Artificial Neural Network (ANN) models for PA lifespan

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Abstract
More than 60% of the Dutch motorways are covered with a porous asphalt wearing course (PA). In spite of many advantages of PA its lifespan is mostly short which causes high maintenance costs. Lifespan of PA is defined by its main damage being raveling. The main factors which cause raveling are asphalt construction/mixture and environmental factors. Therefore it is important to determine to what extent the development of raveling is dominated by these factors. Artificial Neural Networks (ANNs) are especially good in modeling complex problems. Their ability to extract relations between inputs and outputs of a process suits the problem of the PA lifespan well, since it is nonlinear and complex. The paper discusses ANN models developed to analyze the dominancy of parameters and to forecast raveling of PA. The study also shows that ANN models can only be as good as allowed by the data.

Keywords
Porous asphalt, Artificial Neural Network (ANN), lifespan, raveling, models
1. Introduction

Currently about 60% of these highways have a porous asphalt (PA) surfacing. PA is constructed with an aggregate grading that after compaction 20% to 22% air voids are present in the asphalt mix. Water falling on the surface can therefore drain through the material to the underlying layer. Apart from spray suppression, this type of surface also offers the advantages of lowering the noise level from vehicles operating on the road [4]. It is recalled that 25% of the population in the Netherlands is hindered by road traffic noise [5]. Because of the high void content however, the lifetime of PA wearing courses is lower than that of dense asphalt concrete (DAC) wearing courses. Furthermore the life-time of PA has shown a large variability. It is clear that especially the short lifetimes cause a significant maintenance problem not only because of the higher maintenance costs but also because of the high user’s costs that are a result of traffic delays due to road works. It has been calculated that narrowing the lifetime window from 4 – 16 years to 8 – 16 years results in a reduction of the maintenance costs of 20% and a reduction in the traffic delay hours due to maintenance works of 10%.

Artificial Neural Network can be used to solve a wide range of practical problems in all areas including engineering problems. ANN gives road engineers also enough motivation to untangle unknown matters coming up with road design, construction and maintenance using neural networks.

Given the above mentioned considerations a research program was started at the Delft University of Technology that should investigate to what extent the composition of PA determines it’s lifetime in terms of raveling with respect to single layer PA. In this paper the work that is done so far in answering the above mentioned questions, is described. The ANN models discussed, have been developed by the author during a project called the “Development of artificial neural network (ANN) models for maintenance planning of porous asphalt wearing courses” performed for Dutch ministry of Transport, Public Works and Water Management. All ANN models have both analyzing and forecasting ability. They have a feed forward structure and are trained by Back-Propagation algorithm. The results showed that each model opens lots of opportunities for road engineers. The development process and results has been presented in this paper.

2. Stating the problem (PA lifespan) and discussing the solution (ANN)

Raveling of Porous asphalt wearing courses (PA)

The lifespan of asphalt mixture depends on different variables like traffic loads, environmental effects, the composition of the mixture, the characteristic of the different mix components and last but not least on the production and laying process. Because of its high void content, PA is sensitive for damage due to mechanical (traffic) and environmental effects. The most dominant damage type is raveling which implies that aggregate particles get loose from the pavement surface and are whipped off. Furthermore, raveling might result in windscreen damage which in turn might lead to dangerous traffic conditions.

Figure 1 shows raveling as observed on a specific highway in the Netherlands. As one can observe from Figure 1, aggregate particles are clearly whipped off in the right hand wheel
track (indicated by means of the red arrow) and are swept towards the hard shoulder of the pavement (indicated by means of the yellow arrow).

Figure 1: Appearance of raveling on PA

As mentioned before, raveling is caused by mechanical and environmental loads. Next to that the “strength” of the mixture certainly plays an important role. The “strength” is influenced by the mixture composition which, as indicated earlier, can be rather variable. Furthermore the “strength” is affected in a negative way due to aging of the bituminous mortar making it brittle and sensitive to cracking. Also effects like drainages due to gravitation forces of the mortar from the top part of the layer to the lower parts and segregation of the mixture during production and laying have a negative influence on the lifetime of the mixture [11].

Since 1987 the preferences has been given to the PA top layers on highways by the state road authorities in the Netherlands. So the old top layers have been replaced with PA layers. Because the average lifespan of PA top layers is 10 years since 1997 the maintenance has been substantially increased [13].

PA is a relative expensive top layer therefore it is desirable to have a lifespan as long as possible as well as a decrease in number of maintenance moments by which traffic hindering is considerably restricted and the costs for traffic measures during work in progress.

