LTPP Data Analysis

Task Order #03

"Effect of Multiple Freeze Cycles and Deep Frost Penetration on Pavement Performance and Cost"

Quarterly Progress Report

October, November, December 2004

Prepared for:

US Department of Transportation
Federal Highway Administration
400 Seventh Street, S.W.
Washington, D.C. 20590

Detailed Technical Summary of NCE Task Order #03 "Effect of Multiple Freeze Cycles and Deep Frost Penetration on Pavement Performance and Cost"

In this quarter, NCE has continued work on Task 8 and Task 9 of Task Order #03.

Task 8

Conduct detailed analysis of the effects of multiple freeze-thaw cycles verses deep frost penetration on pavement performance

The analysis team continues to work on developing regression models to predict various pavement performance measures this quarter. Significant progress has been made and the regression models are nearing completion. Once finished, a thorough comparison of the deterioration trends in each of the frost regions will be performed. The following sections detail the progress of trend development for pavement roughness, rut depth, strain, and surface distress measures.

Pavement Roughness

Post-construction roughness varies from one project to the next because of differences in construction techniques, specifications, etc. These differences also significantly affect the progression of roughness over time and could add variability to the model. To counter this, the analysis team investigated models to predict change in International Roughness Index (IRI) as the performance measure. Change in IRI was calculated by subtracting the first LTPP measurement from each of the subsequent measurements. Through this process, it was thought that the post construction differences were inherent in the initial IRI measurement and would be removed from the subsequent measurements.

The resultant models, however, did not provide a good correlation with the observed data set. The lack of fit can be partially contributed to the differences in age at which the first LTPP measurement was taken. For example, the first IRI measurement at test section 086002 was taken at an age of 21.3 years while the initial measurement at test section 100101 was taken at 1.1 years. Therefore, the reference measurement used to calculate change in IRI for subsequent measurements was captured at different ages as well as locations on the deterioration curve which was not accounted for in the model.

Based on the observations made using change in IRI, the analysis team decided to develop regression models using absolute IRI. To account for the post construction differences in roughness, initial IRI and the age of initial IRI measurement were incorporated as explanatory variables in the model. The models for this performance measure provided a better correlation (R-squared approximately 0.45) than the change in IRI measure. Figure 1 provides a graph of

actual values measured at test section 307066 with values predicted by the model. Incorporated in the figure are details on the test section which include: LTPP experiment (EXP), annual equivalent single axles (ESAL), base type (BASE), subgrade type (SG), structural number (SN), asphalt concrete thickness (ACTHICK), freezing index (FI), annual number of freeze-thaw cycles (FTC), cooling index (CI), and annual precipitation (PRECIP). As can be seen in the graph the model is predicting the accumulation of roughness with time fairly accurately (indicated by equivalent slopes) but the model is offset from the actual measurements. Although only one example is shown, the offset was observed in many cases and varied for each test section. These differences can be reduced or eliminated by shifting the model to predict the initial IRI at the corresponding age of initial IRI measurement. The shifted model for Test Section 307066 can be found in Figure 2.

The shifted model appears to correlate better with the measured values. In the coming quarters, NCE will evaluate the accuracy of the shifted model including an investigation of goodness-of-fit measures (e.g. R-squared values).

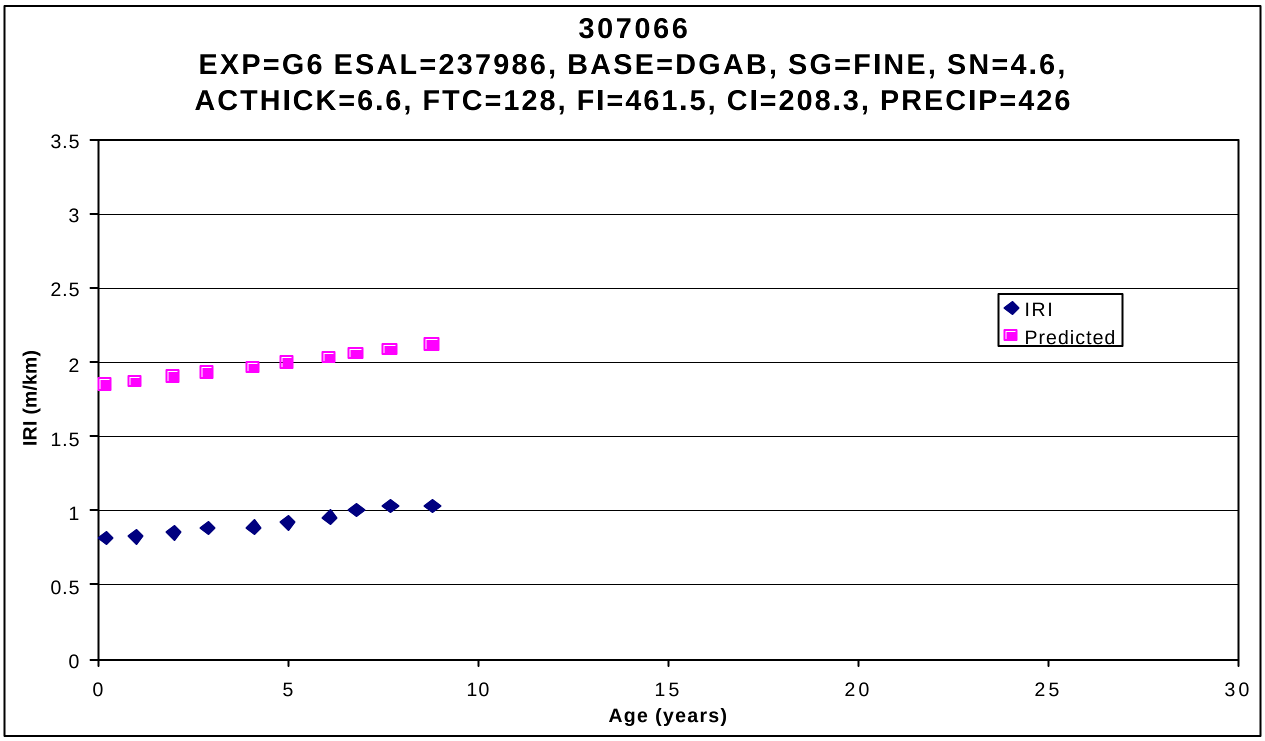

Figure 1. Measured and predicted absolute IRI values for Section 307066.

