Rutting Analysis From a Different Perspective

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Rutting is a common distress in pavements with asphalt concrete surfaces. For many agencies the magnitude of rutting plays a significant role in their rehabilitation decision process. As a result many different approaches have been taken to address the prediction of rutting and its causes. As more agencies shift to the collection of transverse profiles instead of rutting to provide greater repeatability of the measurements and to avoid debates regarding the appropriate straightedge length, additional analytical possibilities are being identified. One such analytical opportunity explored in the present investigation suggests that the area under the transverse profile can be used to hypothesize the origin of the rutting from within the pavement structure. This in turn allows for greater prediction capabilities when the cause of the distress can be further isolated in this fashion. With the benefit of the numerous transverse profiles collected as part of Long-Term Pavement Performance Program monitoring, investigations have been conducted to sort the test sections into data subsets based on the areas described above. Neural networks were developed to model these data subsets. The models are in turn compared with other previously developed models to evaluate the impact of sorting by areal magnitude on the prediction of rutting.

Rutting in pavements with asphalt concrete surfaces is commonly used as an indicator of needed rehabilitation. As such many studies have been conducted to analyze the causes of rutting and to predict its development. Many of these studies, however, have been impeded by one or more of the following deficiencies associated with this important performance indicator. First, and probably foremost, rut depths in and of themselves provide very little, if any, indication of the origin of the rutting. That is, it is difficult to establish which layer within the pavement structure contributed the most to the deformations that are measured at the pavement surface. The second drawback of this particular performance indicator revolves around the lack of standardization in the collection of rut depth data. The common use of a 4-ft straightedge in the past (as at the AASHO Road Test) to obtain these measurements and the resulting limitations with repeatability have made it relatively unreliable for satisfactory pavement performance modeling needs. In addition, wider wheel bases are being used in trucks. These two events introduced large amounts of variation in 4-ft rut depth measurements.

With continuing advances in pavement monitoring technology, such deficiencies no longer need to be tolerated. Most automated units that collect pavement data are now capable of recording transverse profile measurements that minimize or eliminate most (if not all) of the past limitations associated with the collection of rut depth data. Automated collection of transverse profile data has now become one of the more standardized and repeatable operations for the collection of pavement data. Standards under development by ASTM will improve the level of data quality achievable.

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The point yet to be investigated fully is the insight into the origination of rutting within a pavement structure than can be provided by a transverse profile. Boussinesq (*1*) and Burmister Theory (*2–4*) indicate that an analyst should be able to establish weaknesses within a given pavement structure on the basis of the shape and dimensions of deformations at the pavement surface. Although these theories apply to elastic deformation, it is the continued application of the load that causes both the elastic deformation and the plastic deformation. It is assumed that the plastic deformation follows a trend similar to that of the elastic deformation. Although several studies have been conducted in an attempt to pursue this theory further, sufficient data were never available to thoroughly investigate and support studies of this type until the recent efforts of the Long-Term Pavement Performance (LTPP) Program.

With the data available from LTPP test sections this paper evaluates the use of transverse profile data for distinguishing rutting modes to facilitate performance predictions and model development. In addition, the capabilities of neural networks in data analysis are demonstrated.

Neural networks are a form of artificial intelligence that has been quite useful in many areas of robotics and other applications and that has come to the attention of other engineering disciplines in recent years. They provide a very confident means of identifying patterns. In the past they have often been used for handwriting recognition, hand–eye coördination in robots, and many other areas of robotics technology. More recently, these networks are being used by financial analysts to predict the stock market or the winner of Saturday's ball game.

ANALYSIS

The first step in conducting these analyses was to assemble and process all of the transverse profiles. For the LTPP Program transverse profiles were reduced from projections of a hairline at an angle onto the pavement and were photographed from above. The presence of rutting is recorded on the film as departures from a straight line, and the magnitudes of the ruts are directly proportional to the magnitudes of the departures from a straight line. A PASCO Road Recon Unit projects the hairline onto the pavement surface and records the projections on film at 15.24-m (50-ft) intervals. These film projections were later processed to identify the distance between the string line projection and the string line itself. Measurements were taken every 0.30 m (12 in.) across the monitored lane [typically 3.7 m (12 ft) in width]. This series of measurements then makes up the transverse profile.

