APPLICATION OF AN ORDERED-PROBIT MODEL IN DECISION MAKING FOR INFRASTRUCTURE ASSET MANAGEMENT: A CASE STUDY OF PAVEMENT CONDITION ASSESSMENT

Elmira Kalhor[1], Vanessa Valentin[1], Susan M. Bogus[1], Guohui Zhang[1], Natalia Sanabria[1]

[1] Department of Civil Engineering, University of New Mexico

ABSTRACT: Pavement asset management requires the use of a large number of resources for evaluating pavement conditions. In spite of efforts made to optimize the decision making regarding where and when to maintain, repair or reconstruct a road section, there are uncertainties related to identifying an accurate condition of the pavement. In this regard, a more accurate estimation of pavement condition based on appropriate variables could aid the mitigation of risks due to improper managerial decisions and also the reduction of time requirements of the evaluation process. In this study, five traffic-related variables are considered to forecast pavement conditions. Variables are quantitative in nature. The input data consists of 33423 data points collected in the state of New Mexico. An ordered probit model with three discrete categories defining distress severity (i.e., low, medium, and high) is developed for three different flexible pavement distresses: raveling and weathering, edge cracks, and longitudinal cracks. Preliminary results show that average directional factor, combined and single commercial volume have the most significant effect on the pavement condition rankings. The findings of this study are perceived to be useful for predicting pavement condition as an input for a variety of practices in pavement management including investment, design, and rehabilitation policy.

1 INTRODUCTION

Different approaches have been applied to predict the pavement condition based on different variables. Traditional pavement condition prediction models have mostly applied regression analysis to attribute pavement condition to one or some of the road variables such as pavement age, traffic load or pavement capacity.

Shahin et al (Shahin et al. 1987), Johnson and Cation (Johnson and Cation, 1992), and Lukanen and Han (Lukanen and Han, 1994), tried to find the relationship between pavement condition and pavement age. George et al. (George et al., 1989) , Saraf and Majidzadeh (Saraf and Majidzafeh, 1992)and Lee et al. (Lee et al., 1993) developed multivariate models to predict pavement condition. These variables include pavement age, traffic load, and pavement structural capacity.

Regression analysis falls into two main categories: Linear and nonlinear. Among different regression models, the use of linear models is limited to when there is not enough data available (Hill, 1987) since linear models fail to satisfy most boundary conditions (Sadek et al., 1995).Compared to linear models, nonlinear models are more popular in the literature. Johnson and Cation (Johnson and Cation, 1992) and

Shahin et al (Shahin et al., 1987) used polynomial functions in their research to formulate pavement condition based on the distress rankings. However, Sigmoidal and Power regression models were mostly applied in manuals provided by different state agencies (Sigmoidal model was applied in Minnesota (Hill, 1987), Ohio (Saraf and Majidzafeh, 1992) and San Francisco (Haas et al., 1994) whereas Power curves were used in Washington(Hall et al., 1994) and Illinois(Jackson et al., 1987).)

In most of previous studies on this topic, the traffic load has been the primary factor considered since the cracks resulting from traffic load are a major design criteria for flexible pavements (Huang, 1993).Despite the existing forecasting models, the predicted pavement distress is different at the end of designed service period(Sun et al., 2003). Gibby and Kitamura (Gibby and Kitamuar, 1992) conducted a time lag analysis on factors affecting pavement condition in San Francisco, Fairfield, Jackson County, Puyallup, and Alameda County. The factors found to be significant when affecting the condition of the pavement are:

1. Previous pavement condition,
2. Pavement age since last major rehabilitation or reconstruction work,
3. Soil classification,
4. Classification of roadway drainage,
5. Surface thickness,
6. Functional classification
7. Presence or absence of bus service, and
8. Individual jurisdiction.

However, their effort to use time lags analysis had the limitation of using only two time domains. In the absence of more time series of data it is not possible to find a serial correlation which results in an error when the two time domains are related and if not measured may result in inconsistencies.

In 2001, Lou et al. (Lou et al., 2001) used a neural network to forecast short term crack pavement condition. In their model, they formulated the crack condition using time-based pavement structural conditions, pavement material condition and environmental conditions. In the same year, Attoh-Okine (Attoh-Okine, 2001) developed a “Self-Organizing Map Network” to model the pavement roughness as the pavement performance index according to pavement distresses as well as environmental variables. Although both models yield precise results, the input factors which affect the pavement condition are limited to one or two factors.