ANN Structure

Artificial Neural networks(ANN), with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. ANN, like people, learns by example. The examples must be selected carefully otherwise the network might be functioning incorrectly. An ANN is configured for a specific application, such as forecasting or pattern recognition, through a learning process. A trained ANN can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions. ANN processes information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem.

The basic structure of ANN (Figure 2) can be summarized in the following points:

- Neurons or nodes are actually computational elements,
- neurons are typically arranged in layers,
- the neurons that receive the data are called the inputs,
• the neuron that transmits data out of the ANN is called the output,
• internal layers where intermediate internal processing takes place are hidden layers,
• there are as many input units and output neurons as there are input and output variables respectively,
• there are connections between all neurons,
• What is associated with each connection is a real number called the weight of the connection (w) [2].

Figure 2: Basic structure of ANN

Development of ANN models

ANN models can play beside an analysis role also a forecasting role. For forecasting the historical data is essential. By understanding the dynamics of the changing process over time, this type of model can forecast future based on the past data. This type of model is also called time-series model. A time-series model can describe time-dependent processes in which past data influence future data in the presence of underlying deterministic factors. In other words, ANN can be trained to map past and future data, thereby uncovering the hidden relationship governing the data.

To develop ANN models the steps shown in Figure 3 should be taken. Proper preparation of data sets is the most important step in working with neural networks. Having a neural network with well-prepared data will lead to impressive results as it has been explained below:

• Right amount of data needed,
• Data shouldn't be self-contradictory,
• Inputs should have maximum influence on target,
• Data shouldn't have missing values or outliers,
• Data should well present the problem environment.

Data pre-processing means modification of the data before it is fed to a neural network. Pre-processing transforms the data to make it suitable for neural network. Neural networks work only with numeric data. Often, dates and time as well as categories (textual data represented by final set of values) need to be processed before feeding them to the network input.

To design a network, 1) the network architecture (number of hidden layers and units in each layer) and 2) network properties (error and activation functions) should be specified. Linear, Logistic and Hyperbolic tangent can be selected as activation functions for hidden layers and output layer. Minimization of the error function is the main objective of neural network training. Error functions are mostly Sum-of-Squares and Cross-Entropy. Sum-of-Squares is the most common error function for regression problems [12].
A training algorithm should be chosen based on the characteristics of the problem. There is no single best training algorithm for neural networks. Back propagation algorithm is the most popular algorithm for training of multilayer Perceptron and is often used by researchers [1]. The network can be tested by different means. The response of neural network output as one input is varied with the other inputs held constant or a line graph of the actual and network output values or a scatter plot of the actual and forecasted target values or an error dependence graph which allows us to analyze which ranges of the selected input column tend to produce bigger or smaller network errors [3]. When a model is developed from training data, the error on the training data is a rather optimistic estimate of the error rates the model will achieve on unseen data. The aim of developing a model is usually to apply the model to new, unseen data. Thus, one would like to have some method for better approximating the error that might occur in general. Cross validation provides such a method. Cross validation is the strongest method for estimating the true error of a model. Cross validation is also used to choose the number of hidden units/layers. There are different cross validation methods such as Random Sub-sampling and Leave-one-out. Random sub-sampling cross validation has been used during this study.

### 3. Data for ANN models

The database provided by SHRP-NL research program was used in the first part of this study. The Strategic Highway Research Program Netherlands (SHRP-NL) has been performed between 1990 and 2000 and had initiatives from SHRP U.S. The SHRP-NL database contains 34 PA sections; each section has a length of 300 m and is divided in 3 sub sections with a length of 100 m each (102 PA sections in total). In front of and behind of each 300 m section three cores are taken, giving a total number of cores of 6 [6].

### Condition data

The condition surveys consisted of very detailed surveys by well trained inspectors who had to determine the percentage of light, moderate and severe damage. The definitions of light, medium and severe raveling are given in Table 1 [7].
In order to get a number that could be used for model development, an overall raveling value was calculated as follows:

$$\text{Meq} = 0.25 \text{ L} + \text{ M} + 5 \text{ Se}$$

Where:   
Meq = amount of equivalent moderate damage,  
L = amount of light damage [% of total area],  
M = amount of moderate damage [% of total area],  
Se = amount of severe damage [% of total area] [8].

