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Correlation of Quality-Control Data and Performance of PCC Pavements

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The interrelationship between concrete pavement quality indicators and pavement performance is presented. In the study reported here, a literature review was conducted to help identify pavement quality indicators, such as water/cement ratio, strength, slump, air content, and so forth. A detailed field investigation was carried out in five states to collect quality-indicator data. A pavement-condition-rating (PCR) procedure was developed to collect PCR data for various pavement sections. Linear and nonlinear statistical analyses were conducted to develop models interrelating quality-control data with PCR data. The results of the statistical analyses and the nature of the models developed are discussed in detail.

The development of statistically based performance specifications as part of quality assurance programs in highway construction and maintenance is geared toward establishing construction and material quality levels based on expected performance. Payment adjustment schedules can then be adopted by which contractors are paid according to the performance of the final product. Payment penalties are based on failure to meet performance specifications rather than on material specifications. Such programs reduce the need for materials testing as well as the necessity for revising or creating materials-based specifications, and contractors have more latitude in their choice of materials and construction methods as long as the final product performs as expected. Nevertheless, the development and implementation of such specifications for pavement quality-control variables have raised two questions: How do material variables relate to pavement performance, and are these variables adequate indicators of pavement performance and quality?

Establishing interrelationships between pavement performance and quality-control criteria requires a basic understanding of the parameters affecting performance, an identification of those parameters indicative of quality, and a knowledge of their statistical variations. These parameters are usually classified into several categories--environmental, geometrical, boundary, material, construction, traffic loading, and design variables. The degree to which each variable influences performance is often affected by the interaction of numerous parameters, which requires sophisticated statistical analyses of the data in order to establish the relative significance of each variable.

The reliability of such interrelationships is highly dependent on the nature of the data collected, the statistical significance, and the validity. Many sources of material and construction quality data can prove to be biased or inaccurate. This is particularly true when subjective judgments are used to reject on site some materials suspected of not meeting specifications whereas other materials deemed to be in compliance are accepted and used without actual testing to verify whether they meet specifications. To establish accurate relationships between material quality indicators and performance, truly unbiased estimates of those parameters that affect pavement quality must be obtained.

The validity of these relationships also depends on having a reliable method for estimating pavement performance. Ideally, performance should be evaluated through detailed measurements, both destructive and nondestructive, to determine remaining life. Because this is a time-consuming and expensive process, a rapid, cost-effective, reliable pavement condition evaluation system that reflects actual conditions is needed.

In this paper the results of a recent study (1) of the interrelationships between quality indicators and performance of concrete pavements are reported. In that study, historical and construction data on selected quality variables were collected for 104 concrete pavement projects in five states. In addition to these data, the 104 projects were subjected to pavement condition evaluations to establish current performance levels. Statistical analyses were performed to establish relationships between performance rating and quality-indicator data, and 30 models were developed and tested.

A general model and representative data from the Ohio projects in that study are presented here to illustrate the types of performance and quality data required to develop statistically reliable relationships, the types of results that can be obtained from such analyses, and the impact of missing data on model development and reliability. A brief description of quality indicators known to affect concrete pavement quality and performance is presented in the next section. In the third section the pavement condition evaluation system used to rate performance of the pavement projects is discussed. Data collection is outlined in the fourth section, and in the last section the statistical analyses performed and results obtained are summarized.

QUALITY INDICATORS IN PCC PAVEMENTS

When quality-assurance programs are carried out that use statistically based quality-indicator specifications to meet performance requirements, it is necessary to establish whether specific quality indicators, tests, measurements, or observations are truly related to future rigid pavement performance. Not all parameters that influence distress modes are indicative of concrete quality. Rather, external factors such as load, traffic patterns, soil conditions, and climate may significantly influence rigid pavement performance. The relative importance of these factors depends on the type of distress and the performance parameters being considered.

The following primary quality indicators have been identified as essential for rigid pavement construction, long-lasting performance, and least-cost maintenance requirements:

1. Pavement thickness,
2. Concrete strength (tensile, flexural, and compressive),
3. Concrete consistency (slump),
4. Concrete density,
5. Water/cement ratio,
6. Air content,
7. Mix temperature, and
8. Aggregate quality and durability.

These indicators are frequently cited as those parameters that, in response to load, traffic, environment, and so forth, affect rigid pavement performance. These indicators are briefly discussed in the following paragraphs.

