Brain Inspired Cognitive Systems
August 29 – September 1, 2004
University of Stirling, Scotland, UK

APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PREDICTION OF RAVELING SEVERITY

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ABSTRACT

The most unacceptable structural damage of porous asphalt top layers is the loss of stones leading to raveling. Therefore it is important to predict when the porous asphalt top layer will achieve a critical level of raveling so as to allocate funds for necessary maintenance. SHRP-NL database including eight provinces of the Netherlands was used as the data resource. Artificial Neural Network (ANN) was employed to predict severity of raveling having input parameters related to historical raveling and climate, construction and traffic factors. An ANN is able to forecast raveling low with a high correlation factor (R^2=0.986), raveling moderate with (R^2=0.926) and raveling high with (R^2=0.976). Besides another ANN provided sensitivity analysis indicating the relative contribution of factors related to climate (58%), traffic factor (14%), thickness (6%), roughness (12%) and age (10%) for raveling low and high but for raveling moderate climate (46%), traffic factor (15%), thickness (15%), roughness (13%) and age (11%) are the results. Color Contours illustrated that heavy traffic, low thickness and high roughness cause raveling on old asphalt especially in cold rainy days. ANN proved to be a powerful technique to predict and analyze raveling opening great opportunities for development of ANN models for other detriments.

INTRODUCTION

Artificial Neural Networks (ANNs) are information-processing paradigms inspiring in the way biological nervous systems process the information. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. They are configured for a specific application or problem through a learning process. Learning in artificial neural networks as well as biological systems involves adjustments to the synaptic connections existing between the neurons.

Artificial Neural Network can be used to solve a wide range of practical problems and many applications have been reported in areas such as engineering, economics, medicine, business and marketing. Over the last few years the application of ANNs to solve civil engineering problems has increased. The significance of some road problems gives a high inspiration to road engineers to untangle the problems. Some of those unsolved problems in civil engineering are related to porous asphalt top layers.

Porous road surfaces are constructed using conventional asphalt road building materials but with such an aggregate grading that after compaction 20% to 22% air voids are present in the asphalt mix. These voids are connected by narrow air paths between the stones forming tortuous, interconnected drainage channels which run through the total depth of the layer. Water falling on the surface can therefore drain through the material to the underlying layer, which is normally impermeable. Apart from spray suppression, it has been found that this type of surface also offers the advantages of lowering the noise level from vehicles operating on the road.

As a result of environment influences and traffic load damages at the surface of a porous top layer are likely to occur. The most unacceptable structural (or mechanical) damage observed in porous pavement is the loss of stones leading to raveling. After a considerable long period of slow degradation (5-7 years) in porous asphalt top layer, the speed of damage increases. End of life of a porous top layer may be defined as the moment of occurrence of unacceptable damage-spots. It should be also considered that maintenance budgets are always limited. Therefore it is important to predict when the porous paved surfaces will achieve a critical level of raveling so as to allocate funds for necessary maintenance and rehabilitation. Due to the non-linear, time-series nature of ANNs, they seem an appropriate choice for modeling the prediction of porous asphalt top layers durability which is also non-linear. The objective of this paper is to discuss how Artificial Neural network (ANN) models can predict raveling leading to the durability of porous asphalt and also the process of finding the proper architecture for intended ANN.

Therefore a brief review of the Artificial Neural Network (ANN) and Porous asphalt durability is initially presented. This is followed by a presentation of SHRP-NL database, the ANN results and concluding remarks.

ARTIFICAL NEURAL NETWORK (ANN)

In 1969, a theoretical analysis by Minsky and Papert revealed significant limitations of simple models like the Perceptron and many scientists in the field of neural computing were discouraged doing further research. Halfway the 1980's, interest in ANNs increased significantly, thanks to J.J. Hopfield, who became the leading force in the revitalization of neural computing. During the following years, many of the former limitations of ANNs were overcome. The improvements on existing ANN techniques in combination with the increase in computational resources led to successful application of ANNs for many problems. One of the most groundbreaking rediscoveries was that of backpropagation techniques (which were conceived by Rosenblatt) by McClelland and Rumelhart in 1986. These developments led to an explosive growth of the field of ANNs.

