485\,JSPACE + 0.8623\,DOWDIA + 0.2721\,BTYPE$$
$$+0.0093\,KVAL + 0.073\,SHJOINT + 0.5739\,JSKEW + 0.1130\,DRATYPE \quad (1)$$

$$CAN2 = 0.029\,TTEMP - 0.2453\,TPRECIP - 0.1157\,JSPACE - 0.099\,DOWDIA + 0.2130\,BTYPE$$
$$+0.022\,KVAL + 0.7053\,SHJOINT - 0.2283\,JSKEW - 1.4951\,DRATYPE \quad (2)$$

The overall misclassification error is 0.33, implying a 33 percent failure rate associated with the use of the canonical functions for classifying JPCP. In addition, the first canonical variables can explain 91% of the total variance with the second explaining the remainder. Based on the evaluation, the value of CAN1 for 75 percent of the pavements in the good performing pavements classification was greater than 0.5. Consequently, a value of 0.5 for CAN 1 can be used as the threshold for determining which new observations will fall into the good performing pavements classification. Additionally, the two canonical variables give on indication of the design and construction factors that have a major impact on good performing pavements.

8. CLASSIFICATION AND REGRESSION TREE(CART)

In the next step of the study, classification and regression tree (CART) was used as a measure of quantifying the effect of design and construction factors on joint faulting of JPCP. CARTwas developed to classify and group entities on the basis of a set of measurements or characteristics, using tree methodology (Breiman et al. 1984). The main advantage of CART is its ability to build classification or regression trees for continuous and categorical variables. CART proceeds by iteratively finding the variables and the values of the selected variables (discrete or continuous) in the model that produces the maximum reduction in variability of the response (Washington et al. 1997 and Hassan et al. 1999).

Using the statistical package, S-Plus, a tree diagram for joint faulting was constructed. With a shrinking parameter k=0.45, the pruned tree has 16 terminal node for joint faulting. The residual mean deviance (RMD) for tree is 0.7332 mm of joint faulting. The 13 pre-selected variables, 10 variables are used for constructing tree. The tree spilt into two branches according to the presence dowel bar: non-doweled and doweled JPCP. Therefore, most important factor affecting joint faulting is the presence of dowel bar. They are ranked from most important to least important as: the presence of dowel bar, TPRECIP, dynamic backcalcluated k-value, load transfer efficiency (LTE), PCC slab thickness, average joint spacing, the presence of sealant types, TTEMP, cumulative KESAL, and joint skewness. The results of the CART analysis for non-doweled JPCP summarized as follows:

● To reduce joint faulting in intermediate- and high-precipitation zones, an increase in load transfer efficiency (LTE) is required. Sections with more than 85 percent of LTE exhibited 25 percent less joint faulting in comparison to sections with less than 85 percent of LTE. In sections with less than 85 percent of LTE, sealed joint can reduce joint faulting by 27 percent.

● Backcalculated k-value (dynamic value) had significant effect on joint faulting for non-doweled JPCP in low-precipitation zone. The higher group (higher than 74MPa/m of dynamic backcalculated k-value)exhibited 59.5 percent less joint faulting than the lower group (lower than 74Mpa/m of dynamic backcalculated k-value). In low-temperature zone, shorter joint spacing (less than 15ft) reduced 60.6 percent of the joint faulting in comparison to longer joint spacing (more than 4.6m (15ft)). In middle- and high temperature zones, skewed joint reduced 53.3 percent of joint faulting in comparison to sections without skewed joint.

The results of the CART analysis for doweled JPCP summarized as follows:

● Dynamic backcalculated k-value was most important factor to have influence on joint faulting for dowel JPCP. Sections with higher than 50MPa/m of dynamic backcalculated k-value exhibited 48.2 percent less joint faulting in comparison to sections with lower than 50MPa/m of dynamic backcalculated k-value.

● For sections with less than 50MPa/m of dynamic backcalulated k-value, thicker than 22.86 cm (9 inch) of PCC slab thickness reduced 40 percent of joint faulting in comparison to thinner than 22.86 cm (9 inch) of PCC slab thickness.

● For sections with higher than 50MPa/m of dynamic backcalculated k-value, shorter joint spacing (less than 4.6m (15ft)) exhibited 27 percent less joint faulting than longer join spacing (4.6m (15 ft)). For section with longer joint spacing (larger than 4.6m (15 ft)), an increase of dynamic backcalculated k-value (higher than 96MPa/m) reduced 54.3 percent of joint faulting in comparison to sections with lower than 96MPa/m of dynamic backcalculated k-value.

9. SUMMARY AND CONCLUSIONS

Regardless to climatic conditions, the presence of dowel bar was most important design feature to reduce joint faulting for JPCP. For non-doweled JPCP, an increase of load transfer efficiency (more than 85 percent of LTE) was effective to reduce joint faulting in the high-precipitation zone and middle-precipitation zone with sealed joint. In low-precipitation zone, an increase of strong subgrade support (more than 74 MPa/m of dynamic backcaluated k-value) was required for reducing joint faulting. In low-precipitation and low-temperature zone, skewed joint decreased joint faulting for non-doweled JPCP.

For doweled JPCP, strong subgrade support (more than 50Mpa/m) was most important design feature to reduce joint faulting. In weak subgrade support, an increaseof PCC slab thickness (thicker than

22.86cm (9in.)) was beneficial to reduce joint faulting, while in sections with strong subgrade support, shorter joint spacing (less than 4.6m (15ft)) was necessary for decreasing joint faulting.

The results of canonical discriminant analysis, stabilized base, shoulder support, and sub-drainage had influence on joint faulting. The first canonical variable (CAN 1) was greater than 0.5 for pavements classified as good performing pavement for joint faulting on JPCP.

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