In 2003, Sun et al.(Sun et al., 2003) applied an Empirical-Mechanistic Method based stochastic modeling to involve uncertainties in the number of load repetition to failure of a flexible pavement induced by environment and construction-quality based conditions in addition to uncertainties from traffic characteristics. However, in their model, uncertainties were given a bundled credit and were not characterized according to the nature of each variable.

Ordered probit modeling is a useful tool in order to study the effect of various parameters in transportation applications where ordered opinions or categorical frequency are involved (Wahsington et al., 2003). These models has been repeatedly used for analysis of drivers injuries (Abdel-Aty, 2003; Kockelman and Kweon, 2002). Shafizadeh and Mannering (Shafizadeh and F. Mannering, 2006) has successfully used the ordered probit model to study the effect of vehicle-specific and individual-specific factors on drivers’ perception of pavement roughness.

In this study, pavement distress ratings are analyzed under the influence of different traffic variables. The variables considered here include ADT, peak hour volume, combined and single heavy traffic and Directional factor. An ordered probit model is estimated to manipulate available data as to find the extent to which the variables can affect pavement condition.

2 DATA

The data used in this study comes from a pavement evaluation program sponsored by New Mexico Department of Transportation (NMDOT) in 2012. The evaluation of the pavement distress was done by Department of Civil Engineering at the University of New Mexico in 2012. The data gathering program included measuring and recording the severity and extent of all the pavement distresses at approximately 5,011 sites. The evaluation sites were almost one tenth of a mile long starting at each highway milepost. At each collection site the contractor's pavement inspectors visually inspected the severity and extent of the pavement distresses and ranked distresses from low (1) to high (3). In this study, the data used consists only of the evaluation for flexible pavement data.

Pavement inspectors were a crew of trained student of Civil Engineering at the University of New Mexico. The students were trained for two weeks and were asked to fill out the pavement distress evaluation forms according to the criteria defined in Table 1.

The traffic data used for this paper also comes from NMDOT and were updated in 2011. The traffic data were available for less number of routs and so controlled the amount of data input into the model. In other words, we only used ranking data for the routs for which the traffic data were available. Ultimately, a total number of 33423 observations were used to estimate the outputs for an ordered probit model. Among a variety of data, ADT, combined and single heavy commercial peak/Average volume, peak hour volume, and directional factor were used in this paper.

Table 1: Flexible Pavement: Pavement Evaluation Reference Chart

DISTRESS	SEVERITY	NOTES*
Raveling & Weathering: The wearing away of the pavement surface, due to dislodged aggregate particles and loss of asphalt binder.	(1) Low: Aggregate or binder has started to wear away (2) Medium: Aggregate or binder has worn away. Surface texture is rough. Some dislodged aggregate can be found on the shoulder. (3) High: Aggregate and/or binder have worn away, and surface texture is severely rough and pitted.	Most prevalent severity
Edge Cracks: Cracks that lie within 1 foot of the edge of the pavement. Does NOT apply in roads with curb and gutter installations.	(1) Low: Less than ¼-inch wide. No spalls. (2) Med: Greater than ¼-inch wide. Some spalling may be present, but pavement is still intact. (3) High: Severely spalled. Pieces of pavement have broken off the edge of the roadway.	(1) Low: 1% to 30% of test section. (2) Med: 31% to 60% of test section. (3)High: 61% of test section, or more.
Longitudinal Cracks: ANY longitudinal crack NOT in the wheel path, but NOT within 1' of the pavement edge.	(1) Low: Unsealed, mean width of less than ¼-inch. OR sealed with sealant in good condition, any width. (2) Medium: Any crack with average width greater than ¼-inch and less than ¾ inch. May have adjacent Low severity random cracks and some spalling. (3) High: Any crack wider than ¾ inch, may have adjacent moderate to high random cracking and spalling.	(1) Low: 1% to 30% of sample section. (2) Medium: 31% to 60% of sample section. (3) High: 61% or more of sample section.