ANNs are typically used for modeling complex relations in situations where insufficient knowledge of the system under investigation is available for the use of conventional models, or if development of a conventional model is too expensive in terms of time and money. ANNs have been applied in various fields where this situation is encountered. Some examples of fields of work that show the broad possibilities of ANNs are: process control (e.g. robotics, speech recognition), economy (e.g. currency price prediction) and the army (e.g. sonar, radar and image signal processing).

Let us assume a set of processing elements (neurons); at each point in time, each neuron u_i has an activation value, denoted in the diagram as a_i (t); this activation value is passed trough a function f_i to produce an output value o_i (t). What is associated with each connection is a real number usually called the weight of the connection, designated w_{ij} - which determines the amount of effect that the first neuron has on the second. Neurons are the relatively simple computational elements that are the basic building blocks for ANNs. Neurons can also be referred to as processing elements or nodes. They are typically arranged in layers (see Figure 1).

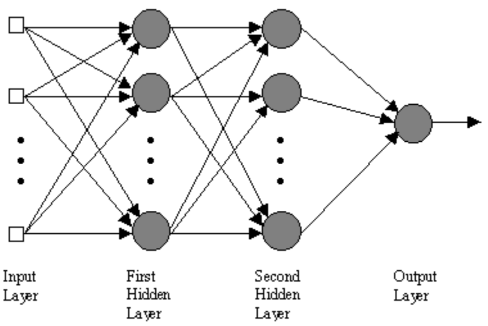


Figure 1- An example of a Multi-layer ANN, showing neurons arranged in layers

By convention the inputs that receive the data are called the input units, and the layer that transmits data out of the ANN is called the output layer. Internal layers, where intermediate internal processing takes place, are traditionally called hidden layers [after Dhar and Stein, 1997]. There are as many input units and output neurons as there are input and output variables respectively. Hidden layers can contain any number of neurons. Not all networks have hidden layers.

The state of the system at a certain point in time is represented by the state of activation of the neurons of a network. If we let N be the number of neurons, the state of a system can be represented by a vector of N real numbers, a (t), which specifies the state of activation of the neurons in a network. Each neuron has an output function that maps the current state of activation to an output signal:

$$o_i(t) = f(a_i(t))$$

Neurons are connected to one another. Basically, it is this pattern of connectivity that determines how a network will respond to an arbitrary input. In many cases we assume that the inputs from all of the incoming neurons are simply multiplied by a weight and summed to get the overall input to that neuron. In this case the total pattern of connectivity can be expressed by specifying each of the weights in the system. It is not necessary for a neuron to be connected to all neurons in the following layer. Therefore, zero values for these weights can occur.

Connections between neurons are often classified by their direction in the network architecture:

– Feedforward connections are connections between neurons in consecutive layers. They are directed from input to output.
– Lateral connections are connections between neurons in the same layer.
– Recurrent connections are connections to a neuron in a previous layer. They are directed from output to input.

The propagation rule of a network describes the way the so-called *net input* of a neuron is calculated from several outputs of neighboring neurons. Typically, this net input is the weighted sum of the inputs to the neuron, i.e. the output of the previous nodes multiplied with the weights in the weight matrix:

$$net(t) = W.o(t)$$

The activation rule - often called transfer function - determines the new activation value of a neuron based on the net input (and sometimes the previous activation value, in case a memory is used). The function F, which takes a (t) and the vectors *net* for each different type of connection, produces a new state of activation.

F can vary from a simple identity function like $a(t+1) = net(t) = W.o(t)$, to variations of linear like hard limiter or Saturating linear functions and even non-linear functions like Gaussian or sigmoid functions.