As noted earlier the shape of the transverse profile is theoretically indicative of where the rutting originated within the pavement structure. As noted in Figure 1 the transverse profiles generally fit into one of four categories representing (a) subgrade rutting, (b) base

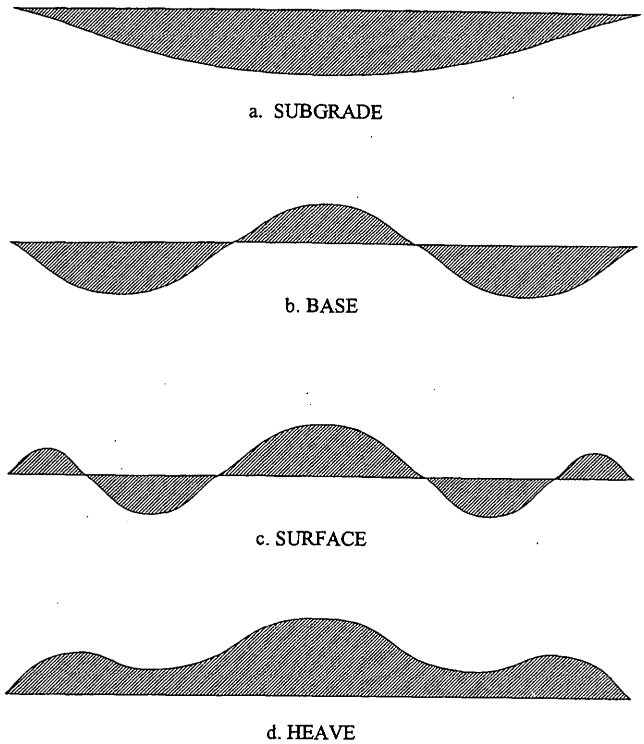

FIGURE 1 Rutting properties.

rutting, (c) surface rutting, or (d) heave (from increases in soil volume because of environmental conditions).

To identify into which of these four categories the various transverse profiles fit, the algebraic area between the transverse profile and the straight line connecting its end points was calculated (Figure 1). The diagrams in Figure 1 indicate that sections from within the deep rutting category will be entirely negative and sections from within the heave category will be entirely positive. Sorting out the distinctions between base rutting and surface rutting are somewhat more involved. In this process it is generally perceived that the marginally positive areas would be considered surface rutting and that the marginally negative areas would be perceived as base rutting.

The area or distortion term was used to determine where in the pavement structure the rutting occurred. If the total distortion was less than -4500 mm^2 and the ratio of the positive area to the negative area was less than 0.4, the rutting was hypothesized to have occurred in the subgrade. If the total distortion was between -4500 and 700 mm^2 and the ratio of the positive area to the negative area was between 0.4 and 1.25, the rutting was hypothesized to have occurred in the base layers. If the total distortion was between 700 and 5000 mm^2 and the ratio of the positive area to the negative area was between 1.25 and 3.0, the rutting was hypothesized to be primarily due to the lateral migration of the asphalt concrete surface layer. If the total distortion was greater than 5000 mm^2 and the ratio of the positive area to the negative area was greater than 3.0, the rutting was hypothesized to be primarily due to frost heave. Table 1 demonstrates the criteria used and the actual number of sections in each group. The dual classification method did not agree for six sections. These sections were left out of the analysis. Cross-profile data were not available for 18 test sections.

The data used in this effort were the same as those used in the early analysis of the LTPP data base (*5*) for analysis of hot-mix asphalt concrete (HMAC) pavements with granular bases. This data set includes 152 sections from the LTPP General Pavement Studies 1 and 2 experiments. Two datum points in time were available for each section: the first was the 0 boundary condition (0 rutting after 0 traffic) and the second was the first measured cross-profile. The cross-profile measurements were analyzed by using RUT (*6*), a program created by the Texas Research and Development Foundation. This program determines the rut depth by using a 4-ft straightedge, a 6-ft straightedge, and the areal distortion of the roadway from the string line described previously. After the data set was sorted by rutting origin (as described above) modeling was initiated by using the 6-ft straightedge values as the dependent variable. Because the 4-ft straightedge has limitations in repeatability, only the 6-ft straightedge was used for the purposes of modeling. Each of the four data sets described was modeled by using neural network technology.

NEURAL NETWORKS

The data were then analyzed by using neural networks. Neural networks are a computational form that loosely models the human brain. The following definition provides some explanation:

> Neural networks are rough models of the mental processes their name implies. Because of their massive parallelism, they can process information and carry out solutions almost simultaneously. They learn by being shown examples and the expected results. Or, they form their own associations without being prompted and rewarded. They are good at pattern-matching types of problems. Because the kinds of things neural nets can do address many of today's problems, a new industry is emerging. This is happening on several continents and involves a wide variety of disciplines (*7*).

They learn by example and are very good at recognizing patterns and modeling data that had been quite difficult to emulate by standard regression techniques.