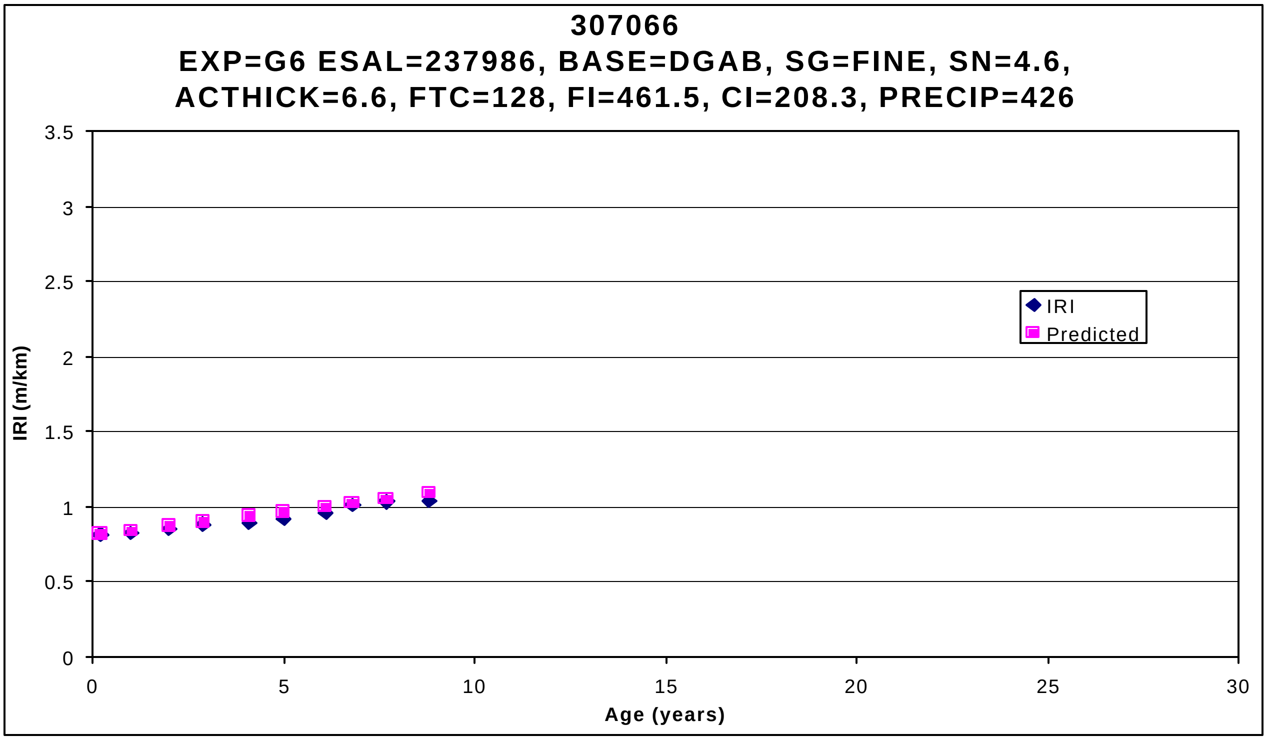

Figure 2. Measured and predicted absolute IRI values for Section 307066 using shifted model.

The analysis team also began comparing accumulation of roughness with age for different environmental settings using the shifted models. Figure 3 provides a comparison of predicted roughness for the Deep Frost, Moderate Frost, and No Frost regions. All explanatory variables were held constant except for FI, PRECIP, and FTC. Details on the values used to generate Figure 3 can be found in Table 1. Additionally, the models were shifted to a standard initial IRI of one meter per kilometer at an age of one year. As can be seen, the contribution of PRECIP and FTC in the model is fairly insignificant in comparison the affect of FI. As such, the Deep Frost Region is showing the largest accumulation of roughness.