Sigmoid activation function is the most proper function for time-based prediction models which can be shown as the following equation:

$$a(t+1) = F_{bs}(net(t)) = \frac{1}{1+e^{-a.net(t)}}$$

Where a is the slope parameter of the function. By varying this parameter, different shapes of the function can be obtained.

Based on sample data that is presented to it during a training stage, an ANN will attempt to learn the relations that are contained within the sample data by adjusting its internal parameters (i.e. the weights of the connections in the network and the neuron biases). The algorithm that is used to optimize these weights and biases is called training algorithm or learning algorithm which can be classified broadly into those comprising supervised learning and unsupervised learning. Supervised learning works by presenting the ANN with input data and the desired correct output results. The network generates an estimate, based on the given input, and then compares its output with the desired results. ANNs being trained using an unsupervised learning paradigm are only presented with the input data but not the desired results. The network clusters the training records based on similarities that it abstracts from the input data. The network is not being supervised with respect to what it is 'supposed' to find and it is up to the network to discover possible relationships from the input data and based on this make certain predictions of an output.[after Dhar and Stein, 1997] The most common learning rule is the backpropagation algorithm. An ANN that uses this learning algorithm is consequently referred to as a backpropagation network (BPN).

Several commercial and academic programs are available to help the development of neural network models. The user basically has to prepare the appropriate input and output files, and to decide the appropriate ANN architecture, besides defining a few other analysis parameters. For the analysis in this paper, the author used a multi-layered neural network called QNET. The program uses a back-propagation algorithm.

POROUS ASPHALT DURABILITY

Porous asphalt has been used as a road surfacing material since the 1950s on military and civil runways. The Transport & Road Research Laboratory investigated the material for use in road applications during the 1970s but the results were not encouraging. Since then new materials have been developed encouraging renewed development and a number of trials have been undertaken in recent years in different countries. On Dutch motorways porous asphalt is widely used since the late 1980s. Later two-layer porous asphalt was developed in the Netherlands, where it has been used on urban roads since 1990. In 1997, the first road section with very small grain size in the top layer was paved. (See Figure 2)

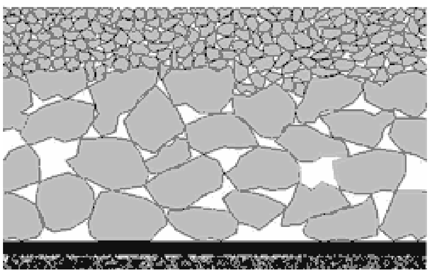


Figure 2- The principle of two layer porous asphalt pavements

Porous asphalt is the topmost of a number of layers within a road structure which differs from conventional materials in that it contains no fine material, only large single size stones, allowing a high percentage of air voids. The presence of air voids in the asphalt allows surface water to quickly drain below the road surface, offering markedly reduced spray and improved visibility.

The open structure of the surface also reduces the compression and expansion of air in the tire tread profiles. The acoustic absorption suppresses mechanical and aerodynamic noise generated by the rolling tire on the road. To explain more precisely, the tires rolling on the road result in air pumping since air is forced away in front of, and sucked in behind, the area of contact between the tire and the road. This pumping generates high-frequency noise. On porous asphalt, the pumping, and thereby also the noise generated to the surroundings, is reduced because the air is instead pumped down into the pavement. The acoustic absorption effect is not restricted to tire/road noise only but is also effective in reducing mechanical noise, radiated from the underside of the vehicle where the oil pan and the gearbox housing form the main sources of engine noise. Dutch experiences with porous asphalt show noise absorption to depend on the thickness of the layer of porous asphalt.