Each neural network was made up of at least three layers. Figure 2 illustrates a pictorial representation of neural networks. Each layer is made up of one or more nodes. These nodes, or processing ele-

TABLE 1 Rut Origin Sorting Criteria

Type	Total Distortion	Ratio of Distortion (Positive/Negative)	Number of Sections
Subgrade	< -4500	< 0.4	61
Base	-4500 < x < 700	0.4 < x < 1.25	24
Surface	700 < x < 5000	1.25 < x < 3.0	15
Heave	> 5000	> 3.0	28

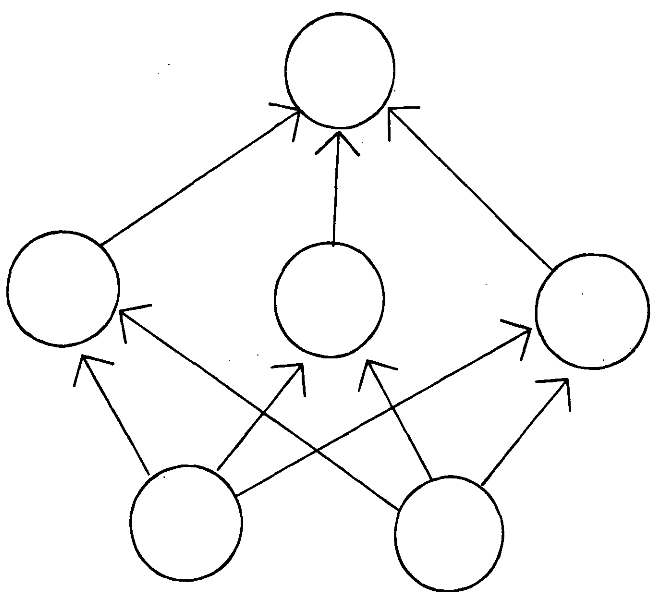

FIGURE 2 Pictorial representation of neural networks.

ments, take in information and sum it, and if it passes a certain threshold value it will be passed to the next layer. The first layer of the network is the input layer. Each node of this layer is an input value. These values are automatically passed to each of the nodes in the next layer via a weighted connection. This second layer is a hidden layer, which is analogous to the interactions of independent variables in conventional statistical analyses. It is hidden because one normally does not see what comes directly out of this layer. It is possible to have more than one hidden layer, but usually, only the most complicated of networks have more than one hidden layer. The values in the nodes of the hidden layer are passed to the output layer, or the third layer, on the basis of whether or not those values meet some acceptance criterion. Again, the connections between the hidden layer and the output layer are weighted. The output layer is, for example, the result that one would see from an equation. The network learns in an iterative process whereby it makes changes to the weights of the connections on the basis of how close the value is to the required output.

To apply neural network analyses it is necessary to obtain software that is called a shell. When data are provided to the shell for as many observations as possible, the shell creates a neural network by using the hidden layers described earlier to model interactions between the variables. The analyst has some control over the result through selection of independent variables to be included and their format [e.g., equivalent single axle loads (ESALs) or log ESALs], selection of the rate of learning, specification of the percentage of test sections to be used only for testing, specification of tolerances between predicted and measured values, and ordering of input data. For this analysis, the shell used was BrainMaker (*8*).

The result after hundreds or thousands of iterations of learning (or study of the available data) is not an equation, such as that which is normally produced from statistical regressions. Instead, it is a small computer program that can receive input and provide predictions. This program can then be used in design procedures or for pavement management systems instead of an equation that one might get by standard regression techniques. Although this may appear to be strange because most analysts are accustomed to having equations to look at and think about, it makes little difference as long as the network has been thoroughly checked out and its capabilities have been thoroughly evaluated.

One of the difficult things about standard regression techniques is finding the right forms of the equation that provide a quality fit to the data. It would be much easier if the operation were in three dimensions, in which everything could be plotted and the functions could be determined visually. However, analysts are virtually always operating in *n*-space when they are developing predictive distress models, so the resultant models are often more approximate than one would wish. One advantage of neural networks is that the analyst does not have to experiment with equation forms until a suitable one is found. The neural network generally sorts that out with its iterative studies of the data and continuing modifications of the network.

RESULTS

For comparative purposes a neural network was developed by using the entire data set to assess distinctions in the dependent variables needed for modeling the various data sets and to compare summary statistics with the other models that have been developed. Comparing the neural network for the entire data set against the linear model developed from the early analyses of the LTPP data base (Strategic Highway Research Program Contract P-020), it is fairly apparent that the neural network concept is capable of computing models with considerably less residual error than the residual error from the standard linear models. The neural network had a coefficient of determination (R^2) of 82 percent and a root mean square error (RMSE) of 0.05, versus values of 49 percent and 0.12, respectively, for the P-020 model. It should be noted here that the P-020 equation was formed with log rut depth as the dependent variable; therefore, RMSE is a multiplicative error term rather than an additive term like the other RMSEs presented in this paper. As can be seen from Table 2 both models were a function of essentially the same independent variables.