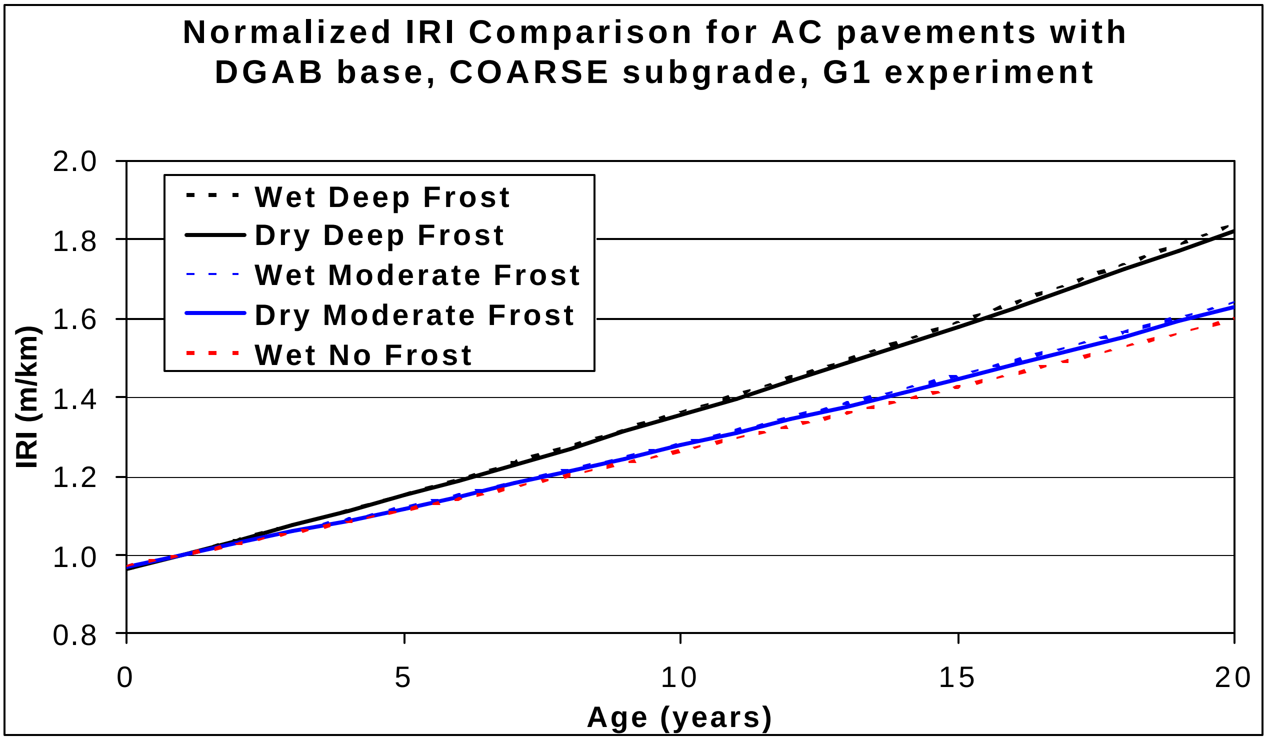

Figure 3. Absolute IRI model predictions for different environments.

Table 1. Explanatory variables used in Figures 3-7.

REGION	FI	FTC	PRECIP
Wet Deep Frost	1000	75[1]	1200
Dry Deep Frost	1000	75[1]	400
Wet Moderate Frost	200	165[2]	1200
Dry Moderate Frost	200	165[2]	400
Wet No Frost	20	30[3]	1200

[1]One of the lowest FTC values found in the Deep Frost Region.
[2]One of the highest FTC values found in the Moderate Frost Region.
[3]The average FTC value found in the No Frost Region.

Rut Depth

The model to predict rut depth was found to exhibit an R-squared value of approximately 0.25. Because the type of base course in the pavement structure affects the relative accumulation of rutting, predictions for four different base types can be found in Figures 4 through 7. The environmental groupings used in these figures are identical to the groupings used for the absolute IRI models discussed previously and are summarized in Table 1.

The model predicts the largest accumulation of rutting in the Dry Moderate Frost region for unbound (DGAB), asphalt treated (ATB), and non-bituminous treated (NONBIT) bases. The largest accumulation of predicted rut depth for permeable asphalt treated bases is found in the Wet Deep Frost Region.

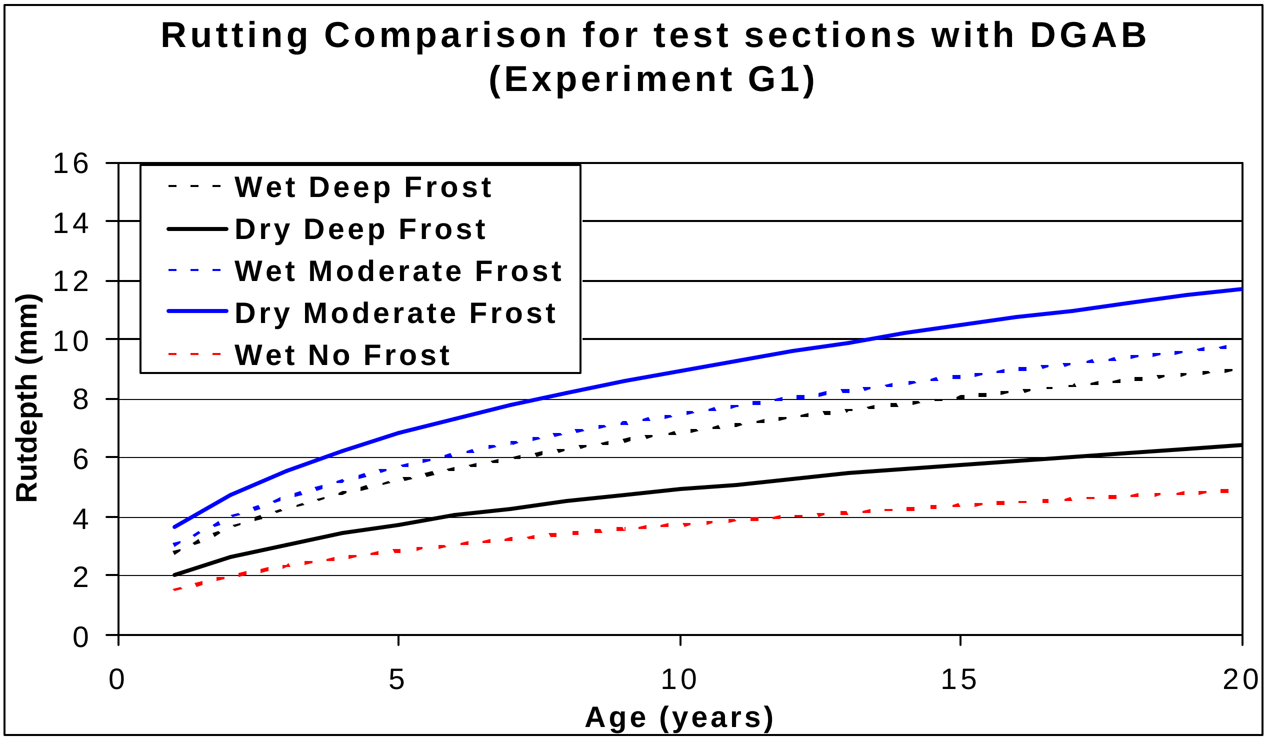

Figure 4. Rut depth model predictions for different environments and DGAB base type.