The primary concern in maximizing the continued effectiveness of a porous pavement is to predict the surface damages, namely raveling, on time. Although there is limited data on the effective life of porous asphalt top layers a reasonable estimation is 5 to 15 years, which will be reachable with proper adherence to site selection criteria, construction, maintenance, and correct use. After a rather long period of slow degradation (5-10 years) the speed of damaging increases. End of life of a porous top layer may be defined as the moment the occurrence of unacceptable damage-spots becomes unpredictable for the road authorities. Therefore it is important to predict when the porous paved surfaces will achieve a critical level of damage in order to allocate funds for necessary maintenance and rehabilitation. Current systems mostly use linear models to predict the durability of porous asphalt.

The major drawback of porous asphalt layers is that they are very sensitive to raveling. The contact between tires and asphalt layers after a course of time make the top stones to come loose, which is called raveling. As a result of raveling many functional demands of the road such as traffic safety, ride comfort and noise level will not be satisfied any more. Since this detriment can develop itself explosively fast, it happens often that the surface layers should be replaced relatively quickly after the first observation of that.

Raveling is also a complex detriment and the appearance of that depends on a lot of factors. Which factors have exactly the most effect and how important are their contribution to raveling is still unknown. Because porous asphalt layers as a current surface layer for motorways have been applied in so many places and since a good maintenance strategy is not simple to obtain, it is important to achieve a better understanding of that. The biggest problem with planning of maintenance is a wide range of durability in porous asphalt layers meaning some of them need maintenance after 8 years and the others after 14 years. By the reason that durability of porous asphalt layers is almost impossible to determine, an optimization in maintenance strategy and also in maintenance costs is barely possible.

Since 1987 the preferences has been given to the porous asphalt top layers on motorways by the state road authorities in the Netherlands. So the old surface layers have been replaced with porous asphalt layers. Because the average durability of porous asphalt surface layers is 10 years since 1997 the maintenance has been substantially increased. The advantages of an enhanced understanding of raveling are inestimably valuable for Dutch ministry for Transport, Public Works and Water Management because a better understanding can lead to a huge reduction in the wide range of porous asphalt durability and also significant savings in maintenance costs of the Dutch motorway network. That's why the objective of this study is an accurate prediction of durability of porous asphalt surface layers.

THE DATABASE

The database provided by SHRP-NL research program was used in this study. The Strategic Highway Research Program Netherlands (SHRP-NL) has been performed between 1990 and 2000 and had initiatives from SHRP program established in 1984 by the U.S government. The performance data gathered from Dutch roads served as the basis for improving essential components of pavement management, such as performance models and maintenance strategies. The performance data cover a period of ten years on a comprehensive set of some 250 test sections, located on in-service roads ranging from motorways to rural roads. Each section was surveyed at least once in a year and the test sections were divided to three subsections. The database contains the development of different detriments for different roads including roads with porous asphalt surface layers. The database has been assessed for its applicability in the practice of pavement management.

The database contains 6057 information records. A total of 150 sections contained relevant information of porous asphalt surface layers including severity percentage of raveling, climate and traffic fields. The severity of raveling has been categorized in raveling low, moderate high which are explained in Table 1.

Table 1 – The categories of raveling severity

Severity of raveling	
Low	6-10% stone losing per m^2
Moderate	10-20% stone losing per m^2
High	>20% stone losing per m^2

Table 2 shows a summary of database values. In average porous asphalt layers showed 13.53% low raveling, 2.17% moderate raveling and 1.32% high raveling. In worth case porous asphalt surface layers will face 55% high raveling. The average climatic conditions show rainfall precipitation of 760 mm per year, with about 59 cold days and 17 warm days. Roads with porous asphalt surface layers mostly will not become older than 13 years. Traffic percentage on test sections is maximal 42%, porous asphalt has an average thickness about 52 mm and roughness about 3 mm.