<table>
<thead>
<tr>
<th>Severity of raveling</th>
<th>Percentage range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>6-10% stone loss per m²</td>
</tr>
<tr>
<td>Moderate</td>
<td>11-20% stone loss per m²</td>
</tr>
<tr>
<td>Severe</td>
<td>&gt;20% stone loss per m²</td>
</tr>
</tbody>
</table>

Mixture data

The mixture composition data were used as retrieved from the six available cores. For each core, information was available on gradation, density, bitumen content, void content, type of stone used. For all possible items, the mean and standard deviation was calculated. It appeared that the coefficient of variation in the amount of material passing a particular sieve size was low (smaller than 10%). This was also the case for the density and the bitumen content. The void content however showed a significant amount of variation. Therefore it was decided to take the mean value of the gradation as well as the mean value for the density and bitumen content as input variables valid for all three 100 m subsections in one 300 test section. For the void content, the mean value and the coefficient of variation were taken as input variables. The latter was taken into account in order to be able to explain differences in raveling performance of the three 100 m subsections within the 300 m long test section, although the mixtures characteristics are the same.

Four stone types were used in the PA mixtures being greywacke, crushed siliceous river gravel, porphyry, greywacke / Greyclaritsite.

With respect to the gradation it was concluded that it doesn’t make sense to include all the information about the percentage passing the individual sieve sizes. It was concluded that the gradation could be characterized by means of the % of fine and % of coarse material and the $d_{50}$ and the $Cu$ of the coarse fraction. Therefore the following parameters were taken as input variables to characterize the stone skeleton.

$\begin{align*}
\text{d}_{50} & = \text{sieve size through which 50\% of the coarse material passes}, \\
\text{d}_{60} & = \text{sieve size through which 60\% of the coarse material passes}, \\
\text{d}_{10} & = \text{sieve size through which 10\% of the coarse material passes}, \\
\text{Cu} & = \text{coefficient of uniformity} = \frac{\text{d}_{60}}{\text{d}_{10}}, \\
\% \text{ fines} & = \text{percentage of material passing the 2 mm sieve}, \\
\% \text{ coarse} & = \text{percentage of material on the 2 mm sieve}.
\end{align*}$

Traffic and climate

The SHRP-NL database contains information about the average daily traffic and the growth rate. In some cases, information on the growth rate was not available and then a value of 5% was adopted. Based on this information and information on the year in which the section
considered was constructed, the cumulative amount of traffic until the dates of the visual
county surveys was calculated. This implies that no distinction was made between truck
traffic and person cars.
The SHRP-NL database contains information about the number of days per year at which the
minimum temperature was 0 °C or lower and the number of days at which the maximum
temperature was 25 °C or higher. This information was used to calculate the cumulative
number of cold days and the cumulative amount of warm days.

4. ANN models

This section discusses developing two ANN models FMeq5 and FMeq8 which forecast and
analyze Meq respectively 5 and 8 years after construction on PA sections. As it has been
already mentioned in section 3 Meq is an overall raveling value which means models FMeq5
and FMeq8 forecast and analyze raveling 5 and 8 years after construction on PA sections. The
models use part of SHRP-NL database discussed in section 3. Both models were developed
according to steps shown in Figure 3 and discussed in last paragraph of section 2.

Model “Forecasting Meq 5 years after Construction” (FMeq5)

ANN approach was applied for modeling FMeq5. The developed FMeq5 model is able to
forecast the amount of equivalent moderate damage 5 years after construction. This is an
important model because it allows one to determine the mixture composition needed to
prevent premature damage to develop. This model receives the input data shown in Table 2.
The parameters Cu and D50 were omitted because preliminary model development showed
their insignificance.

| Table 2: Input and output parameters of FMeq5 |
|-------------------------------|----------------------------------|
| Input                         | Output                          |
| Density (Dichtheid)           | Meq 5 years after construction   |
| Bitumen                       |                                 |
| Void Content (Holle Ruimte)   |                                 |
| Coefficient of Variation of Void Content |                                 |
| Type of stone (Type Steenslag)|                                 |
| %Fine (%Fijn aggregaat)       |                                 |
| %Coarse (%Grof aggregaat)     |                                 |
| Warm Days (Warme dagen)       |                                 |
| Cold Days (Koude dagen)       |                                 |
| Cumulative Volume of traffic 5 years after construction (Cumulatief hoeveelheid verkeer 5 jaar na aanleg)|