TABLE 2 Independent Variables Included in P-020 Model and "All" Network

Model	Independent Variables
P-020	log(HMAC Aggregate < #4), log(Air Voids), log(Base Thickness), Subgrade < #200, Freeze Index, log(HMAC Thickness), Cumulative KESALs
"All" Network	Asphalt Thickness, Air Voids, Asphalt Viscosity @ 140°F, Annual Precipitation, Average No. of Days > 90°F, Average Freeze Thaw Cycles, PI, Subgrade Moisture, Subgrade < #200, Base Thickness, log(Cumulative KESALs)

Note: KESALs=1000 80kN (18 kip) equivalent single axle loads

TABLE 3 Summary Statistics for All Models

Data Set	R^2	RMSE
P-020 (Entire Data Set)	45%	0.18
Network (Entire Data Set)	82%	0.07
Subgrade Rutting Data Set	94%	0.05
Base Rutting Data Set	90%	0.04
Surface Rutting Data Set	98%	0.02
Heave Data Set	96%	0.02

By using the guidance described earlier, sections were then redistributed into one of the four data sets on the basis of the anticipated source of rutting associated with that section. For the most part these distinctions were fairly clear-cut and straightforward.

By using the data sets distinguished by anticipated rutting origin, separate neural networks were created for each data set. As can be seen from Table 3, the summary statistics for these neural network models are again considerably better than those for previously developed linear models. These networks also show a considerable improvement over the network formulated for the entire data set. Each has an R^2 in the 90th percentile range, with RMSEs of 0.04 on average versus the R^2 of 82 percent and RMSE of 0.07 for the network formulated from the entire data set. The predictive capabilities of the networks are illustrated in Figures 3 to 7. Figure 3 illustrates the predicted versus the actual rut depths for the neural network created for the entire data set. The lines in the graphs are the 45 degrees that would describe a perfect prediction. Figures 4 to 7 show the same graphs for each of the data subsets. These graphs show that much better networks can be obtained when the data are separated into the four categories of rutting. One could argue that these improvements could be the result of the relatively smaller data sets used in the analyses; however, considering the levels of improvement shown, it is difficult to accept that this is the entire explanation for the difference.

One result that is particularly unique is the limited number of independent variables required to formulate rutting origin-specific networks. As can be seen from Table 4 the independent variable sets for each of these models are considerably more refined and are oriented toward the form or origin noted. Figures 8 to 11 graphically compare the various models developed for each of the rutting origin data sets. Note that the network (entire data set) and P-020 model graphs are plots of those models obtained with the entire data set applied to these data subsets. All of the parameters in each model except traffic were held at their means for Figures 8 to 11. Figure 8 also includes the results from a linear regression on this data set (Equation). This equation had an R^2 of 32 percent and an RMSE of

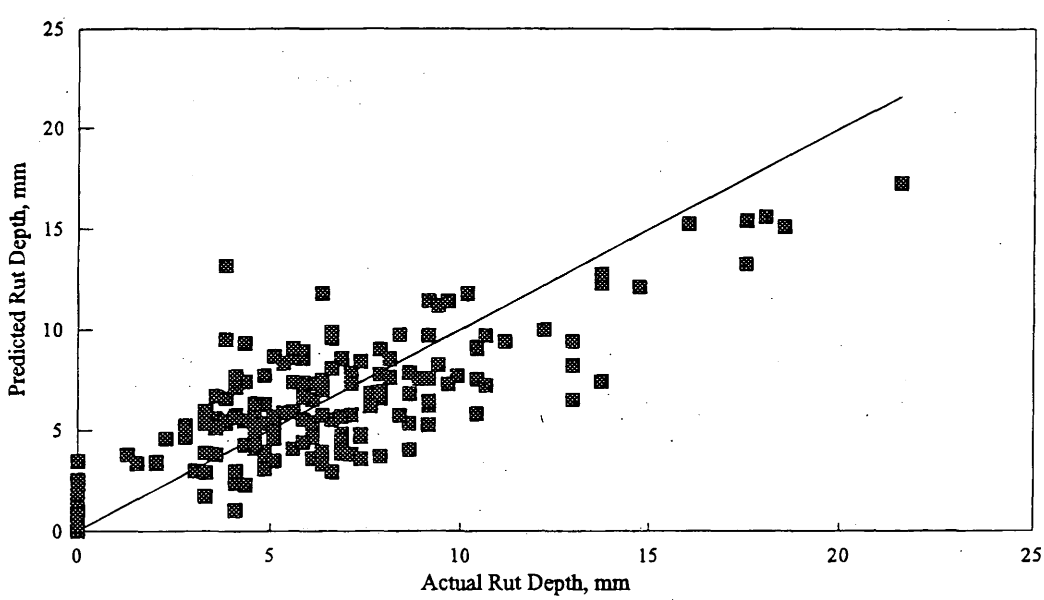

FIGURE 3 Predicted versus actual rut depths for the neural network created with entire data set.