Pavement Thickness

The AASHO Road Test studies of rigid pavements provided substantial data on the inverse relationship between pavement thickness and deflection, an expression of structural integrity and response to load, environment, and so on. One of the most significant factors in the extended AASHO rigid pavement design equation is pavement thickness. The expected change in service life due to overestimated or underestimated thickness was more than 20 percent in most cases, which supports the conclusion that a negative variation in thickness significantly affects pavement life (2). Numerous studies confirm that pavement thickness is a primary factor influencing performance.

Concrete Strength

Flexural concrete strength, in addition to thickness, is one of the most significant factors in the extended AASHO rigid pavement design equation. Concrete strength is known to have a high probability of variation under construction conditions (2). It has also been widely reported to be related to pavement deflection and crack spacing in continuously reinforced concrete (CRC) pavements. Concrete with low tensile strength has been reported to exhibit higher deflections than stronger concrete (3,4).

Concrete strength is also affected by air content and water/cement ratio. Weed (5) reported that concrete compressive strength decreased by 10 percent (400 psi) for each 1 percent increase in air entrainment. He also reported the inverse relationship between compressive strength and water/cement ratio, a finding reported in numerous other studies.

Concrete Consistency (Slump)

Consistency is a practical consideration in obtaining workable concrete. It usually denotes the fluidity or wetness as indicated by slump or corresponding tests. Dry concretes with low slump values tend to crumble unless carefully handled. Although dry concrete can be consolidated into a rigid mass under vigorous vibration, it will exhibit voids or honeycombing unless special care is taken.

Concrete Density

In-place relative density is often cited as a primary parameter in rigid pavement performance. Low density resulting from poorly controlled vibration at construction leads to honeycombing and other failure problems. Walker (6) reported that density decreases with faster vibrations and greater spacings. It has also been reported that higher densities are obtained in mixes with higher slump values (1-2 in.).

Water/Cement Ratio

In hardened concrete, properties such as strength are functions of the density, which in turn is controlled by the ratio of water to cement in the original mix. Thus there are practical limits to the proportions of cement, water, and aggregate in normal mixtures. In the hardening process, a unit quantity of a particular cement can potentially combine with a specific quantity of water. A mix having a high water/cement ratio will have a larger volume of potentially uncombined water. Because capillary-pore space derives from uncombined water, leaner mixes have a more porous structure. It has been well documented that the strength and porosity of concrete paste structures depend almost entirely on the water/cement ratio.

Air Content

The general effects of air entrainment include increased workability, decreased unit weight, decreased strength, reduced bleeding and segregation, and increased durability. Air entrainment permits a lower sand content in the mix and a reduction in mixing water of about 3 percent for each 1 percent entrained air. It has been used to reduce frost damage, with a necessary trade-off in concrete strength. Air content also affects mixture workability.

Mix Temperature

Temperature effects for moist-cured concrete strength depend on the time-temperature history. When concrete is cast and maintained at a given constant temperature, the higher that temperature, the more rapid the hydration and resulting gain in strength at ages up to 28 days. At later ages, the strengths are not greatly different but the higher the curing temperature, the lower the strength. When concrete is cast and maintained at a given temperature for several hours and then cured at 70°F, the higher the initial temperature, the lower the 28-day strength. In general, if the curing temperature is higher than the initial casting temperature, the resulting 28-day strength will be higher than that for a curing temperature equal to or lower than the initial temperature.

Aggregate Quality and Durability

As in asphaltic mixes, the quality and performance of concrete mixtures are substantially influenced by aggregate type, quality, and durability. For example, the porosity or absorption rate of an aggregate affects the water/cement ratio, strength, and so on, and will significantly influence pavement susceptibility to saturation and freeze-thaw damage.

DEVELOPMENT OF PAVEMENT CONDITION EVALUATION SYSTEM

Concrete pavement performance must be evaluated in a rational, concise, and descriptive manner that permits statistical correlation with quality-control (QC) parameters. Performance can be qualified in terms of structural capacity, physical deterioration or distress, or rider quality and other user-related factors, which constitute the serviceability of the pavement. Recent advances in pavement design have dealt with quantifying pavement life by predicting the occurrence of different types of distress. It is generally believed that pavement distress precedes loss of structural capacity and reduction in ride quality.