After data preparation, the data were analyzed. The selection of the data partitions was
randomly. Data records with missing values were deleted from the dataset, the outliers have
not been changed and the input feature was defined as Forward Stepwise. Preprocessing of
numerical data records involved scaling of the input and output. The only categorical column,
“type of stone” was encoded with the method ONE-of-4 because as it is explained before,
four types of stone can be used in PA mixture.
After analyzing and preprocessing the data the number of hidden layers/units and activation/error function has been defined (designing the model). The random sub-sampling cross validation method was used for determination of the number of hidden units/layers. The number of sub-samplings has been set to $K=27$. After each sub-sampling, preprocessing and a training process with 5000 iterations have been performed to find the best number of hidden layers/units. Each sub-sampling dataset was trained with all possible numbers for hidden layers/units and after comparison of the validation errors of all architectures, the model with one hidden layer/2 hidden units had the lowest validation error namely 0.694971. Logistic has been chosen as activation function for the output layer while the hyperbolic tangent was chosen as activation function for the hidden layer. The error function was the sum of squares. The model was trained with the mentioned properties and training algorithm back-propagation.

Figure 4 shows the relative importance of the various factors involved after the training. It shows e.g. that the sum of the relative importance of all mixture parameters is 67% while the type of stone is the most important parameter between the mixture parameters (37%). Climate parameters contribute to about 23% and “warm” days are equally important as “cold” ones. The cumulative traffic load contributes about 10%. The gradation parameters, % fine aggregates and % coarse aggregates contribute each about 7%.

<table>
<thead>
<tr>
<th></th>
<th>Dens.</th>
<th>Bit.</th>
<th>VC</th>
<th>CVVC</th>
<th>Stone</th>
<th>%Fine</th>
<th>%Coar.</th>
<th>Warm Days</th>
<th>Cold Days</th>
<th>Traffic</th>
</tr>
</thead>
<tbody>
<tr>
<td>[%]</td>
<td>4</td>
<td>6</td>
<td>1</td>
<td>5</td>
<td>37</td>
<td>7</td>
<td>7</td>
<td>12</td>
<td>11</td>
<td>10</td>
</tr>
</tbody>
</table>

*Figure 4: Relative importance of the variables*

After that, the model was tested with test set. The actual output and the forecasted output and the absolute error (AE) for test set have been reported in Table 3.
Table 3: Test set target and output values for Model FMeq5

<table>
<thead>
<tr>
<th>Actual value</th>
<th>Forecasted value</th>
<th>Absolute Error (AE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.008604</td>
<td>0.008604</td>
</tr>
<tr>
<td>0</td>
<td>0.014321</td>
<td>0.014321</td>
</tr>
<tr>
<td>2.5</td>
<td>2.629079</td>
<td>0.129079</td>
</tr>
<tr>
<td>8.75</td>
<td>9.249869</td>
<td>0.499869</td>
</tr>
<tr>
<td>0</td>
<td>0.148694</td>
<td>0.148694</td>
</tr>
<tr>
<td>0.25</td>
<td>0.204455</td>
<td>0.045545</td>
</tr>
<tr>
<td>0.25</td>
<td>0.621248</td>
<td>0.371248</td>
</tr>
<tr>
<td>13.5</td>
<td>13.504501</td>
<td>0.004501</td>
</tr>
<tr>
<td>0</td>
<td>0.000002</td>
<td>0.000002</td>
</tr>
<tr>
<td>0.25</td>
<td>0.000012</td>
<td>0.249988</td>
</tr>
<tr>
<td>0</td>
<td>0.022306</td>
<td>0.022306</td>
</tr>
</tbody>
</table>

It should be noted that a few of the independent variables are in fact not independent but interrelated. Density, bitumen content and void content are dependent on each other. Furthermore the amount of coarse aggregate, void content and the density are related to each other. This makes it hard for the ANN analysis to determine precisely the relative importance of the various mixture related parameters. Therefore it is much wiser to rate the result in a more general way by saying that the amount of raveling after 5 years depends for 10% on the amount of traffic, for 23% on climatic conditions and for 67% on the mixture composition and that the stone type has a very large influence.

The model FMeq5 can also show the interaction between any two input parameters for the output with color contours [10]. This can be used to find how input trends interact with output forecasting. Color contours clarify which ranges of each input should be used or occurred to avoid ravelling. For example Figure 5 is the interaction between bitumen and void content. The red areas have the highest risk for raveling and the purple areas the lowest. As it can be seen in Figure 5 the area with bitumen between 3.9% and 4.1% for all void content (the dashed area) has a purple or light blue color which, according to the figure 5 legend, defines a raveling percentage up to 3. In other words, for the bitumen percentage between 3.9% and 4.1% even high percentages of void content cause almost no raveling.
Model “Forecasting Meq 8 years after Construction” (FMeq8)

In a similar way a model (FMeq8) was developed to forecast the amount of raveling 8 years after construction. After some initial trials it was decided to take the parameters shown in Table 4 as input parameters.