Table 2 – Summary of database values

	Raveling Low (%)	Raveling Moderate (%)	Raveling High (%)	Rain (mm)	Warm (days)	Cold (days)	Traffic (%)	Thickness (mm)	Roughness (mm)	Age (Years)
Min	0	0	0	703	5	43	4	49	0	6
Max	100	55	55	804	26	77	42	70	12	13
Average	13.53	2.17	1.32	759.5	16.5	58.6	23	52.4	2.97	7.9

RESULTS

The previously described SHRP-NL data was initially analyzed using QNET Neural Network with the objective of finding an ANN model as function of the available input parameters. A single output layer for raveling was used. The input layer consists of 19 data neurons as follows:

- Input 1,4,7,10,13 (RL): Raveling Low from 1993 to 1997 (%)
- Input 2,5,8,11,14 (RM): Raveling Moderate from 1993 to 1997 (%)
- Input 3,6,9,12,15 (RH): Raveling High from 1993 to 1997 (%)
- Input 16 (WD): average of Warm Days between the years 1993 and 1997 (days)
- Input17 (CD): average of Cold Days between the years 1993 and 1997 (days)
- Input 18 (RP): average Rainfall Precipitation between the years 1993 and 1997 (mm)
- Input 19 (TP): average Traffic Percentage of heavy vehicles daily on test sections (%)
- Input 20 (TH): maximum Thickness of asphalt (mm)
- Input 21 (R): maximum Roughness of asphalt (mm)
- Input 22 (Age): Age of the pavement at 1998 (years)

And the output layer consists of 19 data neurons as follows:

- Output (1): low raveling year 1998 (%)
- Output (1): moderate raveling year 1998 (%)
- Output (1): high raveling year 1998 (%)

A few ANN architectures were tried to find the best configuration for the hidden layers. The best results were obtained for the configuration with 3 hidden layers of 15, 10 and 6 neurons, respectively. All neurons of a given layer are connected to all neurons of the subsequent layer. A sigmoid activation function was used. A training data set compromising 115 random sections out of 150 available (77%) was initially chosen for the learning stage. Figure 3 shows the learning rate of ANN during the learning process (iteration) which produced excellent results. The correlation coefficient for the learning stage was very high with R^2=0.9995 and the Root Mean Square error was RMS=0.0009.

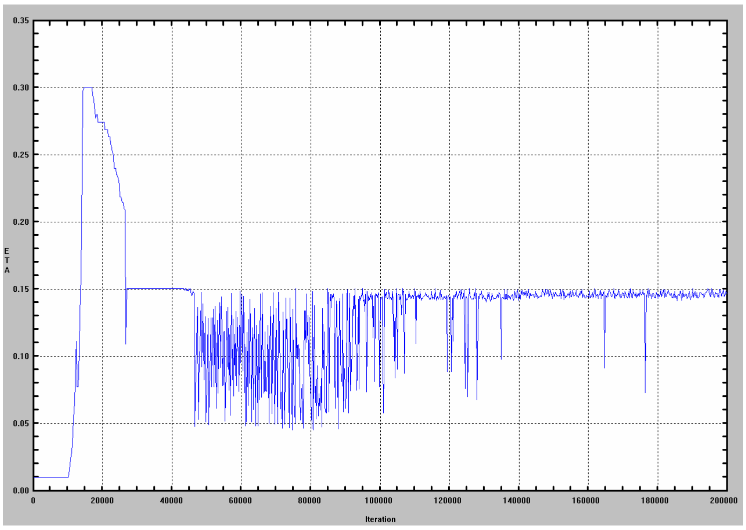


Figure 3 Learning Rate of ANN

After the training stage, the remaining 35 sections were used to validate the model. Predictions were also very good, despite a higher dispersion than in the learning stage. The correlation coefficient for the validation stage of raveling low was R^2=0.986 and the Root Mean Square error was RMS=0.012, for raveling moderate R^2=0.926 with RMS=0.089 and for raveling high R^2=0.976 with RMS=0.041. As it can be seen in Figure 4 the predicted values and the actual values are almost the same. The red line is an optimal agreement and the blue points are predicted patterns and in this case almost all of the blue points (patterns) have a position on the red line (optimal agreement). The lower correlation of the validation stage may be attributed to the relatively small number of sections available or to an over-fitting during the learning stage.