QC criteria, which define acceptable limits on material properties, should be related to the occurrence of different types of material failures or distress. The literature provides ample evidence that these two factors are indeed related. Because pavement distress results from complex interactions among design, construction, materials, environment, traffic, and maintenance in which one distress type can lead to another, those performance parameters identified as quality indicators can often influence more than one type of distress.

Where pavement performance is qualified by distress manifestations, the rating procedures used to assess pavement condition must include a uniform method for identifying and quantifying distress severity and extent. The pavement-condition-rating (PCR) system developed for this study involved rating the pavement based on the presence of visible distress and is a modification of the method developed by the Ohio Department of Transportation (ODOT) (7), which provides a procedure for uniformly identifying and describing pavement distress in terms of extent and severity. The mathematical expression for PCR provides an index reflecting the composite effects of various distress types, their severity, and the extent of the effects on overall pavement condition.

The ODOT method for computing PCR is based on the summation of points deducted for each type of visible distress. Total points deducted is subtracted from 100 to yield the PCR. The distress types identified by the ODOT PCR procedure for concrete and CRC pavements are given below. Distress types have been grouped under three main categories: surface defects, pavement support, and cracking; if applicable, a category for joint deficiencies may also be used. The PCR field manual contains standard descriptions of each distress type as well as assistance in defining distress severity and extent.

1. Jointed concrete pavement
   a. Surface defects
      (1) Surface deterioration
      (2) Patching
      (3) Popouts
   b. Pavement support
      (1) Pumping
      (2) Faulting
      (3) Settlement
   c. Cracking
      (1) Transverse
      (2) Longitudinal
      (3) Corner breaks
   d. Joint distress
      (1) Joint spalling
      (2) Joint sealant damage
      (3) Pressure damage
2. CRC pavement
   a. Surface defects
      (1) Surface deterioration
      (2) Patching
      (3) Pressure damage
      (4) Popouts
   b. Pavement support
      (1) Pumping
      (2) Settlement or waves
   c. Cracking
      (1) Transverse spacing
      (2) Longitudinal
      (3) Punchouts or edge breaks
      (4) Spalling

The subtotal for structural deductions is the total of points deducted for those distress types believed to be related to pavement structural integrity. ODOT plans to use the structural deduction subtotal to identify pavements for further evaluation by using nondestructive methods.

The modified system used in this study was called the Concrete Pavement-Condition-Rating System (CPCR). CPCR uses the same distress types as those used in the ODOT system except that reactive aggregate durability and swell have been added. Mathematical calculation of PCR is the same as that in the ODOT system.

Separate ratings are made for each QC section within a project. QC sections are continuous subdivisions of the project length; each QC section is characterized by its own set of QC data (compressive strength, slump, percentage of air, and so on). For each QC section, the QC data are the independent variables, whereas the CPCR performance data (along with subgroupings) are the dependent variables. QC section length is established by the frequency of available QC data values. For Ohio, each QC parameter is available at a frequency of about six values per directional mile of roadway. At least three parameter values are desirable for characterizing the QC section with adequate reliability. For states or individual projects with greater frequency of QC data values, smaller sections can be used. Short QC sections are desirable because the range of QC data and sensitivity of the CPCR procedure are enhanced. QC section length is set before field performance ratings are conducted.

When the 104 projects included in this study were evaluated, two research teams were used to minimize perceptual bias during data collection and field rating. Thus, the membership of the pavement-rating team differed from that of the team that collected the concrete QC data from historical and construction records and that also selected the projects for field rating and established the QC section lengths for those projects.

PROJECT SITE SELECTION AND DATA COLLECTION

Site Selection

For this study project sites were needed for which unbiased QC test results were available. After a list of desirable quality indicators had been established, as well as design, traffic, and environmental variables for which data would need to be collected, preliminary interviews were held with various state departments of transportation to determine the types and amounts of QC data available.

Two significant factors affected a state's ability to provide needed data for a project. The first was the amount of concrete pavement that is still exposed. In Ohio, for instance, most concrete pavements were originally built during the late 1950s and 1960s. Much of that mileage has been overlaid, and overlaid pavements could not be used in the study because their condition had been altered. The second factor was time constraints on record keeping. Most states dispose of QC data after a given time period. Because much of the concrete pavement in the United States is more than 10 yr old, the records have been destroyed in many instances.