* 10% Rule: If 10% or more of the distress shows a higher severity, use this higher severity to rate the distress

3 METHODOLOGY

In this study, the relationship between the traffic variables and distress severity rankings are modeled using an ordered probit model. The pavement distress severity rankings are both discrete and ordered (from 1 to 3, one being low severity and 3 being high severity). Amemya (Amemiya, 1985) has proved that using an unordered model such as a multinomial logit model for ordered data one can expect consistent model parameter estimates but there will be a lack of efficiency. Hence, ordered probit model is more suitable to address the ordered discrete data.

First developed by McKelvey and Zavonia in 1975, (McKelvey and Zavoina, 1975) ordered probit models have been in use mostly for a variety of transportation applications. Following Washington et al. (Wahsington et al., 2003), in an ordered probit model an unobserved variable, z, is subjected to be defined in order to find the correlation between ordinal pavement severity rankings and variables that may affect these rankings. This unobserved variable is assumed to be a linear function of the variables which are perceived to be influential on the rankings (Eq. 1):

[1] $$z = \beta X + \varepsilon$$

Where X is the vector of variables that affect the ordering of observations, β is the vector of estimable parameters and ε is a random disturbance. Observed ordinal data, y, is then defined as in Eq.[2]:

[2] $$\begin{aligned} y &= 1 \quad if \;\; z \le \mu_0 \\ y &= 2 \quad if \;\; \mu_0 < z \le \mu_1 \\ y &= 3 \quad if \;\; z \ge \mu_3 \end{aligned}$$

Where μ s are referred to as thresholds and define y . The estimation problem is now one of determining the probability of occurrence of each of the ordered responses for the data set. The estimation problem then becomes one of determining the probability of i specific ordered responses for each observation n.. If ε is assumed to be normally distributed across observations with mean =0 and variance=1, an ordered probit model results with ordered selection probabilities as follows:

[3] $$p(y = i) = \Phi(\mu_i - \beta X) - \Phi(\mu_{i+1} - \beta X)$$

Where μ_i and μ_{i+1} are upper and lower thresholds for outcome i and $\Phi(\mu)$ is the cumulative normal distribution

[4] $$\Phi(\mu) = \frac{1}{2\pi} \int_{-\infty}^{\mu} EXP[-\frac{1}{2}\omega^2]d\omega$$

If ε is assumed to be normally distributed across observations an ordered probit model is resulted, and if ε is assumed to be logistically distributed the result is an ordered logit model. Ordered probit applies well for such studies since it can determine unequal differences between the dependent variables' categories. As an example, it does not necessarily assign same intervals' size for low to medium severity and medium to high severity.(O'Donnell and Connor, 1996) (McKelvey and Zavoina, 1975)

4 ESTIMATION RESUTS

As mentioned before, in this study, five traffic values are used to formulate pavement condition which are represented in Table 2.

Table 2: Description of traffic variables used to model distress rankings

Traffic Variable	Definition	Min, Max (Average) Values
ADT	Average Daily Traffic (ADT) represents the total traffic for a year divided by 365, or the average traffic volume per day	0, 205059,(11915)
Peak Hour Volume	The hourly volume during the maximum traffic volume hour of the day divided by 4 times the peak 15-minute rate of flow within that hour	0,593,(495)
Directional Factor	The proportion of traffic traveling in the peak direction during a selected hour, usually expressed as a percentage.	0,100,(75.5)
Single Heavy Commercial Average	24-hour heavy commercial traffic volume (Single truck configuration)	0,2,(1)
Combined Heavy Commercial Average	24-hour heavy commercial traffic volume (truck and trailer)	0,4,(2)

Three ordered probit models were estimated for the following distress severity rankings: (1) low, (2) Medium, and (3) high. The models parameters were estimated at a 90% confidence. The coefficient estimation results for the ordered probit model for the severity rankings of longitudinal cracks, is presented in Table 3.

The information provided by the model gives an understanding on how the perceived longitudal cracks severity ranking are linked to traffic data such as average traffic data, combined and single heavy commercial peak and the peak hour volume.

Among the evaluated parameters directional factor has the highest absolute coefficient with a t-statistic of -5.314 Combined and single heavy commercial traffic are the next most influential parameters respectively and ADT has the least coefficient value for this distress type. The sign of the coefficients obtained in the model shows how the change in the value of the parameter will affect the rankings. With a positive coefficient one would expect the high severity ranking while with a negative coefficient less severity or no severity is likely. As shown in Table 3, ADT, combination heavy traffic, peak hour volume and the directional factor were found to be significant when considering distress severity for longitudal cracks. ADT, combined heavy commercial volume, and the directional factor made it less likely that the road segment was rated with a distress severity of low while the peak hour volume made it more likely that the distress severity was rated as high.