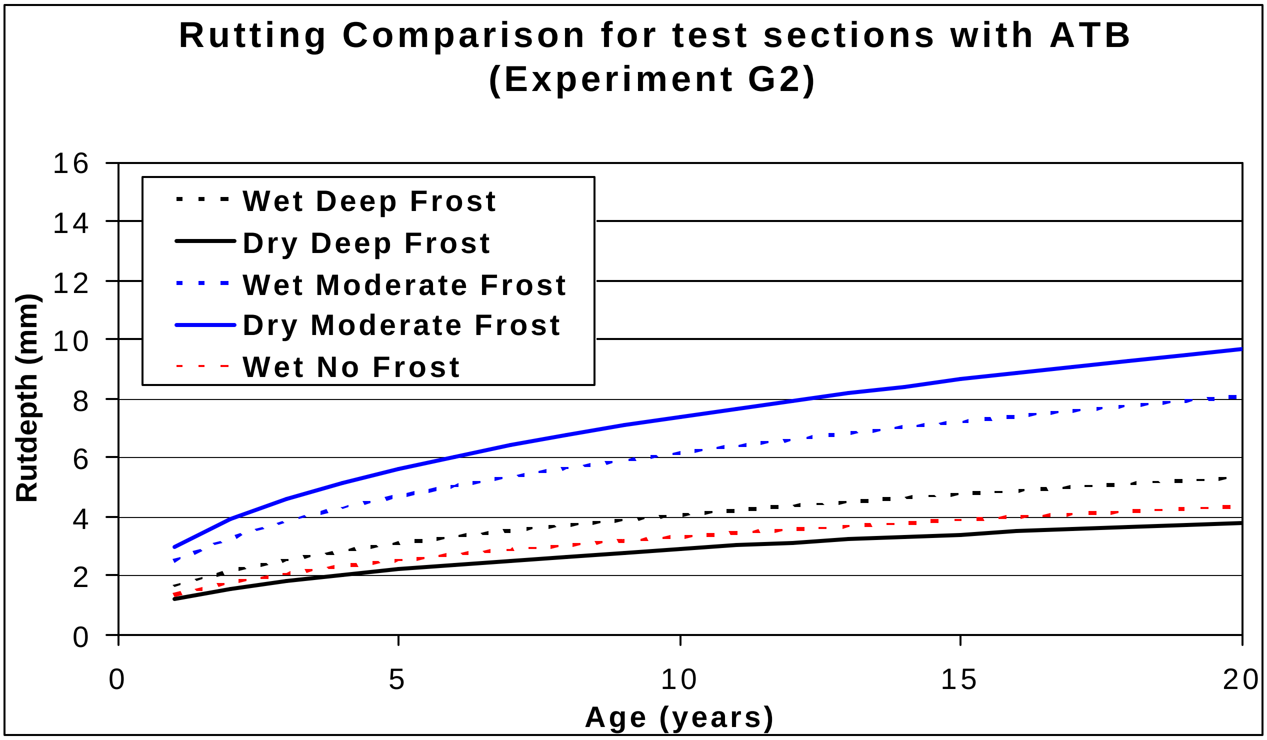

Figure 5. Rut depth model predictions for different environments and ATB base type.

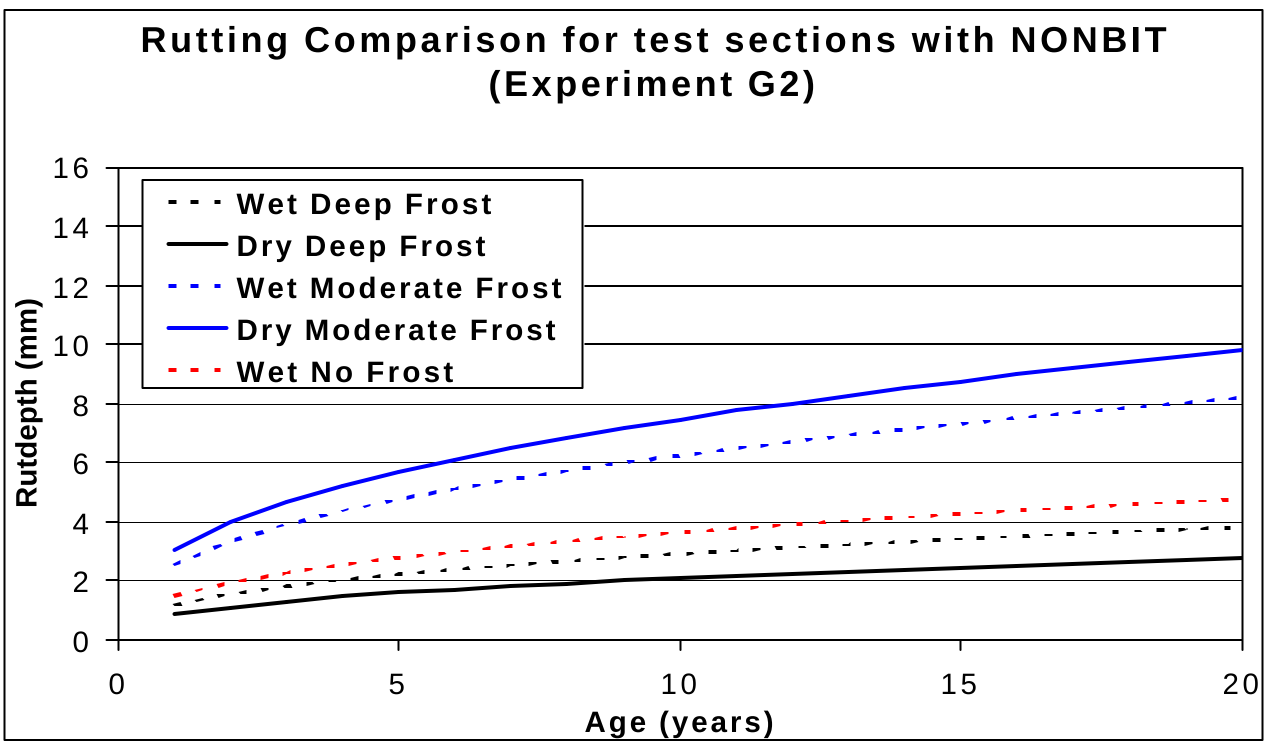

Figure 6. Rut depth model predictions for different environments and NONBIT base type.