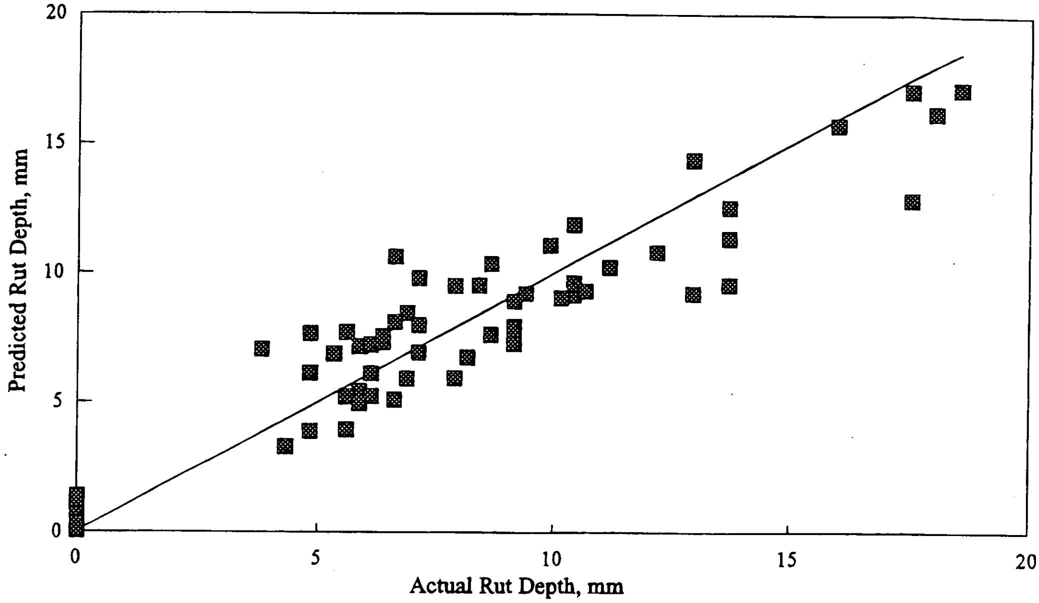

FIGURE 4 Predicted versus actual rut depths for subgrade rutting data set.

0.35 in the log of rut depth. This RMSE is a multiplicative error term, just as the error terms for the P-020 model analysis are also multiplicative. The regression analysis was limited and did not extend to nonlinear regression, but it will give the reader a chance to examine the kinds of improvements that can be made when using the neural network for analysis purposes.

CONCLUSIONS

From the analyses described here two conclusions can be made. Although application of neural networks for pavement performance modeling is still a fairly new concept, it does appear that they are capable of predicting pavement performance considerably better

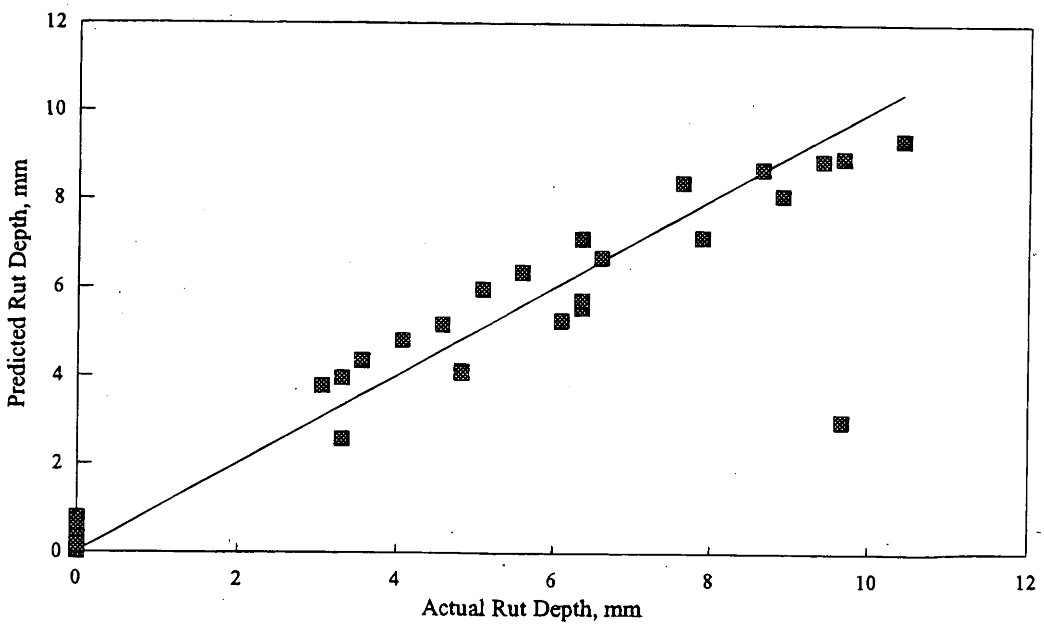

FIGURE 5 Predicted versus actual rut depths for base rutting data set.