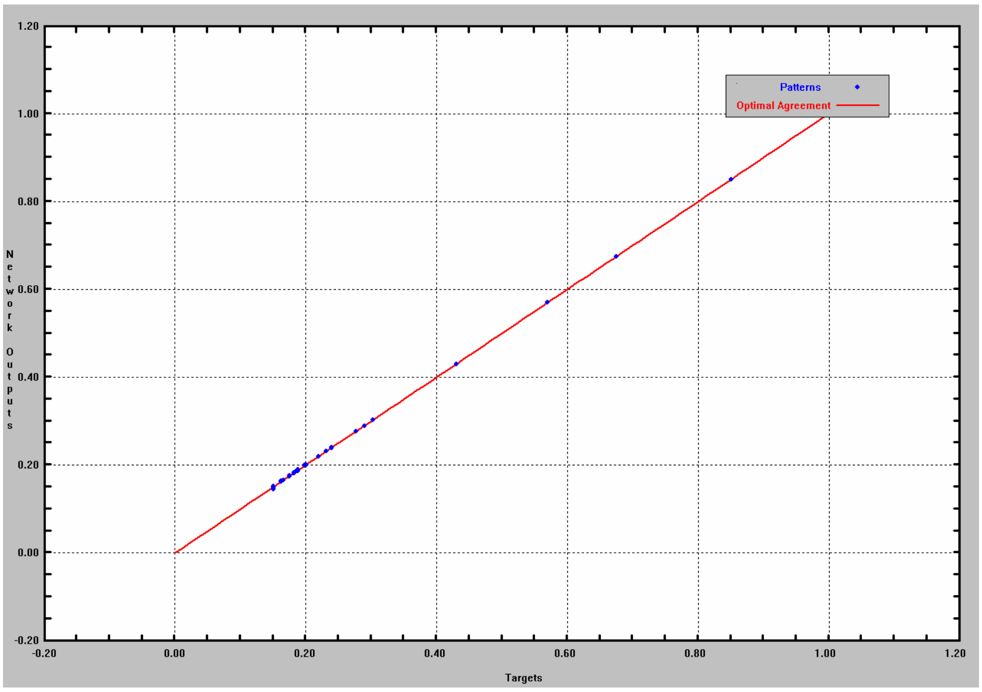
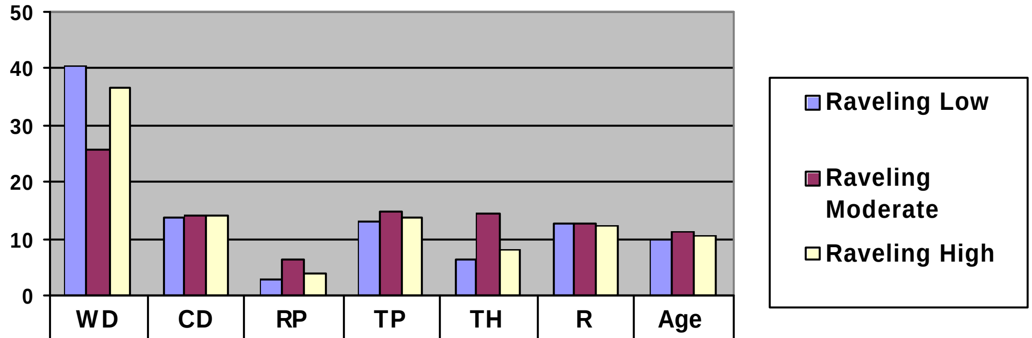