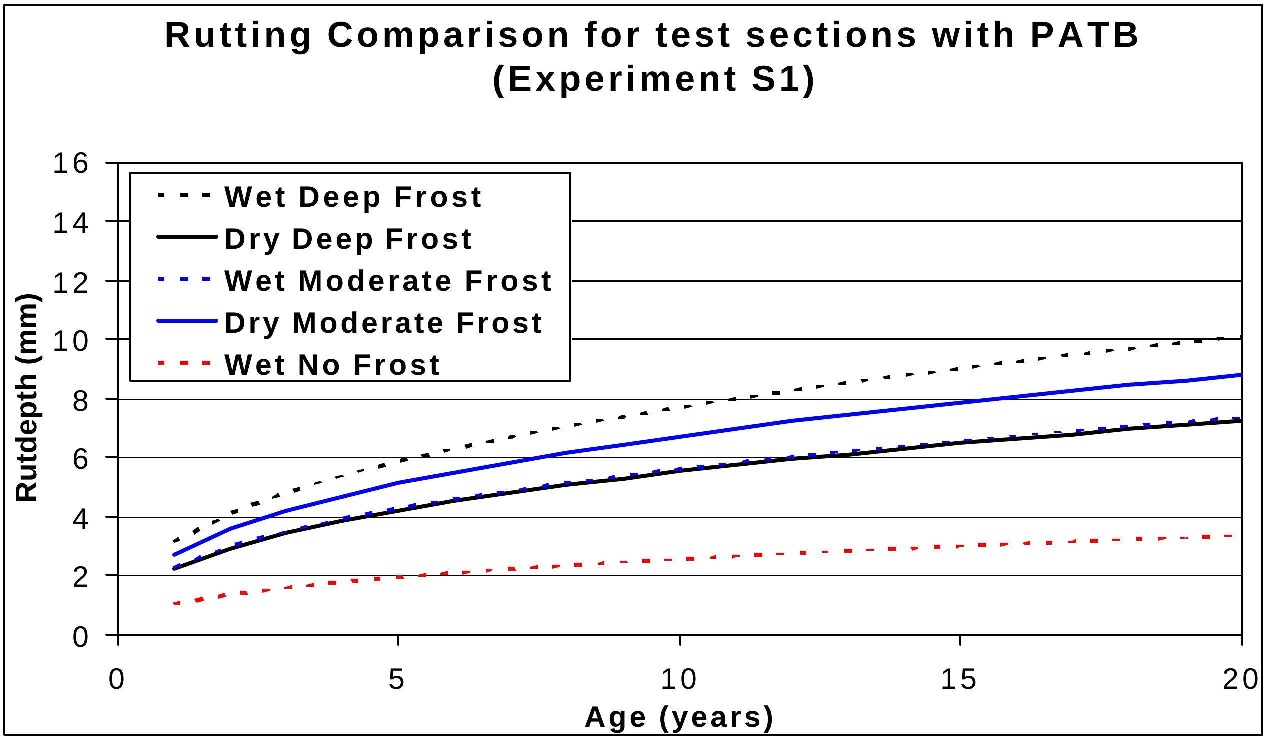

Figure 7. Rut depth model predictions for different environments and PATB base type.

Strain at the bottom of the AC layer

Data from FWD testing was used to determine the strain at the bottom of the asphalt concrete layer using methods described in "Use of Falling Weight Deflectometer Multi-Load Data for Pavement Strength Estimation."[1] Deflections under the load and at offsets of 12 and 24 inches were normalized to a standard load and used in the strain equations. The strain values were then adjusted to a standard temperature through the use of a resilient modulus master curve.[2] The established method is only for flexible pavements; therefore, this variable was not included in the rigid dataset.

Currently, this regression model is predicting a reduction in strain with an increase in age. The analysis team will continue to investigate this model in the coming quarters.

Surface Distress

For the flexible pavements, all three severity levels for each distress type were combined through the use of deduct curves developed for the South Dakota Department of Transportation[3] to obtain a deduct value for each distress. Fatigue cracking (FC), block cracking (BC), longitudinal wheel path cracking (LWP), and transverse cracking (TC) were considered in the study. Because LWP often progresses to FC, the two distress types were combined (FWPC). LWP was converted from a linear unit to a unit of area to be consistent with FC. This was done by

applying a standard width of 0.3 meters to the recorded length of LWP. All severities of LWP were considered as low severity to compute deduct values that would be combined with the FC.

The format of distress data collected on rigid pavements does not match the required format used in the established deduct curves.[4] Therefore, the severity levels were summed for each distress type. This total distress was then normalized based on the size of the test section. For example, the sum of all three severities of longitudinal cracking were summed and divided by the total length of the section. Corner breaks, longitudinal cracking, and transverse cracking were considered in the study for rigid pavements.

Figure 8 provides a scatter plot of FWPC as a function of pavement age. As can be seen from the figure, there is a large amount of variability in the data and there are a large number of zeroes which are recorded across the entire range of ages. For these reasons, regression models alone did not provide a good correlation with the measured values.