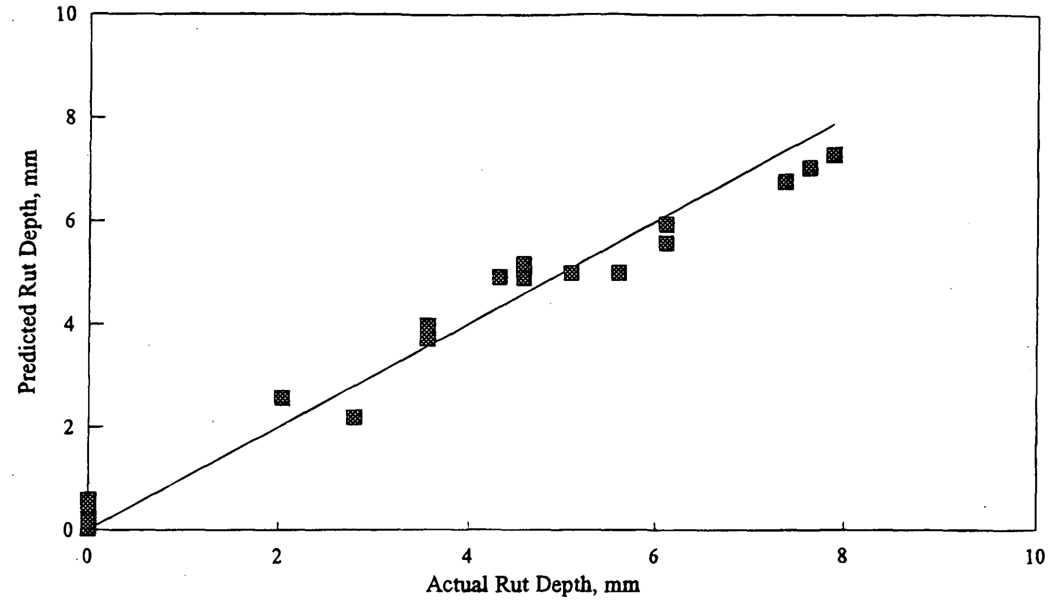

FIGURE 6 Predicted versus actual rut depths for surface rutting data set.

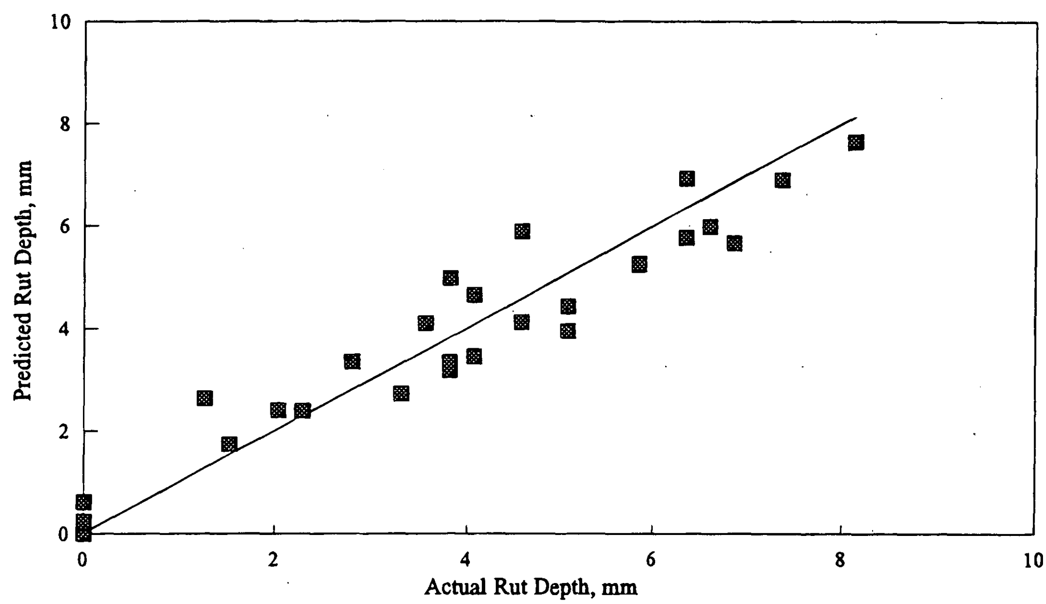

FIGURE 7 Predicted versus actual rut depths for heave data set.