Five states were selected for inclusion in this study: Florida, Louisiana, Maryland, New York, and Ohio. Selections were based on availability of QC data, pavement accessibility, willingness to participate, and geographic location (for variation in environment). A total of 104 projects was selected. Of these, 25 were in Florida, 8 in Louisiana, 11 in Maryland, 10 in New York, and 50 in Ohio. The projects included plain jointed, dowelled jointed, and CRC pavements with thicknesses ranging from 8 to 10 in. The Florida pavements were relatively new (4 to 9 yr old), whereas the Louisiana projects were 16 to 20 yr old, Maryland pavements were 10 to 13 yr, New York pavements ranged from 12 to 15 yr, and Ohio projects from 5 to 14 yr. Traffic also varied from a cumulative equivalent axle load of 0.2 million to 15.5 million lb.

Data Collection

The CPCR procedure discussed in the preceding section was used to rate each of the 734 PCR sections established in this study. A PCR section consisted of approximately 0.5 mile of roadway, except in New York where 0.25 mile was used; one lane in each traffic direction was rated. It was originally planned to consider each direction (lane) separately, but because only 8 percent of the QC data was identified by lane, the PCR values and distress measurements were averaged over both lanes.

Along with PCR values, a riding comfort index (RCI) was assigned to each lane section rated, and direct distress measurements were made. Two 200-ft sections per lane were evaluated for distress measurements of the 0.5-mile section lengths, and one 200-ft section per lane was used for the 0.25-mile section lengths. Distress measurements consisted of estimating the lineal feet of medium- or high-severity transverse crack spalling, the area of cracking, and number of punchouts for CRC pavements.

STATISTICAL ANALYSIS OF DATA

Statistical Techniques Used

The ultimate objective of this study was to determine which of the quality indicators influence pavement performance and to what extent. The techniques available are linear and nonlinear multiple stepwise regression methods, such as those of the Society for Automation in the Social Sciences (SASS) and the Statistical Package for the Social Sciences (SPSS).

Although it is somewhat simplistic to expect that a subject as complex as pavement performance can be analyzed with linear models, the nonlinear models are difficult to use if the form of the nonlinear model is not known beforehand and are further complicated when several independent variables are being considered. Thus in this study linear stepwise regression was employed. Selection of a linear regression model does not, however, restrict analysis to linear forms of the independent variable; it is possible to define dummy variables in terms of nonlinear forms of the independent variables as well as interaction terms between some forms of the independent variables. This approach was selected for analysis.

Quantifying Qualitative Variables

Qualitative variables are those to which numerical values cannot be assigned, such as climate (wet or wet and freezing) or subgrade type (good, fair, poor). Stepwise regression methods include qualitative variables as part of the variable list by assigning arbitrary numerical values for different variable levels, such as 0 for wet and 1 for wet and freezing. Because the net effect of qualitative variables modifies the intercept, however, the influence of such variables in these models is generally rather poor. In this study, various techniques such as BMDP, SASS, and SPSS were tried by using qualitative variables for climate, base type, and subgrade type. Such variables cannot be used to determine interactive effects, however, and because their use resulted in poor models in this study (the best R^2 was 0.28), it was decided to quantify climate and subgrade. Climate was subdivided into three variables--mean annual rainfall, frost penetration, and freezing index. The subgrade type was quantified by assigning an average California bearing ratio (CBR) value based on soil classification. Poor soils were assigned a CBR of 5; fair soils, a CBR of 8; and good soils, a CBR of 12.

Missing-Value Problem

One of the most frustrating aspects of the analysis was the problem of missing values for the QC data. State transportation departments do not always agree on the type of QC tests to be done, and the types of tests conducted often vary from project to project within a state. Also, some QC data have been lost over the years. Thus, values were not available for many of the QC variables for a significant number of the sections under investigation. Table 1 lists the QC variables used in this analysis and the number of PCR sections having nonzero values for these variables. Although it appears that many of these variables had reasonable populations, it was rare that sections had data for most of these variables at the same time. The first, most obvious approach was to substitute project average values for section variables with missing data by using the following justification:

1. If project average values were not substituted, the models would have to be developed on significantly smaller populations [252 sections instead of 529 for models involving temperature, and 260 instead of 558 sections if temperature (N30 and N31) is ignored].
2. In most instances, the projects where substitution could be made already showed reasonable uniformity in data.