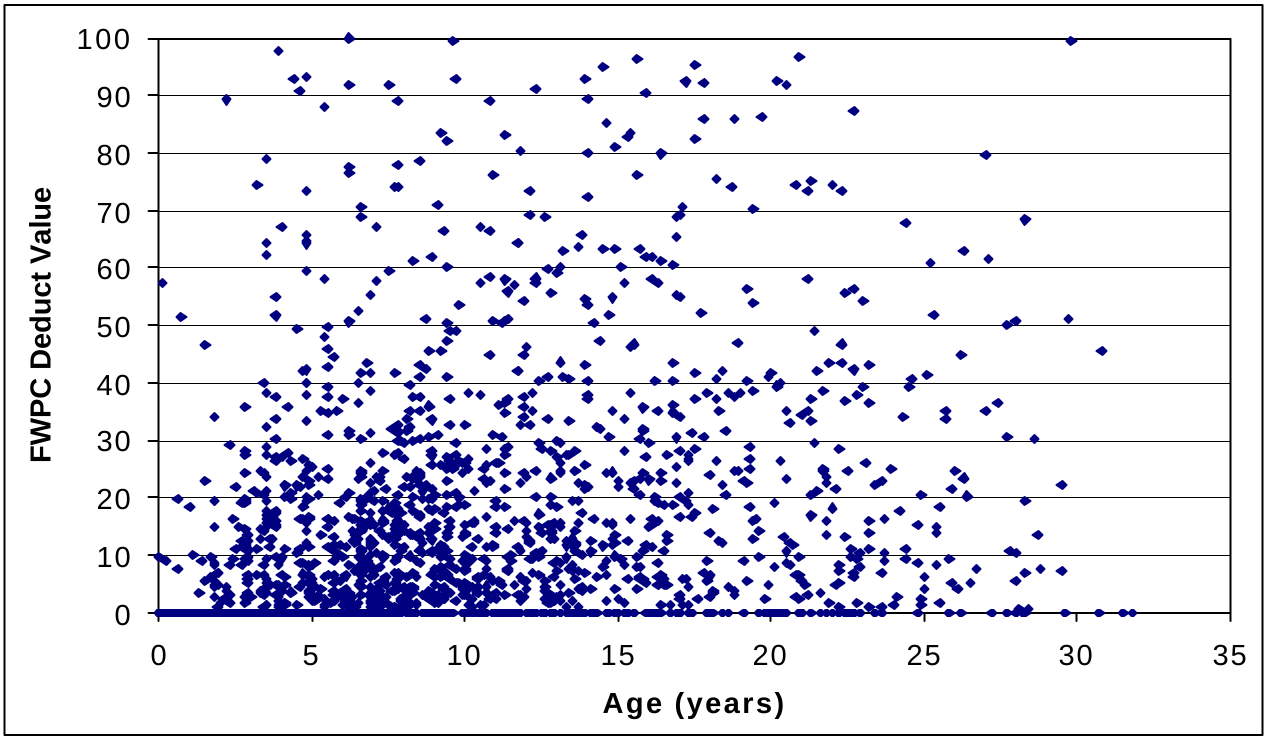

Figure 8. Plot of measured FWPC deduct values.

A small subset of the measured FWPC values was plotted and can be found in Figure 9. Each series in the figure represents data from one test section. It appears that a substantial portion of the variability in the data can be attributed to the differences in age at which distress initiates. For example, distress initiation occurs just after construction at two of the sections shown while another section does not initiate distress until age 17. There does appear to be a reasonable trend in the accumulation of distress with age after the initiation of distress.

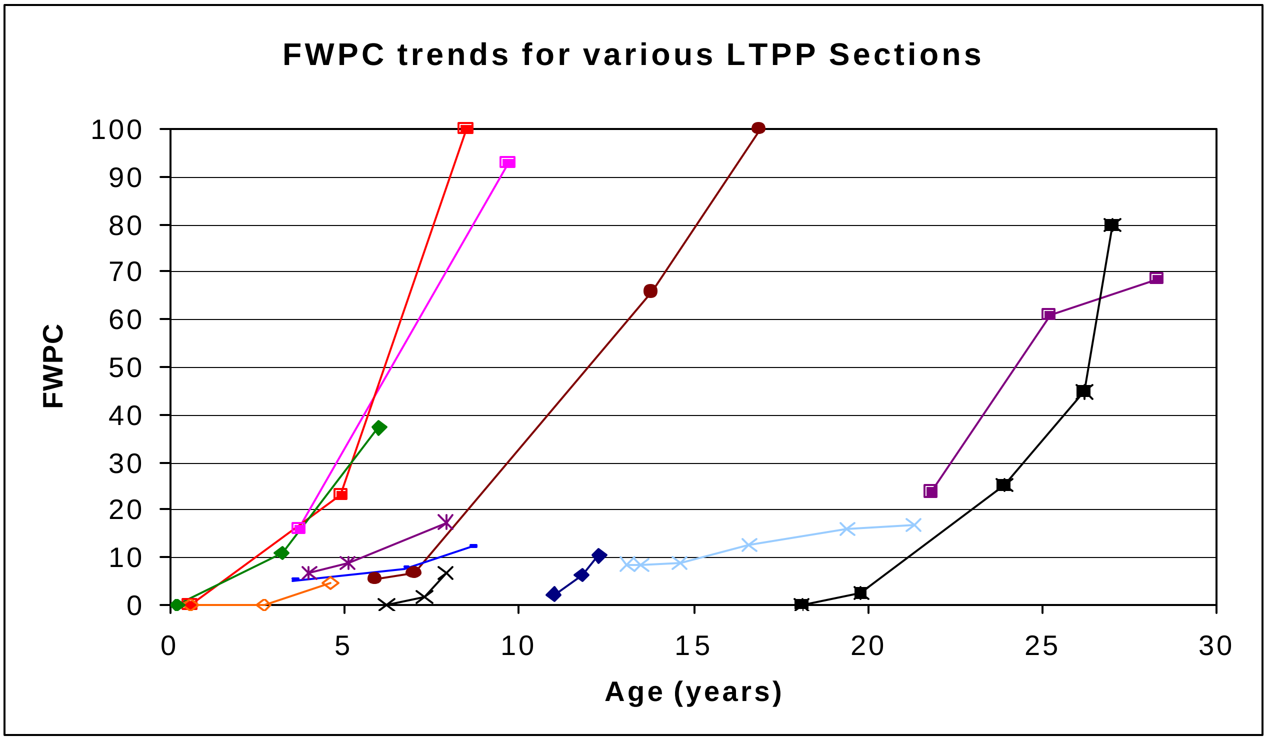

Figure 9. Subset of FWPC data set.

Given the nature and form of the distress accumulation with age, the analysis team is attempting to predict distress progression using two models concurrently. The first model will be used to predict the age at which distress initiation occurs while the second will estimate the accumulation of distress with age (after initiation).

The first model will use logistic analysis to predict age at which distress first appears. Logistical models predict the probability of an "event" occurring (e.g. distress initiation or non-zero distress value) given a set of variables. An example of a logistic model can be found in Figure 10. In order to predict an age from the given model, a cut-off probability must be established. As the cut-off probability increases, the accuracy of the model predicting "events" goes down while the accuracy of predicting "non-events" goes up. Therefore, the selection of the cut-off probability depends on the nature of the data and the relative importance of "events" compared to "non-events." In the case of distress prediction, "events" and "non-events" are of equal importance so a cut-off value was selected that predicted each with equal accuracy. The age at which the cut-off probability is achieved in the logistical model is selected as the predicted distress initiation age.

The analysis team continues to work on the logistical analysis as well as the regression models that will be used to estimate the trend in distress accumulation. The regression models will be developed using only non-zero distress values and "Age" will be replaced with "Age after distress initiation."