TABLE 4 Independent Variables Included in Each Model

Model	Independent Variables
Entire Data Set	HMAC Thickness, Air Voids, Asphalt Viscosity @ 140°F, Annual Precipitation, Avg. No. of Days > 90°F, Avg. Freeze Thaw Cycles, PI, Subgrade Moisture, Subgrade < #200, Base Thickness, log(Cumulative KESALs)
Subgrade Rutting Data Set	Annual Precipitation, Avg. No. of Days > 90°F, Avg. Freeze Thaw Cycles, PI, Subgrade Moisture, Subgrade < #200, log(Cumulative KESALs)
Base Rutting Data Set	Annual Precipitation, Avg. No. of Days > 90°F, Base Thickness, Base Compaction, log(Cumulative KESALs)
Surface Rutting Data Set	HMAC Thickness, Asphalt Content, Air Voids, HMAC Aggregate < #4, Viscosity @ 140°F, Avg. No. of Days > 90°F, log(Cumulative KESALs)
Heave Data Set	Annual Precipitation, Avg. No. of Freeze Thaw Cycles, PI, Subgrade Moisture, Subgrade < #200, log(Cumulative KESALs)

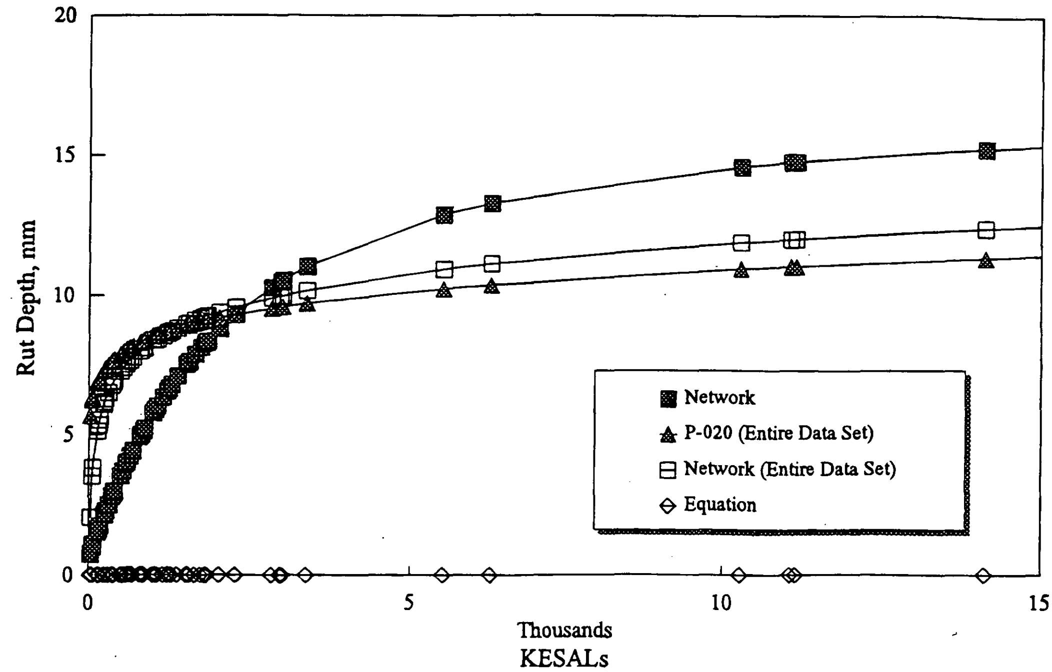

FIGURE 8 Predicted rut depths using various models on subgrade rutting data set.

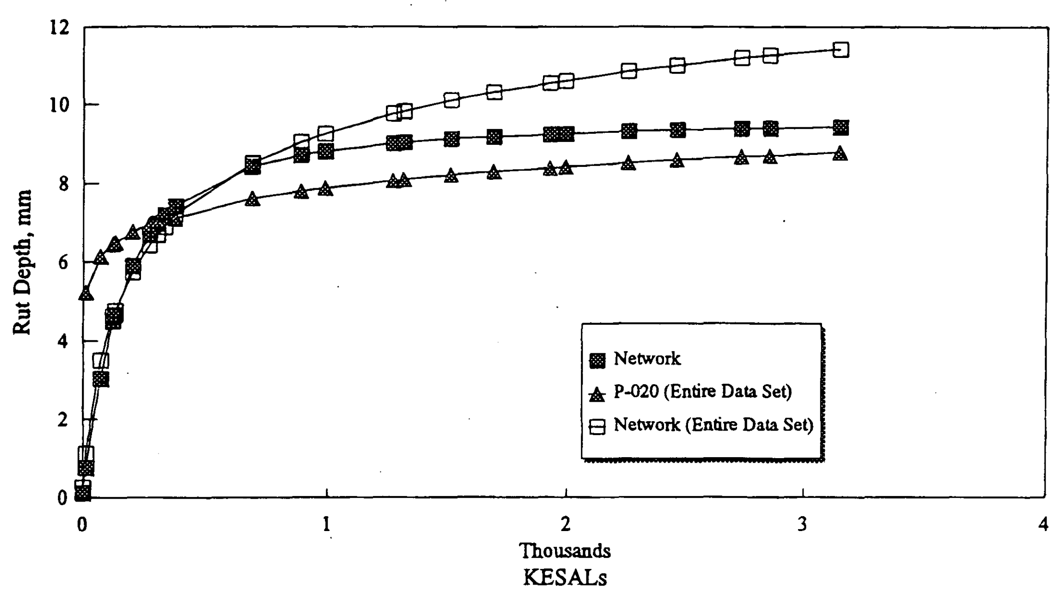

FIGURE 9 Predicted rut depths using various models on base rutting data set.