In the second approach, the correlation matrix was examined to see whether any relationship existed between the dependent variables.

Numerous attempts were made to overcome the missing-data problem through models involving the other variables, with notable lack of success. The only exception was a model relating the water/cement ratio (N36) to slump, air content, and core compressive strength.

Another approach was tried with a technique developed at Ohio State University (8) for handling missing-value problems. In this technique, the missing values are replaced with zeros; a regression relationship is developed from all data, which forces the intercept through near zero. Then the data are shifted by an amount equaling the derived intercept, a regression relationship is redeveloped, and the process is iterated until a stable intercept is obtained. This intercept represents the most

Table 1. Variables used in analysis.

Variable	Description	No. of Sections[a]
N9	Annual rainfall	734
N10	Frost penetration	734
N11	Freezing index	734
N13	Subgrade CBR	734
N15	Joint/crack spacing	734
N16	Cumulative traffic	734
N17	Age	734
N18	Design thickness	734
	Pour temperature	
N30	Minimum	460 (564)
N31	Maximum	460 (564)
N32	Slump	561 (638)
N33	Percentage of air entrained	515 (610)
N34	Air content	6 (6)
N35	Unit weight	170 (255)
N36	W/C ratio	262 (276)
N37	Yield	155 (158)
	Flexible strength	
N38	0 to 3 days	36 (115)
N39	4 to 7 days	179 (275)
N40	8 to 14 days	86 (185)
N41	>14 days	89 (93)
	Cylinder strength	
N42	0 to 3 days	6 (6)
N43	4 to 7 days	336 (462)
N44	8 to 14 days	200 (367)
N45	>14 days	269 (377)
N46	Core strength	488 (661)
N47	Core age	394 (456)
N48	Thickness deviation	564 (611)

[a]Numbers in parentheses indicate number of sections having nonzero values after project average values were assigned.

probable value of the missing variable. Because of the complex nonlinear relationships among variables, however, this effort did not yield reasonable results in this study.

Stepwise Regression Analysis

Because it was expected that the performance prediction model would be quite complex, with nonlinear interaction between independent variables, a large number of dummy variables were defined in terms of the elementary forms of the independent variables. The dummy variables were defined in terms of 1/x, x*x, 1/x*x, log x, 1/log x, SQRT(x), and x**0.75. In addition, a number of two-level interactions (interaction of variable i with variable j) and three-level interactions (interaction of variable i with variables j and k) were defined.

Table 1 gives the list of independent variables used in the predictive models. Two other variables were defined along with their nonlinear forms discussed above: H = design thickness (N18) + thickness deviation (N48) and TEMP = minimum pour temperature (N30) + maximum pour temperature (N31). Using the variables described in Table 1 resulted in 529 sections having nonzero values for all variables. Of these, 307 sections had granular bases and 222 had stabilized bases. The inclusion of any other variables, it was found, would have drastically reduced the population.

Three models were developed to predict pavement performance as measured by PCR from the variables listed in Table 1. These models were

1. General model, 529 sections;
2. Granular-base model, 307 sections; and
3. Stabilized-base model, 222 sections.

As will be discussed later, temperature did not always enter the models; when N30 or N31 or both were involved, their effect was relatively small. Thus, in order to include New York data and to broaden the data base, the same three models were also developed and N30 and N31 were omitted from the variable list. Exclusion of N30 and N31 resulted in 558 sections for the general model, 335 sections for the granular-base model, and 223 sections for the stabilized-base model.

An attempt was made to model jointed and CRC pavements, without great success. All Ohio CRC pavements were built on stabilized bases, all Maryland pavements were CRC on granular bases, and Florida and New York projects were all jointed pavements. Thus, separating by both pavement and base type not only leads to models with small populations but also restricts each model to only one state. Because such a restriction would make the models less useful, this approach was not pursued.

In addition to six PCR models, models were also developed for the PCR subgroups [structural deduction (ST.D.), surface deduction (SU.D.), support deduction (SP.D.), and cracking deduction], defined as follows for jointed pavements:

1. Structural = pumping + faulting + transverse cracking + longitudinal cracking + corner breaks,
2. Surface = surface deterioration + popouts + patching,
3. Joint = joint spalling + pressure damage + sealant damage,
4. Support = pumping + settlement + faulting, and
5. Cracking = transverse cracking + longitudinal cracking + corner breaks.