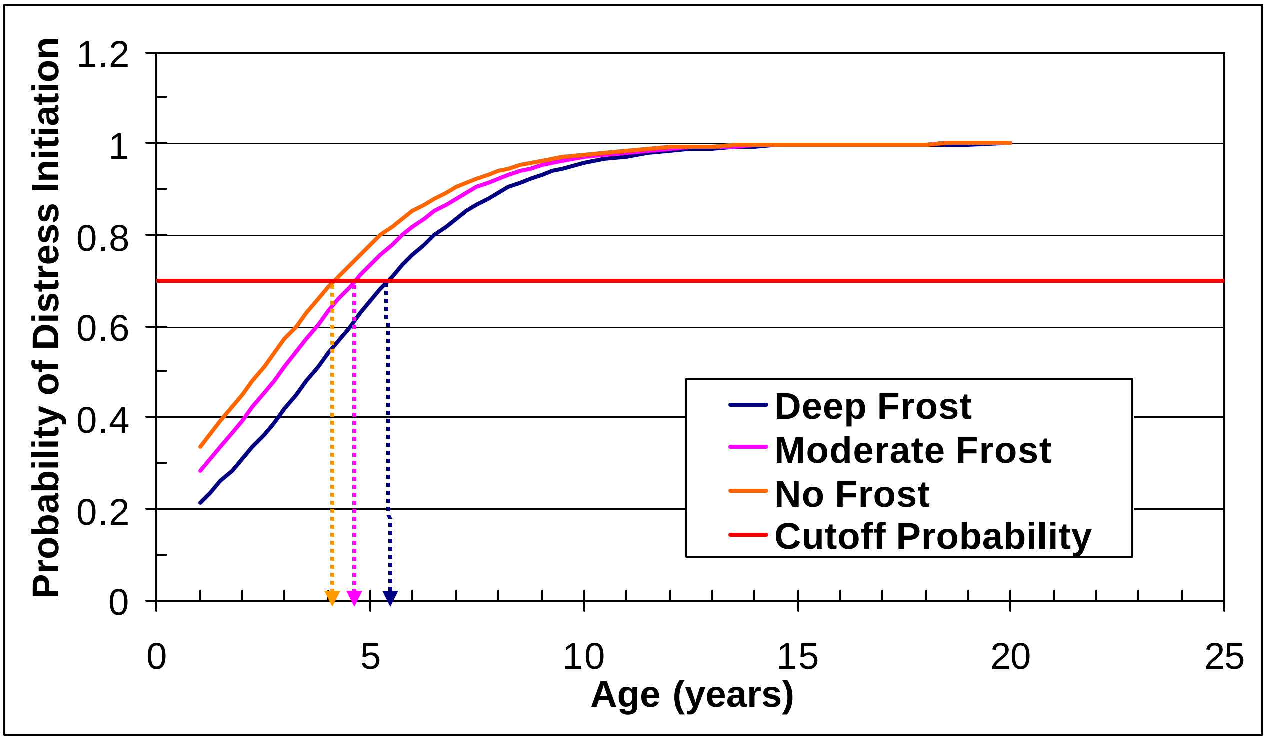

Figure 10. Example of logistical analysis to predict distress initiation.

On-going Activities

NCE will continue to work on developing models for the various performance measures. In particular, the team will determine the best method for accounting for extreme outlying observations in the dataset. Figure 11 is a plot of student residuals as a function of Hat values[6] which is a graphical tool to evaluate observations in a data set. The student residual is the ratio of a residual to its standard error. Large absolute values of the student residual (larger than 2.5) are an indication of outliers in the data. The Hat diagonal refers to the diagonal elements of the Hat matrix in the least squares estimation[7] and quantifies the leverage of each observation on the predicted value for that observation. Therefore, the cluster of points located further to the right in Figure 11 is a group of influential observations.

The analysis team is currently investigating these points to determine if they are outliers or important extreme cases that are warranted in developing an accurate model. If the points are determined to be outliers, robust regression will be used to limit the impact of the outliers on the model. On the other hand, because this is a national study, some of the variables may be set to extreme limits resulting in extreme performance observations that should not be considered outliers. The impact that these observations have on the model should not be reduced. This can

be illustrated by reviewing the design of SPS-1 projects. Each of the 12 test sections at an SPS-1 project has a different structural capacity but all experience the same traffic loading. By experimental design, certain variables (in the case of SPS-1 projects, the ratio of traffic loading to structural capacity) could be set to the extreme ends of the spectrum. If this is the case, the influential observations are a necessary part of the data set which will be used to develop performance models.

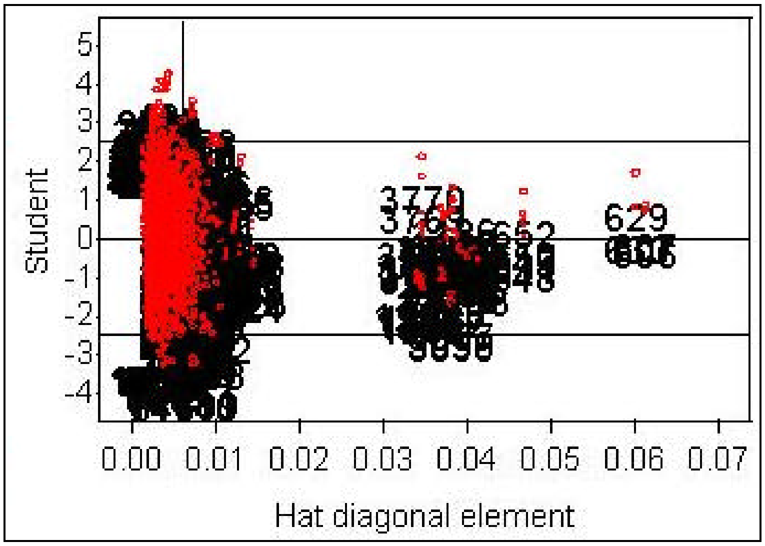

Figure 11. Outlier-Influential observation detection plot

These issues will be resolved within the next several quarters allowing all of the models to be finalized. Upon completion, a thorough comparison of deterioration in the different frost regions will be conducted.