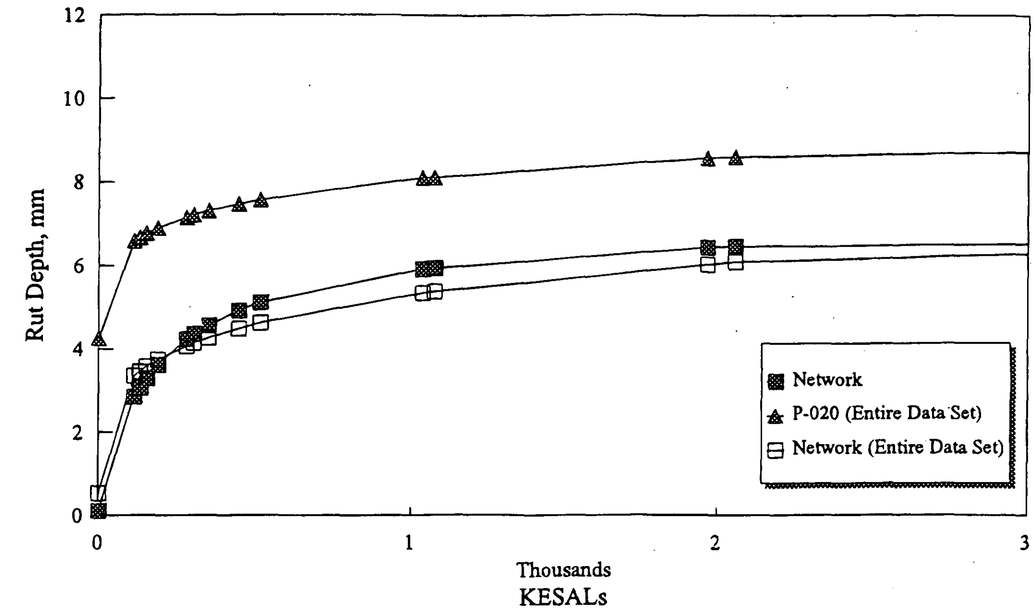

FIGURE 10 Predicted rut depths using various models on surface rutting data set.

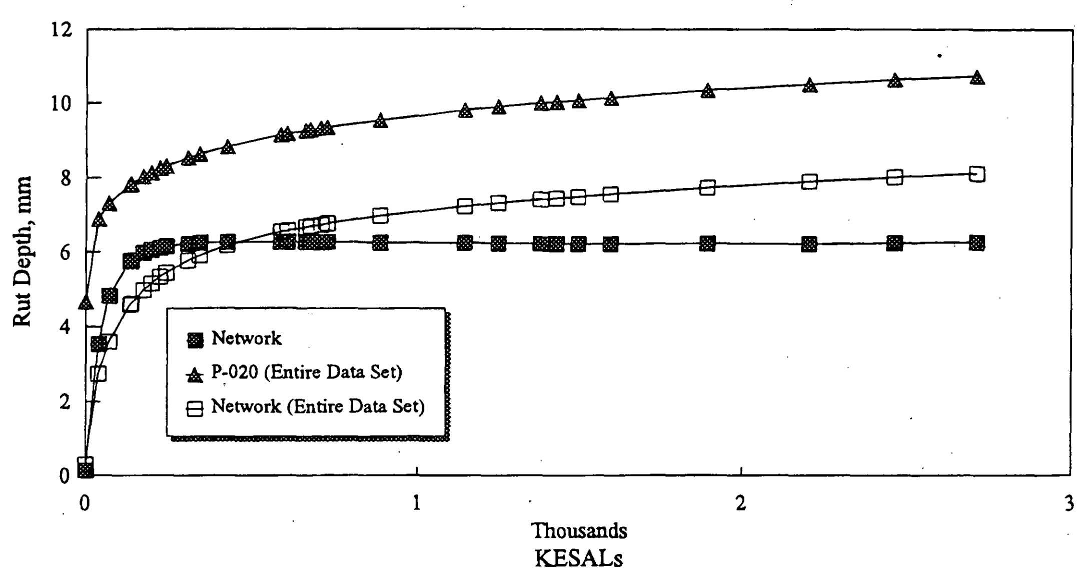

FIGURE 11 Predicted rut depths using various models on heave data set.

than the linear models of the past. It will be necessary to experiment with those networks and check the models to ensure that all of the trends are logical.

The second conclusion is that the division of sections by rutting origin does allow for the development of more refined and specific models, which also appear to be more accurate as a result.

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