Figure 4- ANN raveling values of 35 test sections used for validation

An important feature of program QNET is that it allows quantifying the relative contribution of each input neuron to the computed output value. Hence it is possible to investigate the most relevant factors affecting raveling in porous asphalt surface layers. To experience this relationship another ANN model was made using Warm Days (WD), Cold Days (CD), Rainfall Precipitation (RP), Traffic Percentage (TP), Thickness of asphalt (TH), Roughness of asphalt (R) and Age of asphalt (Age) as input parameters and raveling low, moderate and high as outputs (same as the first model only without historical data of raveling). Individual contributions of inputs are shown in Figure 5. Contributions were grouped for output neuron percentage of low, moderate and high raveling. As can be seen the contribution of warm days is the highest and rain fall precipitation the lowest. Cold days are about 14% in all sort of raveling severity. Rainfall can effect with an average of 4% and traffic percentage up to 14%. Age contributes rarely more than 10%. Roughness is more important than Thickness but if the severity become moderate thickness become as significant as roughness. The weather factors can contribute to 57% while traffic factor stays at 14%.



	WD	CD	RP	TP	TH	R	Age
Raveling Low	40,41	14,08	3,04	13,25	6,32	12,88	10,02
Raveling Moderate	25,87	14,12	6,39	14,8	14,69	12,84	11,3
Raveling High	36,64	14,14	4,03	14,06	8,33	12,24	10,58

Figure 5- Relative contribution percentage of input parameters for the outputs

QNET also allows analyzing how the parameters interact with each other in different severity of raveling. The interaction of cold days with asphalt age is absolutely important to know. Figure 6 shows particularly the interaction between input parameter 2 and 7, namely average of cold days (CD) and asphalt age (Age) causing raveling. Any color shows a percentage range. The red color has the highest value (40% and higher). The average of cold days can be between 43 and 77 and for age between 6 and 13 (see Table 2). As it is clear in Figure 6 on old asphalt top layers the cold weather cause raveling but if it is younger than 8 years even 70 cold days does not cause so much of raveling. In other words how older the asphalt is how more sensitive it becomes to cold days which lead to raveling. For example when the road is older than 10 years and more than 70 days per year are cold, there is a chance up to 40% that raveling happened. Furthermore with the same way of analyze it can been shown that in interaction between thickness and roughness, roughness become significant when the thickness is more than 60 mm. The roughness of less than 7 mm does not cause raveling. The rainy cold days make it up to 20% possible for occurrence of raveling. The combination of cold days and heavy traffic cause fast development of raveling severity. If the traffic percentage is more than 35%, it interacts strongly with cold days. The asphalt which is older than 10 years together with 40% traffic causes also quick evolution of raveling.

CONCLUSIONS

The raveling values were computed for 150 sections of the SHRP-NL program for which a complete set of raveling low, moderate and high, warm and cold days, rain fall precipitation, traffic percentage of heavy vehicles daily on test sections, thickness, roughness and asphalt age was available. Artificial Neural Network was used to model the prediction of raveling, which is the key to define durability of porous asphalt surface layers.

An extremely accurate model using QNET neural network was developed. This ANN model gave a coefficient of correlation of 0.9995 during the learning stage and 0.986, 0.926 and 0.976 correlations during the validation stage; it is believed that this feature can be improved as more data becomes available.

The studied database (SHRP-NL) covers a wide range of relevant information including age, detriment, climate, and construction data. Another ANN model allowed quantifying the relative contributions of these factors on raveling values and credited most of low raveling to the climate factors (about 58%), followed by traffic factor (14%), thickness (6%),

roughness (12%) and age (10%). The most significant part of climate factors is warm days. In raveling high contribution of factors is almost the same but in raveling moderate when raveling starts to develop fast, climate factors become less important(about 46%) whereas asphalt thickness increase its contribution to 15%. ANN Color Contours illustrated lots of interaction between input parameters which causing raveling.
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Relevantly it was showed that heavy traffic; low thickness and high roughness cause raveling on old asphalt top layers especially in cold rainy days.

Artificial Neural Network (ANN) proved to be an extremely powerful technique to predict and analyze raveling in porous asphalt top layers and similar ANN models may be developed for other type of detriments and different kind of top layers.