Table 3: Ordered Probit Model estimation results for longitudinal cracks

Independent Variable	Estimated Coefficient	t statistic
Traffic parameters		
Constant	0.635	19.293
ADT	-0.241D-04	-4.336
Combined Heavy commercial volume	-0.0067	-10.481
Peak Hour Volume	0.0001	2.154
Directional Factor	-.0026	-5.314
Model parameters		
µ1	1.267	158.39
µ2	2.104	169.88
Estimation characteristics		
Number of observations	33423	
Log – likelihood	-37406.32	
Restricted log-likelihood	-37735.05	

For ravelling and weathering cracks, combined heavy commercial volume seems to have the biggest influence with relatively big coefficient and then comes directional factor. However, other variables are less influential as before. Among effective variables, single heavy commercial is the only variable that increases the probability of getting a high severity rank for ravelling/weathering cracks.
In the case of edge cracks, the order of influential variables is different with single heavy traffic the most influential (with the greatest coefficient value observed so far). The value of coefficient regarding combined heavy traffic volume and directional factor are also noticeably high. Still, ADT has the least coefficient value with a low t-statistic. In this case, combined and single heavy commercial volume raise the likelihood of ranking the segment's edge crack as highly severe and ADT, peak hour volume and directional factor make it less likely that the segment is ranked as less severe regarding edge crack.

Table 4: Ordered Probit Model estimation results for Raveling-Weathering cracks

Independent Variable	Estimated Coefficient	t statistic
Traffic parameters		
Constant	1.692	52.050
ADT	-0.216D-04	-3.637
combined heavy commercial volume	-0.0138	-21.566
Single heavy traffic	0.002	2.756
Directional Factor	-.00466	-9.932
Model parameters		
µ1	1.506	181.739
µ2	2.952	232.960
Estimation characteristics		
Number of observations	33423	
Log – likelihood	-36097.46	
Restricted log-likelihood	-37285.19	

In addition to the aforementioned distress types the model was run for other distresses such as, bleeding, transverse cracks, alligator cracks, and patching which typically are of interest to state department DOT. However, due to the lack of data the models did not converge and hence the results are not included in this paper. Data for other distresses such as fatigue cracking and rutting were not available for analysis.

Table 5: Ordered Probit Model estimation results for Edge cracks

Independent Variable	Estimated Coefficient	t statistic
Traffic parameters		
Constant	0.411	12.477
ADT	-0.106D-04	-1.835
combined heavy commercial volume	0.004	6.782
Single heavy traffic	0.084	11.337
Peak Hour Volume	-0.0001	-2.985
Directional Factor	-.003	-7.003
Model parameters		
µ1	0.975	133.924
µ2	1.67	157.622
Estimation characteristics		
Number of observations	33423	
Log – likelihood	-38185.40	
Restricted log-likelihood	-39210.69	

5 CONCLSIONS AND FUTURE WORK

In this study, an ordered probit model was developed to investigate the relationships between rankings of severity of three different types of distresses (i.e., ravelling-weathering, longitudinal cracks and edge cracks) and traffic variables. The model was able to predict the threshold values for the severities of the three distresses. Among the traffic variables, the directional factor seems to have more influence on the rankings in terms of higher coefficient. On the other hand, the average daily traffic (ADT) was the least influential on all three distresses analyzed. However, variables considered in this study were mostly from available data at the time, and more variables including pavement structural variables and also construction variables are to be included in the future work.

Future studies could build on the proposed modeling approach by including additional variables related to geometric, construction characteristics and maintenance schedule of the roadway segments evaluated. In addition, random parameters models and marginal effects could be considered as an attempt to improve the model estimation results. Time effect analysis could also be considered by expanding the data set and considering pavement deterioration throughout the years. In addition, the results of the model should be compared with other modeling tools such as Artificial Neural Networks to test the efficiency of the model. At the time, authors are working on such a comparative model.

The results of this study suggest that use of an ordered probit model could have implications for asset management, specifically to pavement maintenance. The estimation of an ordered probit model could allow decision makers to forecast pavement conditions based on traffic conditions and take decisions with regards to maintenance, repair and rehabilitation of roadway pavement. These results could be used for budget forecast, resource allocation and for establishing construction/maintenance/rehabilitation project lead times in pavement management systems.