Task 9

Conduct detailed analysis of the extent to which local adaptations of materials standards and empirical pavement design practices have been effective at reducing the rate of pavement deterioration

As of the end of the quarter, one Pooled Fund state is yet to respond. These completed questionnaires will be sent to the Technical Advisory Committee for review and comments. NCE will also be requesting contact information for agencies adjacent to the pooled fund states. A separate questionnaire will be sent to those states as well.

NCE is in the process of compiling the information that was submitted by those states that responded to the questionnaire. NCE has neither analyzed the data nor made any conclusions at this time.

Resources Used

Figure B.1 in Appendix B shows the current work schedule for Task Order #03 through December 2004.

This task order remains a couple of months behind schedule compared to the planned timeline. This is a carry over from the delay in starting on Phase 2 from the previously planned schedule and the added work of developing the additional databases that were used in the trend analysis for Task 3, as well as the delay in the return of the state questionnaires. NCE will continue to concentrate on getting back on schedule; however, a no-cost time extension will need to be considered in the next quarter.

The expenditures have continued to be about 30 percent below planned expenditures as a carryover from the two month delay between presentation of the Phase 1 Report and startup on Phase 2 as well as some time lost in waiting for the information from the states in response to the questionnaire. As NCE gets further into Phase 2 of the project, the expenditures will come more in line with the planned expenditure rate. Figure B.2 in Appendix B shows the planned costs versus actual costs for Task Order #03 through December 2004.

References

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2. Mahoney, J, et al. "Mechanistic-Based Overlay Design Procedure for Washington State Flexible Pavement," Washington State Department of Transportation, January, 1989.

3. Jackson, N., et al. "Development of Pavement Performance Curves for Individual Distress Indexes in South Dakota Based on Expert Opinion," Transportation Research Record, 1996.

4. Shahin, M.Y., "Pavement Management for Airports, Roads, and Parking Lots," Kluwer Academic Publishers, 1998.

5. AASHTO Guide for Design of Pavement Structures, Volume 2. American Association of State Highway and Transportation Officials, 1986.

6. Fernandez, G (2002) Data mining using SAS applications CRC press NY http://www.cabnr.unr.edu/gf/dm.html

7. SAS Institute Inc (2002) SAS online documentation Version 8 http://v8doc.sas.com/sashtml/stat/chap55/sect37.htm

Appendix B

Task Order #03

Work and Costs Summaries

Through December 2004

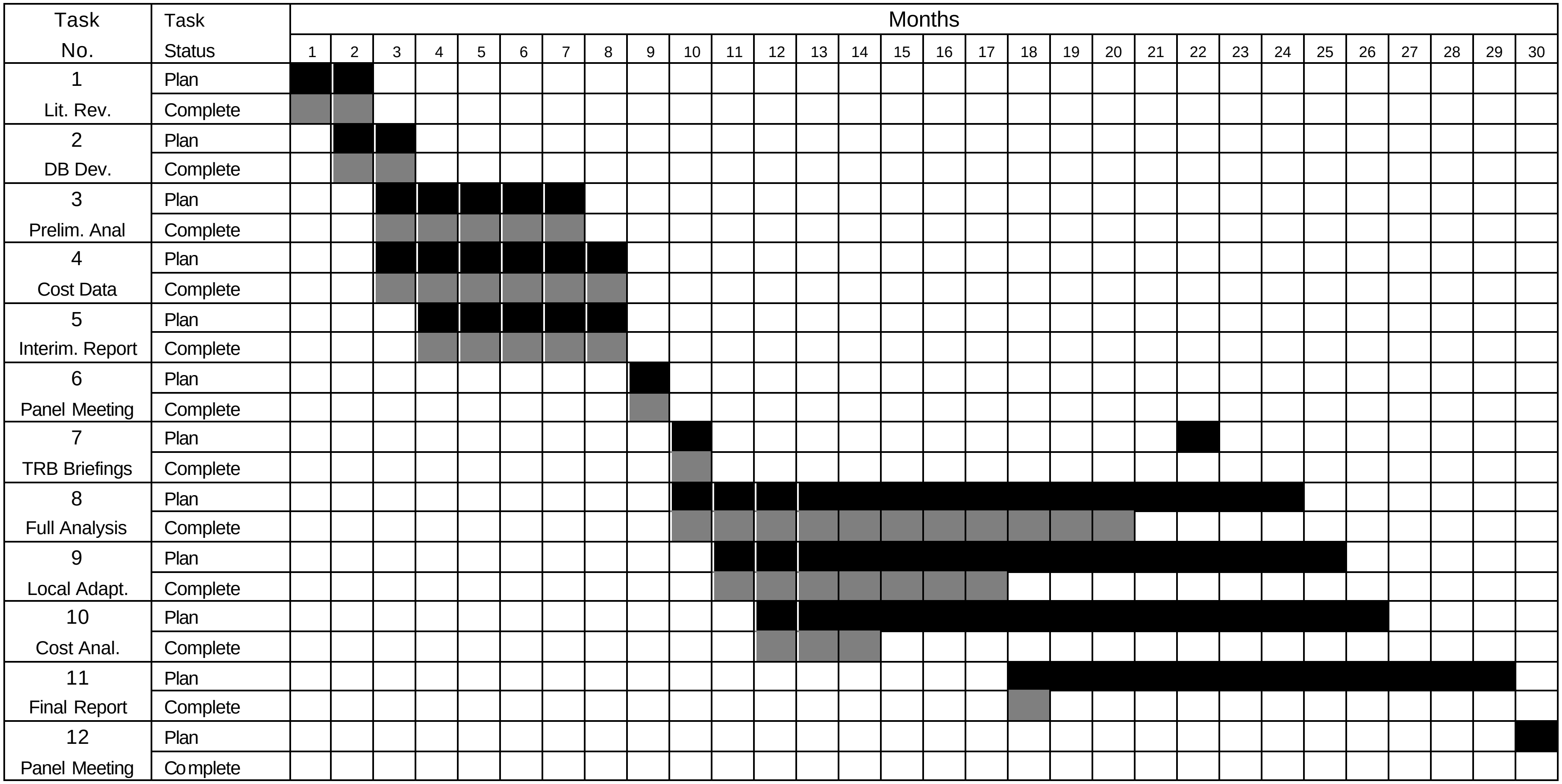

Figure B.1 Work Schedule for Task Order #03 through December 2004