For CRC pavements, deduction totals were defined as follows:

1. Structural = patching + pumping + settlement + transverse cracking + longitudinal cracking + punchouts,
2. Surface = surface deterioration + popouts + patching + pressure damage,
3. Support = pumping + settlements, and
4. Cracking = transverse cracking + longitudinal cracking + punchouts + crack spalling.

Table 2 shows a summary of the 30 models developed for this study. As can be seen, the equations are all relatively long, ranging from 9 to 34 terms. Except for the cracking-deduction model with temperature, the granular-base models have the highest correlation coefficients (R^2) and the lowest standard error of estimate (comparing within a dependent variable group), and the stabilized-base models generally have the lowest correlations and the highest standard errors. The stabilized-base models have the lowest populations, which partly explains the poorer relationship, but by this argument, the general models should have the best correlation, which was not the case. It is more likely that the quality of stabilized bases is quite variable by design. Some of the bases are asphalt treated, whereas others are cement treated, and the asphalt/cement content most probably varies for both. Ideally, bases should be described by modulus and thickness, but such information was not available for this study.

CONCLUSIONS AND RECOMMENDATIONS

It is interesting to note that the term H*H/log N16 entered most of the 30 models developed. This term describes the effect of pavement thickness in the AASHTO rigid pavement design equation. Also included in many models is the term log N16/N46*N46, which describes the effect of concrete strength

Table 2. Correlation coefficients.

Model	R^2	Standard Error	No. of Terms
PCR			
GEN-T[a]	0.634	4.62	25
GRN-T	0.780	3.39	25
STB-T	0.529	5.59	10
GEN	0.653	4.49	29
GRN	0.742	3.69	20
STB	0.567	5.36	15
Structural deduction			
GEN-T	0.692	3.52	30
GRN-T	0.750	2.53	23
STB-T	0.710	4.07	19
GEN	0.663	3.75	27
GRN	0.733	2.76	18
STB	0.651	4.44	15
Surface deduction			
GEN-T	0.737	1.10	26
GRN-T	0.797	0.91	19
STB-T	0.613	1.15	16
GEN	0.728	1.12	27
GRN	0.739	1.03	20
STB	0.590	1.20	16
Support deduction			
GEN-T	0.791	2.22	34
GRN-T	0.842	1.83	21
STB-T	0.716	2.57	18
GEN	0.779	2.039	33
GRN	0.837	1.92	20
STB	0.695	2.66	17
Cracking deduction			
GEN-I	0.662	2.38	24
GRN-T	0.692	1.54	21
STB-T	0.721	2.87	12
GEN	0.683	2.30	31
GRN	0.711	1.53	23
STB	0.661	3.16	9

Note: GEN, general model; GRN, granular-base model; STB, stabilized-base model.

[a]T indicates that N30 and N31 were included in the model.

(assuming that flexural strength is related to compressive strength) in the AASHTO equation.

The sensitivity analysis of the AASHTO rigid pavement equation is shown below. Similar analyses were conducted for the predictive models.

Variable	Effect
N13	6.4
N16	-34.7
N18	214.0
N46	59.2

The AASHTO design equation predicts the design life (N16) to a particular serviceability index (Pt) as a function of subgrade reaction, concrete flexural strength, and pavement thickness. It is, however, possible to predict the terminal serviceability index as a function of traffic, subgrade reaction, concrete flexural strength, and pavement thickness. A partial comparison of this equation with the predictive models for PCR is thus possible if modulus of subgrade reaction (k) is related to CBR and if concrete flexural strength is related to compressive strength. The following transformation equations were used:

$$k = 55.85 N13^{0.552} \quad (1)$$

and

$$\text{Flex} = 9 \cdot \text{SQRT}(N46) \quad (2)$$

Both the k relationship and the Flex equation were derived from published relationships (9,10).

As shown in the sensitivity analysis, the AASHTO equation is sensitive to pavement thickness (N18) and rather insensitive to subgrade support (N13).

Table 3. Model trends.