6 Reference

Abdel-Aty, M., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. *Journal of Safety Research*, 34: 597–603.

Amemiya, T., 1985. *Advanced Econometrics*. Harvard University Press, Cambridge, MA, USA.

Attoh-Okine, N. O., 2001. Grouping Pavement Condition Variables for Performance Modeling Using Self-Organizing Maps. *Computer-Aided Civil and Infrastructure Engineering*, 16: 112–125.

George, K. P., Rajagopal, A. S., and Lim, L. K., 1989. Models For Predicting Pavement Detroriation. *Transportation Research Record 1215, 1-7.*

Gibby, A. R., and Kitamuar, R., 1992. Factors Affecting Condition of Pavement Owned by Local Governments. *Transportation Research Record,* 1344:116-123 .

Haas, R., Hudson, W.R., and Zaniewski, J., 1994. *Modern Pavement Management*. Krieger Publishing Company, Malabar, Fl. USA.

Hall, K. L., Lee, Y., Darter, M., and Lippert, D. L., 1994. *Forecasting Pavement Rehabilitation Needs for the Illinois Interstate Highway System.* Transportation Engineering Series, Illionois Cooperrative Highways Research program, series No.251.

Hill, L. D., 1987. MN/DOT'S IMPLEMENTATION OF A PAVEMENT LIFE PREDICTION MODEL. *2nd North American Pavement Management* , Canada.

Huang, Y. H., 1993. *Pavement analysis and design*. Prentice-Hall, Englewood Cliffs, N.J,USA.

Jackson, N. C., Kay, R. K., and Peters, A. J., 1987. Predictive Pavement Condition Program in the Washington State Pavement Management System. *2nd North American Pavement Management,* Toronto, Canada.

Johnson, K. D., and Cation, K. A., (1992). *Performance Prediction Development Using Three Indexes for North Dakota Pavement Management System*. *Transportation Research Record 1344, 22-30 .*

Kockelman, K. M., and Kweon, Y.-J., 2002. Driver injury severity: an application of ordered probit models. *Accident; analysis and prevention*, 34: 313–21.

Lee, Y., Mohseni, A., and Darter, M., 1993. Simplified Pavement Performance Models. *Transportation Research Record: Journal of the Transportation Research Board,*1397:7-14.

Lou, Z., Gunaratne, M., and Dietrichm, B., 2001. Application of Neural Network Model to forecast Short-term pavement crack condition: Florida Case study. *Journal of Infrastructure systems*, 7:166–171.

Lukanen, E. O., and Han, C., 1994. "Performance History and Prediction Modeling for Minnesota Pavements." *3rd international conference on Managing Pavements*, Texas, USA, 63–73.

McKelvey, R. D., and Zavoina, W., 1975. “A Statistical Model for the Analysis of Ordinal Level Dependent Variables.” *Journal of Mathematical Sociology*, 4: 103.-120.

O’Donnell, C., and Connor, D., 1996. Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choice. *Accident analysis and prevention*, 28: 739–753.

Sadek, A. W., Freeman, T. E., and Demetsky, M. J., 1995. *The development of Performance prediction models for virginia’s intrstate highway system Volume II model development*. Richmond.

Saraf, C. L., and Majidzafeh, K., 1992. Distress Prediction Models for a Network-Level Pavement Management System, Transportation Research Record, 1344: 38-48.

Shafizadeh, K., and Mannering, F., 2006. Statistical Modeling of User Perceptions of Infrastructure Condition : Application to the Case of Highway Roughness. *Journal of Transportation Engineering*, 132: 133–140.

Shahin, M. Y., Nunez, M. M., Broten, M. R., Carpenter, S.H., A., and A., S., 1987. New Predictive tools for Modeling Pavement Deterioration. *Transportation Research Record,* 1123: 40-46.

Sun, L., H., Hudson, W. R., and Zhang, Z., 2003. Empirical-Mechanistic Method Based Stochastic Modeling of Fatigue Damage to Predict Flexible Pavement Cracking for Transportation Infrastructure Management. (April), 109–117.

Washington, S. P., Karlaftis, M. G., and Mannering, F. L., 2003. *Statistical And Econometric Methods For Transportation Data Analysis*. CHAPMAN & HALL/CRC, USA.