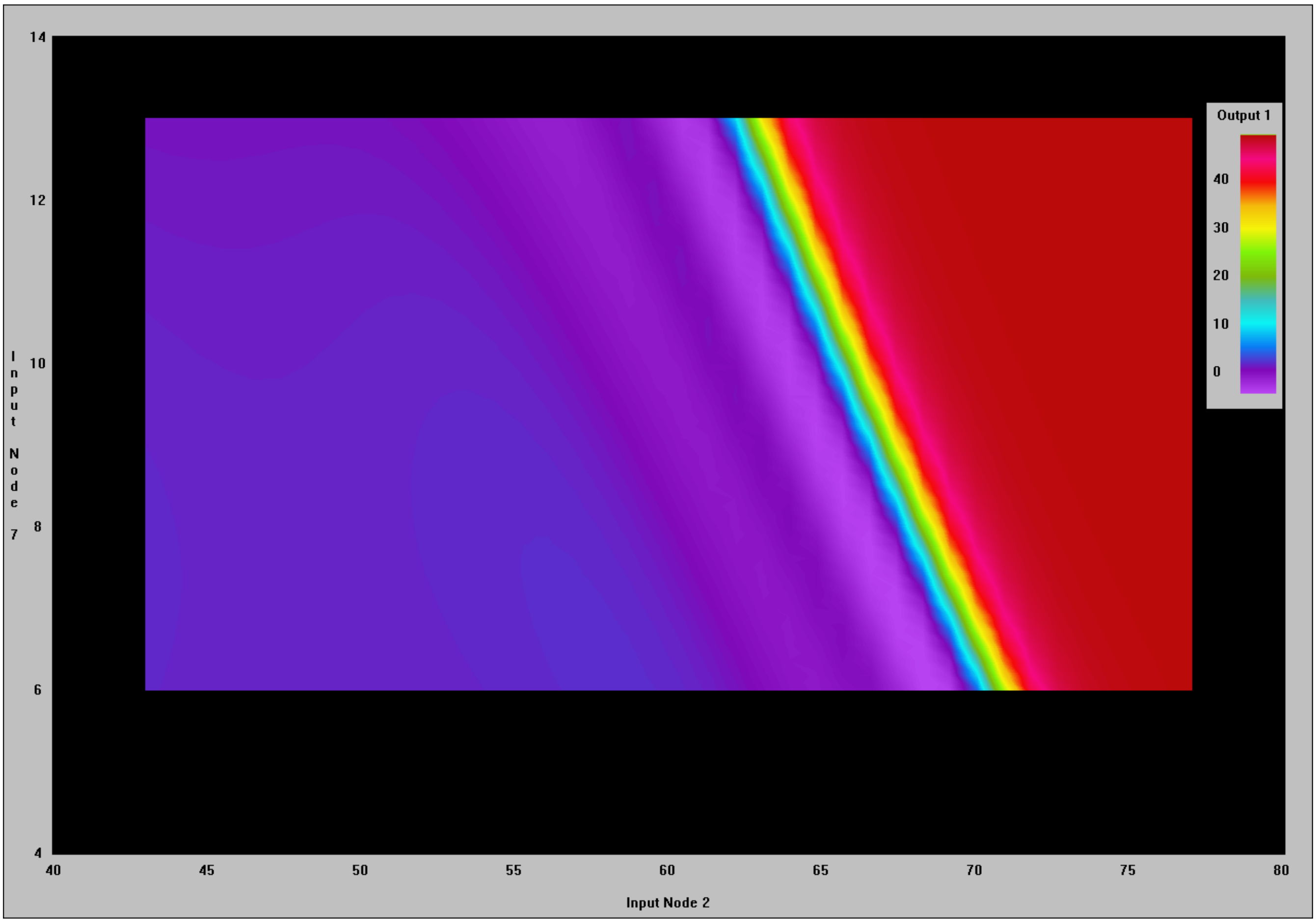

Figure 6- Interaction color contour between Cold Days and Asphalt Age for Raveling

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