Variable	No. of Models Entered	No. Affected Beneficially	No. Affected Detrimentally
N9	25	5	20
N10	25	20	5
N11	24	15	9
N13	30	28	2
N15	11	5	6
N16	30	5	25
N17	30	10	20
N18	29	28	1
N30	8	4	4
N31	7	3	4
N32	20	12	8
N33	28	3	25
N36	6	2	4
N46	30	29	1
N48	29	26	3

Sensitivity analyses of the predictive models showed that thickness was an important variable but its effect was some 10 times lower than in the AASHTO equation, whereas subgrade played a somewhat larger role than in the AASHTO model.

One of the major difficulties in comparing with the AASHTO model is that it predicts terminal serviceability rather than decline of serviceability. The relationship shown in the sensitivity analysis covers a range in Pt from 2.5 to 1.5 (the limits of validity for this equation), i.e., for pavements that have nearly failed. Nevertheless, the pavements evaluated in this study were still in relatively good condition, as reflected by the PCR, which ranges from 50 to 98 with a mean of 75. Thus, the comparisons are not strictly valid. Another difficulty in comparing the predictive models with the AASHTO equation is that the latter is dependent on only four variables, whereas the predictive models incorporate the effects of 8 to 12 variables. Because variation in performance is distributed among a much larger list of variables, the effect of each would be smaller than in a model with fewer variables.

Sensitivity analysis results showed that the models are generally consistent with one another and that the effect of the variables is generally consistent with expectations; there are some exceptions. It is generally accepted that increased rainfall is detrimental to performance; however, the stabilized-base model without temperature shows a positive effect. Also, increased age and traffic should decrease performance, but the granular-base model with temperature shows the opposite trend. It is, however, encouraging that these inverted effects were confined to the stabilized-base models, which had rather poor correlation coefficients.

Most trends shown in Table 3 were more or less consistent with experience. The effects of rainfall (N9), subgrade support (N13), design thickness (N18), thickness deviation (N48), and compressive strength (N46) were according to expectation in a majority of cases, and the reversal of trends was primarily limited to the stabilized-base models with low R^2-values.

The analytical results make it apparent that variation in climate, subgrade support, and pavement thickness have by far the greatest effect on pavement performance and that the effect of concrete quality indicators is secondary. One of the primary reasons for the lack of effect of QC variables is that the values of most QC indicators are controlled via concrete mix design to fall within an acceptable range; i.e., concrete is generally designed to have a slump between 2 and 4 in. and an air content

Table 4. Range of values for variables used in study.

Variable	Mean	Standard Deviation	Minimum	Maximum
N9	45.3	9.8	32.0	65.0
N10	12.0	9.6	0.0	35.0
N11	147.7	177.5	0.0	400.0
N13	8.1	1.8	5.0	12.0
N15	44.0	22.1	0.0	60.0
N16	4.4	3.5	0.2	17.7
N17	11.3	3.8	4.0	20.0
N18	9.1	0.5	8.0	10.0
N30	58.6	10.3	25.8	81.0
N31	78.4	10.2	38.3	95.3
N32	2.1	0.6	0.7	4.4
N33	5.6	1.0	2.0	8.6
N36	0.44	0.17	0.26	0.76
N46	5,350.0	1,076.0	2,753.0	7,833.0
N48	0.20	0.24	-0.97	0.94

around 4 percent. The acceptable limits have been determined from years of experience and when they are exceeded, job-site inspections are expected to reject unacceptable batches. Table 4 presents the means and standard deviations of the QC variables in this study and shows that the allowable limits were rarely exceeded.

Also, a minimum concrete strength is required for satisfactory performance, but once the minimum has been exceeded, performance is not significantly affected. This is confirmed by most of the models, which show that compressive strength does not have a large effect. As shown in Table 4, the mean value for N46 was 5,300 psi with a standard deviation of 1,080 psi; i.e., most concrete exceeded the minimum specification of 4,000 psi.

Of the concrete quality indicators, compressive strength (N46) is generally the most important variable, but the relative ranking depends on the particular model selected. Air content (N33) was also fairly significant, both statistically in that it entered 28 of the 30 models and also because the magnitude of effect is generally larger than that for the other QC variables. Temperature parameters (N30 and N31), when they entered the models, exhibited rather large effects at times, but the statistical significance of these variables is questionable, as previously discussed.

It might be tempting to conclude from this analysis that measuring concrete quality is not justified, but such a conclusion is probably erroneous. Without any control, these variables would undoubtedly have had a significantly larger variation than was found in this study, with a significantly greater effect on performance.

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