After data preparation and preprocessing random sub-sampling cross validation was performed with K=20 and the number of learning iterations for each sub-sample was 10000. As a result of cross validation, the architecture with one hidden layer and 5 hidden units was selected. The model has been trained with the mentioned properties. Then the well trained model had to be tested. A scatter plot for the model FMeq8 is shown in Figure 6. The actual values have been plotted as red points on the red optimal line (x-axis) and the forecasted values have been shown as blue points (y-axis). The smaller the intervals are between the red and blue points, the better the network will perform. The average interval (average absolute error) was about 3 which is small given the fact that Meq ranged between 0 and 160 (see figure 6).

Table 4: Input and output parameters of FMeq8

<table>
<thead>
<tr>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density (Dichtheid)</td>
<td>Meq 8 years after construction</td>
</tr>
<tr>
<td>Bitumen</td>
<td></td>
</tr>
<tr>
<td>Void Content (Holle Ruimte)</td>
<td></td>
</tr>
<tr>
<td>Coefficient of Variation of Void Content</td>
<td></td>
</tr>
<tr>
<td>Type of Stone (Type Steenslag)</td>
<td></td>
</tr>
<tr>
<td>Warm Days (Warme dagen)</td>
<td></td>
</tr>
<tr>
<td>Cold Days (Koude dagen)</td>
<td></td>
</tr>
<tr>
<td>Meq 5 years after construction</td>
<td></td>
</tr>
</tbody>
</table>
Figure 6: Scatter Plot for Model FMeq8

Table 5 shows the relative importance of input parameters was compared for FMeq5 and FMeq8.

It appears from Table 5 that for forecasting of raveling on PA, mixture properties always contributes between 50% and 60%. Gradation properties are not important if PA wearing courses are not older than 5 years. Climate cause raveling up to 23% in the first 5 years of PA lifespan but after 5 years this contribution starts to disappear. The traffic stays less important than climate. When the PA wearing courses are 8 years old, the damage appeared in the first 5 years, is 38% important in further development of raveling.

<table>
<thead>
<tr>
<th>Input name</th>
<th>Model FMeq5</th>
<th>Model FMeq8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mixture Properties (Density, Bitumen, Void Content, CV of Void Content, Type of stone)</td>
<td>53</td>
<td>57</td>
</tr>
<tr>
<td>Gradation</td>
<td>14</td>
<td>0</td>
</tr>
<tr>
<td>Climate</td>
<td>23</td>
<td>5</td>
</tr>
<tr>
<td>Traffic</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>Meq 5 years after Construction</td>
<td>N/A</td>
<td>38</td>
</tr>
</tbody>
</table>

5. Conclusions

From the results of the ANN analyses some interesting conclusions could be drawn with respect to the required mixture composition. It became clear e.g. that of the four aggregate types involved, greywacke gives the best performance. The results in fact show that crushed siliceous river gravel should not be used. Reality however is that the latter type of aggregate is
commonly used since it is readily available and therefore relatively cheap. This type of aggregate could be used since PA mixtures made of it passed the specifications set for PA and because a guarantee period of only limited length was normally specified. Since projects were granted on the basis of the lowest price, there was no incentive for contractors to use a better, but more expensive, type of aggregate. It should be stated that contractors are aware of the fact that use of greywacke results in a better performing PA mixture.

It also became evident that a bitumen content as low as 3.9% is not acceptable in any case. Furthermore the results showed that the bitumen content should increase when the void content is increasing. In practice this might be a bit hard to achieve but it indicates that if high void contents are required for noise reducing purposes, application of fibers or use of a polymer modified binder might be necessary in order to allow higher binder contents to be applied.

It is noted that these observations are well in line with practical experience. However, until now no tools were available to quantify the effects. It is therefore believed that the models presented can be an important tool for authorities and contractors to assess the risks involved in adopting certain mixture compositions. This is an important issue in case of “design – build – maintain” contracts.

A Better forecasting of ravelling saves considerably in yearly budget of Dutch ministry of Transport and a better asphalt design avoids short lifespan and decreases maintenance costs. These goals can be nearly achieved using ANN models and the possibilities of ANN for development of an integral Maintenance planning system for Dutch highway Network are considerably high.

6. References